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An Empirical Analysis of External and Internal Factors Affecting Manufacturing Firm Failure and Resilience from 911 through COVID-19

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1. Introduction

Corporate failure is a common business and economic phenomenon that fluctuates over time, particularly during economic cycles. While bankruptcy is not completely synonymous with firm failure, bankruptcy and liquidation are the observable equivalents in available databases used in most empirical studies of business failure. Figure 1 illustrates the number of bankrupt and liquidated public firms in the Compustat database. We can see that the number of firm failures is affected by the business cycles with the peaks around the dot-com bubble crash (2000-2002), financial crisis (2007-2009), and Covid-19 pandemic (2020)[1]. Total number of bankrupt firms in the manufacturing industry is 193 while the total number of all bankrupt firms is 662. Rather than simply predicting firm failure, this study aims at exploring the effects of both internal and external factors on failure and survival of the U.S. manufacturing firms.

[Insert Figure 1 here]

The COVID-19 pandemic has heightened the focus on business resilience. In evaluating the resilience of firms after the 2008-9 financial crisis and in early 2020, McKinsey & Company (2020) found that firms that balance margins, growth, and optionality (i.e., pay fewer dividends, keep more cash reserves) were more resilient after the 2008 crisis than those that focus on maximizing total shareholder returns. However, based on current data, the impact of the great recession in 2008-9 on long-term unemployment in the US was worse than we have experienced as a result of COVID-19. The recovery of jobs in the COVID crisis has also been faster than in the 2001 economic downturn. Part of this difference is due to the ability of firms to utilize digital tools in their business models. The ability of many organizations to pivot to online operations has led to a softer impact from the pandemic so far. However, with new strains of the virus, supply chain disruptions, and inflationary pressures, the long-term impacts of COVID-19 on the economy, and especially on manufacturing firms remain to be seen.

More specifically, COVID-19 is a special situation compared to other economic downturns (Crick and Crick, 2020; Cortez and Johnston, 2020). Industry impacts have been uneven. The ability of some firms and sectors to pivot, particularly to online sales or distribution systems, or to remote work has softened the impact for professional services, financial services, and education. For some firms in the retail industry and some restaurants, online sales with home delivery alternatives have not only softened the downturn but led to higher sales. In addition, sales of home furnishings, appliances and other household items have increased as consumers spend less on travel and more on home consumption to remain productive at home offices and home schooling. Housing sales in suburban areas increased while urban real estate initially

[1] We identify firm failures by bankrupt and liquidated firms noted in the Compustat database. When Compustat stops updating information of firms, it provides the reason why those firms are delisted from the database.

tended to slump. While demand for many goods has recovered, supply chain issues and inflationary pressures may threaten manufacturing firms more severely. It is therefore important to separately examine how business cycles and COVID-19 have impacted manufacturing firms, which are differently impacted because of their financial structures, employee labor base, and the B2B nature of most of their operations compared to service and retail firms.

Federal support under the Cares Act and the American Rescue Plan, the Paycheck Protection Program, Restaurant Revitalization Fund, Shuttered Venue Operators Grants, and other programs have helped support businesses in some service sectors who were not able to switch to digital delivery or work-from home modalities immediately or at all, such as airline travel. The tourism and travel sectors were particularly hard hit. While the unemployment rate decreased to only 4.6% by October 2021, the lowest overall rate for decades, the leisure and hospitality sectors have now added back about 83% of all the jobs lost in March and April 2020. Unfortunately, perhaps as many as 200,000 small businesses simply closed their doors in 2020 when the pandemic hit. But in a testament to American resilience, the US Census Bureau is reporting a record number of business starts in 2021, a much higher rate than after the great recession[2]. Many manufacturing operations were deemed essential and were not subject to lockdowns. However, employee safety concerns and shifts in demand, as well as supply chain disruptions have impacted manufacturing firms. In addition, the capital intensive nature of many manufacturing operations, along with the related financial leverage may lead to cost-stickiness and higher risk of failure during demand downturns and liquidity shocks.

When businesses fail, it also places stress on the macro-economic environment and public sector. Government revenues from sales taxes, income taxes, and property taxes may decline dramatically when business failures are pervasive. This is particularly true when the downturn results from an unexpected external shock, such as the financial crisis of 2008-9, a natural disaster, or the current pandemic. In fact, business bankruptcies in the US more than doubled during the 2008-2010 period, compared to the previous three years. During periods of widespread economic stress, government policymakers deploy policies to stimulate economic growth, including lowering interest rates or initiating public infrastructure investment. In the current pandemic, in addition to lowering interest rates, policymakers have implemented forgivable loans to small businesses to reduce employment layoffs and prevent business failure and provided additional unemployment benefits to workers whose jobs have been interrupted. However, the length and magnitude of the impact of economic downturns and the ability of the economy to recover is not the same for all regions. There were wide disparities in recovery rates that states across the US experienced following the Great Recession, and top-quintile-performing states achieved roughly 30 percent more GDP than bottom-quintile performers after a decade of recovery from the 2008-9 recession (McKinsey & Company, 2020). Economies that performed better became more resilient through diversification and investment in innovation into growth industries.

[2] See https://www.census.gov/econ/bfs/methodology.html.

The negative impact of economic shocks is amplified by the fact that firms do not have adequate foresighted decision models to plan and prepare for such shocks (Amankhah-Amoah and Zhang, 2015). At the macroeconomic level, policymakers may not have an adequate understanding of how their policy actions and decisions will impact firms and affect the business management decisions. Existing predictive models of business failure and credit loss widely used by the banking industry do not provide foresighted decision support for management to help prevent such losses (Brainard, 1967). And most macroeconomic models do not integrate with robust predictions of how individual firms will respond to policy decisions.

This research addresses the research question: How do external and internal factors affect business failure? The answer of this question is expected to help address a more general question: How can firms improve their resilience to cope with economic shocks as well as on-going competitive pressures and changes? We contribute to the literature by not only examining business failure over a long period of time through a number of economic cycles, we deploy innovative machine learning modeling and incorporate unstructured data to gain a deeper understanding of the exogenous shocks firms encounter and how firms can effectively respond to them to survive.

The paper is organized as follows: the next section discusses the prior literature on business failure and resilience. This is followed by our theoretical framework and hypotheses. We then discuss the methodology including variable definitions and data collection. We then discuss the findings of our models, followed by discussion and conclusions.

2. Related literature

2.1 Business failure

Business failure has long been studied in the literature of management and business. Many studies use the traditional method of discriminant analysis (e.g., Beaver, 1966; Altman, 1968; Deakin, 1972; Altman, 1984) or logit/probit model (e.g., Ohlson, 1980; Zmijewski, 1984) to predict business failure/bankruptcy. Other studies use different methods like linear regression (e.g., Collins, 1980), rough set approach (e.g., Dimitras et al., 1999).

We examine both internal and external factors systematically to predict the U.S. manufacturing firms' failure. Several other studies in the literature also studied external (risk) factors (e.g., Everett & Watson, 1998), and (internal and external) perceived causes (e.g., Gaskill et al., 1993). Altman et al. (2019) discuss that three common causes of business failure are unexpected international competition, lack of technological innovation, and poorly executed strategic investing decisions. In addition to the traditional financial determinants of business failure, our study incorporates qualitative variables derived from text analysis of unstructured data, which is informed by the work of Mai et al. (2019).

Since the emergence of COVID-19, there have been a few studies to examine how firms are coping with the pandemic as well as the incidence of business failure during the pandemic. For example, Amankwah-Amoah et al. (2021) developed a theoretical model describing how firms must adjust to exogenous shocks as well as predictable changes in the business environment to avoid failure. Li et al. (2022) examined text from earnings calls to determine whether the vulnerability or exposure of the firm to COVID-19, as well as the firm response affected stock returns. Using word embedding, they developed dictionaries describing six exposure variables and four response variables from firm earnings calls to discuss the impact of COVID-19. They also included culture variables developed by Li et al. (2021) to determine whether culture had a significant impact on the firms' stock returns. They found that culture had a significant effect on the ability of firms to respond to COVID-19 related economic exposure to affect stock returns.

Our research builds on the prior literature by incorporating a number of traditional financial variables used in evaluating business solvency with additional variables derived from textual analysis in the 10K over an extended period of time. The goal of our research is to shed light on how firms can sustain their resilience throughout various types of unexpected economic events and natural disasters.

2.2 Business resilience

Numerous scholars have addressed the issue of business resilience from different perspectives. Annarelli and Nonino (2016) conducted a comprehensive review of articles between 1990 and 2014 and identified over a thousand articles addressing resilience in the management, engineering, and economics literature, with a steep increase in publications on the topic starting in 2006. Conz and Magnani (2020) conducted a systematic examination of articles published between 2000 and 2017 in the business and management literature, noting a significant increase in publications on the topic after the 2008-9 financial crisis.

From the *business strategy perspective*, a firm's resilience plays a vital role to help firms dealing with shocks and uncertainty. It helps firms to improve financial volatility, sales growth, and survival rates (Ortiz-de-Mandojana & Bansal, 2016). Note that firm's resilience is a dynamic process that firms absorb, adapt, and recover from shocks and uncertain environments (Conz & Magnani, 2020; Ortiz-de-Mandojana & Bansal, 2016). As an element of the firm's resilience, supply chain resilience also plays an important role for firms' development, particularly in the manufacturing industry. Ponomarov & Holcomb (2009) show that the greater the supply chain resilience, the greater the sustainable competitive advantage. Daniel et al. (2013) implies that quality control and quality feedback might be useful for a manufacturing firm's business strategy.

Shocks (e.g., natural disasters) can cause a more severe disruption of the supply chain than only the direct effects (Inoue & Todo, 2019; Xie et al., 2018). Xie et al. (2018) find that dynamic resilience could have reduced business disruption resulting from the Wenchuan earthquake by 47.4% during 2008–2011 and could have shortened the recovery period by one year. There is apparently agreement in the literature in business and management that firm's and supply chain resilience and adaptive policies are the keys for firms to deal with shocks (Boin & van Eeten, 2013; Koronis & Ponis, 2018). Unfortunately, these two key terms have broad meaning and differing interpretations in the literature. Moreover, most of the previous studies examine the firm's and supply chain resilience by qualitative methods with ordinary reasoning, and a few empirical studies with static results (i.e., there are no learning processes). Our paper provides a data-driven approach and machine learning techniques to help managers and firms understand business failure.

From the *economic perspective*, numerous scholars have reviewed how firms respond to various types of shocks such as supply shock (Fasani & Rossi, 2018), demand shock (Wen, 2006; Kee & Krishna, 2008; Leduc & Liu, 2016), both supply and demand shock (Guerrieri et al., 2020; Hassan et al., 2020; del Rio-Chanona et al., 2020), and policy shock (Kang et al., 2014; Basu & Bundick, 2017; Baker et al., 2016). Demand-side shocks can generate realistic business cycles (Wen, 2006) and can affect firms differently depending on their age. In some contexts, there is a relationship between supply and demand shocks. For example, Guerrieri et al., (2020) show that, in the COVID-19 pandemic, Keynesian supply shocks can happen: supply shocks that trigger changes in aggregate demand may be larger than the shocks themselves. Moreover, Hassan et al. (2020) show that in the COVID-19 pandemic, firms' primary concerns relate to the collapse of demand, increased uncertainty, and disruption in supply chains.

In regard to policy shocks, Kang et al. (2014) show that economic policy uncertainty (shocks) in interaction with firm-level uncertainty depresses firms' investment decisions. Specifically, the policy uncertainty causes significant declines in output, consumption, investment, and employment (Basu & Bundick, 2017; Baker et al., 2016). Firm's strategies respond to regulatory uncertainty by participating in policy making and increasing strategic flexibility (Engau & Hoffmann, 2009; Shaffer, 1995). These economic studies, however, are not based on the learning processes of the current data. Learning policy is important since shocks and uncertainty change over time.

3. Theoretical framework and hypotheses

3.1 Theoretical framework

The goal of this research is to extend the prior literature on business failure and resilience, to operationalize the integrated business failure framework of Mellahi and Wilkinson (2004) which was further refined by Amankwah-Amoah et al. (2021), shown in Figure 2. According to this framework there are two levels (or sources of factors) that affect business failure which are exogenous and endogenous levels. In our study, we define exogenous level as external factors and endogenous level as internal factors.

Business resilience involves both taking advantage of unexpected opportunities and mitigating the damage from new threats. Firms may need to modify their business models by engaging differently with customers and suppliers, realigning their workforce, accelerating their digital capabilities, and optimizing their asset base through divestitures or acquisitions. Financial structures may also need to be modified as credit markets change and public sector relief resources and incentives are implemented. The magnitude and cross-sectoral impact of significant economic downturns and disasters make it challenging for firms to survive and for policymakers to navigate through crises. Individual firms are in dire need of guidance on how to make timely decisions to survive the crisis and foresighted decisions to thrive after the crisis (Altman & Hotchkiss, 2010).

Motivated by Amankwah-Amoah et al. (2021)'s framework we propose our modified business failure framework (Figure 3) for discussing various strategies and hypotheses that may influence a firm's ability to survive or that lead to failure.

3.1.1. A dynamic model of business survival and failure

Our model begins with a firm operating at a steady state with a set of resources and capabilities comprised of physical assets and human competencies that have been acquired using various capital resources. To evaluate the firm's success, failure, and resilience, it is important to examine the nature of the assets and resources available to the firm.

Our model uses these initial firm states, and then examines the impact of external shocks, and firm responses and actions to predict the firm outcome of failure or survival. Our model consists of the following elements.

- firm states, a collection of information that represents the status of the firm, such as human resources (e.g., number of employees), financial resources and capital (e.g., various working capital, inventory, asset and debt and equity levels), as well as prior financial performance experience (e.g., ROA, EBITAT, Tobin's Q, and sales growth);
- external shocks, including both disasters and changes in market conditions, supply and demand shocks, distresses, etc;
- firm actions, both tactical and strategic, such as expenditures, investments or divestitures, or financing adjustments which are derived from quantitative disclosures from cash flow and income statements (e.g., advertising, R&D, capital expenditure, acquisition, investing, sell stock, purchase stock, and borrow), and firm actions and responses extracted from rhetoric in firm disclosures using textual analysis (e.g., community engagement, cost-cutting, digital transformation, new product development);
- firm outcomes (i.e., failure or survival).

3.2 Hypotheses

3.2.1. The Firm's initial state – firm resources, capabilities, and capital structure

The firm's initial state reflects the industry it operates in, and the assets and resources it has to pay obligations and to generate profits for owners. Traditional economic theory ties firm productivity to the optimal combination of labor and capital. As summarized by Mellahi and Wilkinson (2004), organizational engineering scholars have identified four factors or characteristics that influence the success or failure of organizations. Two of these factors are related to industry characteristics – population density (Delacroix et al. 1989; Hannan and Freeman 1988; Hannan et al. 1991; Peterson and Koput 1991), and industry life cycle (Agarwal et al. 2002; Balderston 1972). A third factor is organization size (Barnett and Amburgey 1990; Hambrick and D'Aveni 1988; Wholey et al. 1992). The fourth factor noted is organization age (Baron et al. 1994; Bruderl and Schussler 1990; Fichman and Levinthal 1991; Levinthal 1991; Stinchcombe 1965), which is somewhat endogenous to the model as the age of the firm might be seen more as a result of survival rather than a determinant of failure.

Resources on the balance sheet – To evaluate the firm's success, failure, and resilience, it is important to examine the size and nature of the assets and resources available to the firm. Prior research suggests that firm size may positively impact survival (Freeman et al. 1983; Hannan and Freeman 1984; Sutton 1997), since larger firms can attract greater financial resources as well as human capital, and can benefit from stakeholder legitimacy and market share advantages. This leads to our first set of formal hypotheses.

H1a: Long term assets such as property, plant and equipment have a positive correlation with firm survival.

H1b: Cash has a positive correlation with firm survival.

H1c: Higher working capital has a positive correlation on firm survival.

H1d: Inventory has a positive correlation on firm survival.

H1e: Intangible assets including goodwill have a positive correlation on firm survival.

Productive resources not on the balance sheet – One of the more challenging aspects of examining firm performance and resilience is incorporating the impact of resources that are not typically recorded in the financial statements. A common saying goes "the most important assets of the firm walk out the door at 5:00 o'clock"; employees provide an important productive resource. While having too many employees might indicate an inefficient cost structure, the proportion of unionized employees in the US has decreased over time, and current labor shortages are a bigger problem in the manufacturing industry than over-employment. Therefore we assume that employees provide a significant earning resource for the firm and that firms with higher employee levels, reflecting the firm's ability to attract talent, will have a higher likelihood of survival.

H2: Employment levels will have a positive correlation on firm survival.

Sources of capital resources - Firms have the opportunity to regulate their sources of capital. While private firms may have limited opportunities for access to capital markets there are many other sources of equity available to private firms. For public firms the optimal ratio of debt to equity financing has been the subject of business and financial experts for decades. With regard to financial risk, high financial leverage and low liquidity can cause business failures when interest rates rise or there are funding shocks as in 2008-9. Amankwah-Amoah and Zhang (2015) describe three cases in the airline services industry in which over extension of debt from acquisitions led to business failure. Occasionally unexpected liabilities can arise from litigation or environmental events, which may lead to filing for bankruptcy (for example Remington Outdoor Company). We therefore propose that high degrees of leverage will be detrimental to firm survival.

H3: Higher levels of debt will decrease firm survival.

H3a: Higher levels of interest expense will decrease firm survival.

As previously noted, McKinsey found that during the 2008-9 crisis firms with higher levels of retained earnings were more resilient. While there may be some debate about the return of capital to investors in the form of dividends, firms with growth potential are likely to be able to retain earnings in the firm. This may result in more financial flexibility in times of economic stress.

H4: Higher levels of retained earnings will increase firm survival.

3.2.2. The Exogenous environment

While firms can control their internal resources, they cannot easily control the external environment. While the general economic and industry environment may normally be easily anticipated, our model assumes that there may be unexpected exogenous shocks which may cause the firm to fail or to which the firm will need to react to survive.

General and industry environment. As previously noted, industry density and competition have been found to have a significant impact on firm success or failure. The competitive landscape of the firm must be carefully considered from the beginning and on an on-going basis. The firm must examine their products, services, customers, and channels that strategic business units derive revenue from. Decision making and risk management in a competitive business environment is complex. Firms strive to maximize their profits and revenues, but many factors may contribute to business failure. With regard to business operations, poor operating performance may result from new channels of competition within an industry, commodity price shocks, over capacity, or poorly executed acquisitions. Lack of technical innovation can threaten the survival of firms with less competitive technologies. Deregulation of key industries can also result in unexpected competition. The general level of competition in an industry is commonly measured using the market size of the firm in relation to their competitors. The Herfindahl-Hirschmann index is a common measure of market concentration and is used to measure industry competition.

In their recent book on financial distress, Altman and his coauthors discuss the common causes of business failure (Altman et al. 2019). For example, unexpected international competition, or loss of regulatory protection from competition, may lead to business failure. Lack of technological innovation can result in the firm being less competitive in the marketplace, either in product offerings, sales and distribution options as well as operational efficiency and cost. Poorly executed strategic investing decisions, such as acquisitions that are not well integrated can also lead to business failure. We therefore propose that industry competition may lead to firm failure.

H5: Competition in an industry will have a negative impact on firm survival.

Disasters. One of the most obvious negative external events that could lead to firm failure are natural disasters. Natural disasters could come from weather events such as hurricanes or flooding, from geological events such as earthquakes and volcanic eruptions, or from the combination of climate change and other factors such as has been recently observed, such as the increase of wildfires across the US. Such natural disasters can destroy productive assets or they may affect the supply or distribution channels of the company, or even the ability of customers to purchase the firm's products. Firms that have adequate hazard insurance may be able to recover quickly, however there typically will be at least a short term disruption of the company's business activities.

In today's interconnected world, distress and disruption caused by natural or anthropogenic disasters (e.g., hurricanes, COVID-19) have increasingly strong impacts on the nation's economy. One crisis may propagate through society and result in destruction of public infrastructure, degradation of public health and workforce, strain of public health resources, and economic downturn. While some businesses may prosper during a crisis, many others may fail if they are unable to quickly react to the changing environment. The COVID-19 pandemic has dramatically shown that business resilience involves both taking advantage of unexpected opportunities and mitigating the damage from new threats.

When disasters occur, firms may need to modify their business models by engaging differently with customers and suppliers, realigning their workforce, accelerating their digital capabilities, and optimizing their asset base through divestitures or acquisitions. Financial structures may also need to be modified as credit markets change and public sector relief resources and incentives are implemented. The magnitude and cross-sectoral impact of significant economic downturns and disasters make it challenging for firms to survive and for policymakers to navigate through crises. At the micro level, individual firms are in dire need of guidance on how to make timely decisions to survive the crisis and foresighted decisions to thrive after the crisis (Altman and Hotchkiss, 2010).

It is expected that external shocks will have a negative impact on the firm's survival. Although for firms that survive the immediate shock, the process of creative destruction may have a positive impact on the firm's survival in subsequent years. Therefore our hypothesis is stated as

H6a: The occurrence of natural disasters will be negatively correlated with the firm's ability to survive.

Another common external shock that can be detrimental to the firm's survival is a significant change in the level of competition. This increased competition could come from foreign sources or from product improvements that competitors used to gain market share. Alternatively the exit of competitors from the market may result in an advantage to the remaining firms. We assume that increased competition will result in a higher likelihood of firm failure.

H6b: An increase in the firm's competitive environment will be negatively correlated with firm survival.

Firm survival may also be threatened by changes in the general and industry environment. Beyond general competitive pressure, firms may experience a dramatic downturn in demand caused by regulatory changes, negative reputational issues, or the inability of customers to access the firm's products. Exogenous factors can also appear in the form of a liquidity crisis such as was a common problem in the 2008 financial crisis. Exogenous shocks from employee related factors may occur when there are labor strikes, layoffs, or employee fear of health impacts as were countered during the COVID-19 crisis. Other exogenous shocks may come from operational shocks such as the suspension of business operations during the COVID-19 pandemic or from supply chain disruptions.

H6c: Exogenous demand shocks are negatively correlated with firm survival.

H6d: Exogenous liquidity shocks are negatively correlated with firm survival.

H6e: Exogenous employee related shocks are negatively correlated with firm survival.

H6f: Exogenous disruption of business operations and supply chains are negatively correlated with firm survival.

3.2.3. Firm actions and responses (strategic and tactical responses)

When an unexpected event occurs, management will need to respond appropriately. Intelligent enterprise risk management (ERM) planning can identify many potential business risks allowing foresighted business decisions to avoid or mitigate many risks that could threaten the entity's survival through business continuity plans, insurance or hedging activities. To survive or recover from an economic downturn, firms may take a number of approaches, including finding new sales channels or customers, accelerating digital capabilities, adjusting their cost structure, and optimizing assets and increasing liquidity. However, most managers are subject to availability bias (Tversky and Kahnamann, 1973) and place too much focus on recent experience, rather than implementing processes that would alert them to changes in the business cycle and systems that would provide resilience for the firm to withstand economic shocks. For example, while a pandemic was predicted by many experts, most leaders in both the public and private sectors did not prepare for COVID-19.

While many service organizations were able to switch to remote work formats, manufacturers were not often able to do this. Health concerns, supply chain issues, and current labor shortages in some sectors have resulted in some firms reconsidering their hiring requirements, and weighing the tradeoffs between formal education and on-the-job training. For manufacturing, construction, and retail firms that deal with physical products, one of the most difficult operational challenges recently has been addressing supply chain bottlenecks. While just-in-time manufacturing and low buffer inventories have been advocated for the past 3 decades, we now see that disruptions of the supply chain can lead to serious work stoppages and revenue losses in many industries. Diversification of the supply chain will become an increasingly important response going forward, particularly for critical components, and firms will need to seriously consider the tradeoffs between sourcing locally, from a cheaper foreign source, or storing larger inventories in case of logistical disruptions. Another response may be in-sourcing previously out-sourced components, or redesigning products to mitigate component shortages.

As exogenous shocks are encountered, it is incumbent on management to recognize these external forces and identify sources of misalignment and take corrective action. These corrective actions can be either strategic or tactical. For example, management may respond to a downturn in demand tactically by increasing advertising, or more strategically by increasing research and development for new products that may be more attractive to the market. Another strategic response to a demand downturn may be to divest the underperforming division. When productive capacity is destroyed by a disaster, we would expect to see capital expenditures to rebuild the plant and equipment destroyed. Supply chain disruptions may be addressed by an acquisition to secure the components needed. A liquidity crisis may be addressed by the infusion of equity or securing longer term borrowings. These management responses can be ascertained through changes in the financial statements of the firm, particularly in the cash flow and income statements. Our hypothesized relationships between these actions and firm survival are as follows.

H7a: An increase in advertising will be positively correlated with firm survival.

H7b: An increase in capital expenditures will be positively correlated with firm survival.

H7c: An increase in research and development will be positively correlated with firm survival.

H7d: An acquisition will be positively correlated with firm survival.

H7e: An equity infusion will be positively correlated with firm survival.

H7f: An increase in long term borrowings will be positively correlated with firm survival.

Management responses to exogenous events may also be ascertained from the rhetoric that management describes in their financial disclosures. For example when the business suffers a downturn in demand due to a natural disaster or to reputational risks or other regulatory events they may engage in increased community dialogue to reassure customers and investors, to counter bad publicity, and to garner public support for their operations. On a tactical level, firms that experience shocks resulting in a downturn in demand will often undergo cost-cutting initiatives which may be described by management in their reports. More strategic response to business distress and demand downturns may involve new product development which may be discussed by management. As we saw during the pandemic, a common response to lockdowns was the pivot to digital operations for sales as well as employee work for financial service industries.

H8a: Cost cutting responses are positively correlated with firm survival.

H8b: Community engagement responses are positively correlated with firm survival.

H8c: Digital transformations are positively correlated with firm survival.

H8d: New product development responses are positively correlated with firm survival.

3.2.4. Interactions between exogenous shocks and firm responses and firm survival

Because we wish to examine the systemic and long-term nature of business survival, we also will examine the interactions between the original state of the firm, the exogenous shocks they encounter, and the effectiveness of responses to ensure firm survival. Our model and figure 3 illustrates these relationships by feedback loops between firm states, exogenous shocks, firm responses, and the survival or failure outcome of the firm. For example, we assume that liquidity shocks coupled with equity infusions will mitigate firm failure. For brevity, we do not detail hypotheses for all possible interactions between the exogenous shocks and firm responses described above, but we do test them in our models.

3.2.5. The resulting state, resource outcomes and firm performance.

The outcome of management's responses to external events may be measured in the firm's failure or survival. Intermediate signals about the effectiveness of management's response may be observed in the periodically measured financial performance in the income statement, sales growth and net income, cash flows, share prices, and other performance measures. If management's decisions and responses were not successful the company may experience financial failure and cease to exist.

4. Methods, Variables, and Data

4.1 Method

In order to study business failure and resilience, we use both traditional and machine learning techniques. We employ the classic logistic regression model to fit the data. The logistic model (or the logit model) is a linear binomial classification method that can be used to model the probability of business failure, modeled as a binary dependent variable of 0 (survival) and 1 (failure). After obtaining the logistic model, we will use the model to study how a variety of factors influence business failure.

4.2 Data

4.2.1. Data sources

Because we are modeling a complex economic phenomenon over a long period of time, our study draws data from a variety of sources. The data are obtained from SEC filings on the EDGAR database and Compustat from US public companies from 1996 to 2021. We match the records from different sources using firm CIK numbers and years. Since a firm may not have records in all three data sources for the required variables, after merging the data sources, we obtain 457 bankrupt firm-year observations and 135,037 non-bankrupt firm-year observations.

In this study, we focus specifically on U.S. manufacturing firms. Manufacturing firms represent a broad cross section of firm sizes across the U.S. and allow us to identify a complete set of variables relating to factors affecting firm failure. In particular, manufacturing firms usually have inventory, debt, and employment data, providing the best data set for examining the issue of firm resilience. Therefore, manufacturing firms are the best universe for our model. In the data set, we have 145 bankrupt manufacturing firm-year observations and 52,796 non-bankrupt manufacturing firm-year observations.

Furthermore, we remove some outliers (e.g., firms with negative sales and less than 5 employees), resulting in 122 bankrupt manufacturing firm-year observations and 48,411 non-bankrupt manufacturing firm-year observations. There are many missing values in the data set which result in elimination of firm year data. After elimination of missing values, we have 70 bankrupt firm-year observations and 11,548 non-bankrupt firm-year observations.

4.3 Variables

4.3.1. State variables

As previously discussed, our state variables mirror the traditional production function of labor and capital. We start with traditional quantitative operational accounting resources measurements including working capital, cash, retained earnings, and inventory as well as debt levels. Each of these variables is scaled in relation to asset size or sales depending on the most relevant scale level. To reflect non-accounting resources we have included in our state variables the number of employees scaled by assets. Finally we include prior year performance variables for return on assets, pretax return on assets, market value and sales growth (*ROA*, *EBITAT*, *Tobin's Q* and *sales growth).*

Our first exogenous variables are control variables typically used in academic accounting research (e.g., Kubick et al. 2015; Cen et al. 2018). Specifically, we reflect the marketing environment by calculating the Herfindahl-Hirschman Index (HHI) for each firm year. Market conditions and competition include HHI to measure industry concentration/competition within the 3 factor subindustry code (i.e., three-digit SIC code). Structured market strategy variables from firm 10K data include advertising and R&D.

Exogenous shock variables are measured in two categories. The first category are business shocks categorized into six events that may affect businesses in an economic downturn or other unexpected event. These include disruption in business operations, demand disruptions, layoffs of employees, liquidity shocks, lockdowns, and supply chain shocks. These variables are derived from the 10K text analysis using dictionaries drawn from Li et al. (2021). We defined each item as 1 if the rank of the word counts of the six exposures are above the sample means, and 0 otherwise.

We also measure shocks from natural disasters. These were derived using the Form 10-Ks text analysis and a word count dictionary of specific disaster related words such as flood, fire, storm, hurricane, etc. With regard to natural disasters, we used terminologies from several sources such as the National Oceanic and Atmospheric Administration (NOAA) database and Emergency Events Database (EM-DAT) to construct a dictionary of natural disasters. Thus, we count the number of words in Form 10-Ks related to this natural disaster word dictionary. The complete word list is reported in Appendix B1.

4.3.2. Action variables (firm responses)

To measure firm responses to economic shocks, we first drew quantitative variables from the financial statements. To reflect short term responses we include increasing advertising expenditures and research and development. For longer term responses we included capital expenditures, acquisition spending, investing, and sales of property plant and equipment, sales of stock, purchases of stock, borrowing, and repayment.

To qualitatively measure firm responses and actions, we drew from six exposure variables and four response variables created by Li et al. (2021). Using their word dictionary, we created word counts of the four responses from the Form 10-Ks: community engagement, cost cutting, digital transformation, and new product development. We defined each item as 1 if the rank of the word counts of the four responses are above the sample means, and 0 otherwise.

Appendix A defines the detailed measurement and variables names we used to operationalize our theoretical model. Our key variable is *business failure*, defined by the code of reason for a firm being deleted in Compustat. We defined *failure* as a binary variable equal 1 when the code is either 02 for bankruptcy or 03 for liquidation, and 0 otherwise. This means firms that were deleted from Compustat due to acquisition, merger, leveraged buyout or other non-failure reasons are not considered business failures. As previously described, the state variables include a firm's financial (resources) characteristics variables (Appendix A1), and firm financial performance and its lags (Appendix A2). Exogenous shock variables are measured from text analysis using Form 10-Ks (Appendix A3), and firm response variables are from Form 10-Ks text analysis dictionaries developed by Li et al. (2021) (Appendix A4). Natural disasters are measured from text analysis using word counts of terms derived from NOAA disaster reports, while industry competition exogenous shocks are measured using the 3 factor HHI calculation (Appendix A5). Additional firm actions/response variables are deduced from quantitative financial statement data – long-term investing and financing conditions and strategies (Appendix A6), and firm action/response variables – short-term advertising and R&D (Appendix A7).

4.4. Summary Statistics

Table 1 shows the summary statistics of all variables for the main logistic model in this study.

[Insert Table 1 here]

5. Results

Our analysis first involves developing the best predictive model, then exploring elements within the model to obtain useful information and insights about the exposures and responses that may avoid or lead to firm failure.

5.1 Exploratory Data Analysis

Before fitting the model, we perform some exploratory data analysis. The total number of independent variables is 55. As a first step, we look at the Spearman correlation between these variables. The correlation matrix is illustrated as the heatmap in Figure 4. The color yellow indicates high correlation.

We can see that there are some highly correlated independent variables, particularly those financial statement variables that are related to accounting definitions (e.g., retained earnings/assets (*reat)* and retained earnings/current liabilities (*relct*)). Therefore, it is important to remove some independent variables to reduce the correlation.

[Insert Figure 5 here]

We determine which variables to remove by looking at the dendrogram, which clusters the highly correlated features (see Figure 5). The dendrogram illustrates how each cluster is composed by drawing a U-shaped link between a non-singleton cluster and its children. The top of the U-link indicates a cluster merge. The two legs of the U-link indicate which clusters were merged. The length of the two legs of the U-link represents the distance between the child clusters. The shorter the length, the higher correlation between the child clusters. For example, *reat* and *relct* (retained earning to total assets and retained earnings to current liabilities), and *EM_exposure* and *LD_exposure* (lock down exposure and employee exposure) are the two most correlated pairs, while *invtsale* and *indsppe* (inventories to sales and the indicator of sale of property plant and equipment) are among the least correlated.

The dendrogram gives us a natural clustering of the independent variables into firm characteristic and performance variables (in green and red), exposure and response textual variables (in turquoise), and qualitative action variables (in purple). The dendrogram will serve as a guideline when we remove the independent variables later. We can choose one or several variables from each cluster and still adequately represent all the variables in the cluster.

5.2 Balanced Logistic Regression and Classic Logistic Regression

We use the logistic model to fit the data. The accuracy is the classic criterion to evaluate how well the model fits the data. However, our data set is highly imbalanced (i.e., 70 failed and 11,548 non-failed firm-year observations). A more appropriate criterion is the balanced accuracy, defined as the average of the true positive rate (i.e, percentage of correctly predicted bankrupt observations) and the true negative rate (i.e., percentage of correctly predicted non-bankrupt observations). For example, if we had a model that simply outputs surviving firms regardless of the independent variables, we would have an accuracy of 11,548/(70+11,548), which is almost 100%, while the balanced accuracy is close to (0%+100%)/2 = 50%. Therefore, the balanced accuracy is a more appropriate performance criterion for our imbalanced data set.

[Insert Exhibit 1 and Exhibit 2 here]

To maximize the balanced accuracy, we employ *balanced logistic regression*, which assigns different weights to failed and surviving observations that are inversely proportional to their percentages in the data. In our case, the weight of failure observations is about 160 times that of surviving observations.

Although the balanced accuracy is more appropriate, it may be difficult to calculate the p-values of the coefficients under this criterion. Since p-values are important metrics for our analysis of exposures and responses that follows, we will also use classic logistic regression (i.e., equal weights on all the observations).

In the rest of this study, all the results on p-values are obtained from classic logistic regression, and all the other results (e.g., permutation importance of independent variables, partial dependence of bankruptcy on independent variables) are obtained from balanced logistic regression.

5.3 Model (Balanced) Accuracy

We fit the balanced logistic model and the classic model. We first present detailed performance measures in the form of the confusion matrix, which tells us how many failed and surviving observations are predicted correctly.

As we can expect, the classic logistic model tends to predict survival (i.e., 62 of the failed firm observations were classified as surviving). By putting much higher weights on the rare failure observations, the balanced logistic model is very accurate in predicting failure observations (69 out of 70).

Finally, the balanced accuracy of balanced logistic regression is 95.9%, while that of the classic logistic regression is 56.0%.

5.4 Reducing correlated independent variables

As discussed before, we would like to remove highly correlated independent variables. We determine which variables to remove based on the dendrogram in Figure 5. We gradually decrease the number of remaining variables until the balanced accuracy drops significantly.

First, we select the following 45 features:

- 'hhi', 'BO_exposure', 'CE_response', 'CC_response', 'DM_exposure', 'DT_response', 'EM_exposure', 'LQ_exposure', 'NP_response', 'SC_exposure', 'disaster', 'roa', 'Q', 'salegrowth', 'roalag1', 'salegrowthlag1', 'actlct', 'cheat', 'chlct', 'invtsale', 'xintsale', 'logat', 'reat', 'seqat', 'atemp', 'indinvt', 'indcapx', 'indaqc', 'inddvc', 'indxad', 'indxrd', 'indxint', 'indivch', 'indsiv', 'indsstk', 'indprstkc', 'indsppe', 'indsppiv', 'indivaco', 'inddltis', 'inddltr', 'indfiao', 'gdpgrowth', 'inflation', 'interestrate'

The balanced accuracy with these 45 features is 95.3%.

Then we select the following 34 features:

- 'hhi', 'BO_exposure', 'CE_response', 'DM_exposure', 'DT_response', 'EM_exposure', 'LQ_exposure', 'NP_response', 'disaster', 'roa', 'Q', 'salegrowth', 'salegrowthlag1', 'actlct', 'invtsale', 'xintsale', 'logat', 'atemp', 'indinvt', 'indaqc', 'inddvc', 'indxad', 'indxrd', 'indxint', 'indivch', 'indsstk', 'indprstkc', 'indsppe', 'indsppiv', 'indivaco', 'inddltis', 'indfiao', 'gdpgrowth', 'inflation'

The balanced accuracy with these 34 features is 94.3%.

Finally, we select the following 14 features:

- 'hhi', 'BO_exposure', 'CE_response', 'EM_exposure', 'disaster', 'roa', 'Q', 'actlct', 'invtsale', 'xintsale', 'indinvt', 'indxint', 'indivch', 'indsppiv'

The balanced accuracy with these 14 features is 88.8%.

In summary, there is a significant drop in accuracy when we have only 15 features. With 34 or 45 carefully selected variables, the accuracy is almost the same as the one with all the variables.

5.5 Permutation importance of independent variables

Here we use *permutation importance*, a commonly-used concept in machine learning, to evaluate the importance of independent variables. Permutation importance is defined as the decrease in classification accuracy when one variable is randomly permuted across all the observations while the other variables are kept the same.

We will look at permutation importance under the reduced balanced logistic models (with 45 and 34 variables, respectively). Permutation importance under reduced models is more accurate. This is because two highly correlated variables may be important collectively. But when evaluated separately, each one of them has reduced importance. By using only one variable from these two correlated, the importance of the variable reflects its true importance more accurately.

Figure 6 and Figure 7 show the permutation importance of all the variables in the 45-variable model and the 34-variable model, respectively. For each variable, the box plot shows the median of the importance (the orange line), the first and the third quartiles (the box), 1.5 times the interquartile range (IQR) beyond the third quantiles (the whiskers extending from the box), and the outliers (the circles).

First, comparing Figure 6 and Figure 7, we can see that some variables that were not important in the 45-variable model become important in the 34-variable model. One example of such variables is the demand exposure (*DM_exposure*). This is because we remove two variables, namely the supply chain exposure (*SC_exposure*) and the cross cutting response (*CC_response*), from the 45-variable model to the 34-variable model. Intuitively, these two variables are very correlated to the demand exposure, which can be also seen from the dendrogram in Figure 5 (i.e., three three variables are very close in the x-axis). This suggests that these three response variables are collectively important. But when they are all in the model, the individual importance is reduced. Once we keep only one of these correlated variables, the importance of the selected variable emerges in the reduced model.

Next, we can see that there are some variables that are important for both models (e.g., earnings before interest and taxes on assets (*ebitat*) and the prior year EBITAT (*ebitatlag1*)). In general, the graph in Figure 7 on the 34-variable model identifies the important variables better.

[Insert Figure 6 and Figure 7 here]

Figure 7 implies that demand exposure is most important, followed by the prior year earnings before interest and taxes on assets, then log of total sales, then log of total assets, then retained earnings to current liabilities ratio, each with a feature importance greater than .10.

5.6 Statistical significance based on p-values

Table 2 shows the coefficients and direct effects of all variables on business failure. We can see significant relationships are found for new products (*NP_response*), *(EBITAT)*, Tobin's Q (*Q*), current ratio (*actlct*), cash to assets ratio (*chat*), cash over current liabilities (*chlct*), retained earnings on total assets (*reat*), total debt to total assets (*dtat)*, and interest rates, with p-values below 0.05.

[Insert Table 2 here]

5.7 Exogenous shocks and firm responses

Natural disasters and firm responses

In order to measure the effectiveness of firm responses to the natural disasters, we employ logistic regression to examine the interactions between disasters and each of the firms' action/response variables. The results are shown in Table 3.

[Insert Table 3 here]

The interaction of disaster and response from the financial statements shows little significance for the financial variables. However, from the last four rows of the table, we can see that when there is a disaster, responding with community engagement (CE_response), cost cutting (CC_response), digital transformation (DT_response), and new product development will increase the firm's survival. While the latter three responses may be more difficult to implement, the results show the importance of an effective communication plan on the part of firm leadership when disasters occur.

Exposure shocks and firm responses

The interactions between the six text variable exposure shocks (disrupted business operations, decreased demand, employee disruptions, liquidity shocks, lockdowns, and supply chain disruptions) and firm responses measured by text analysis (community engagement, cost-cutting, digital transformation and new products) are shown in Table 4.

[Insert Table 4 here]

An examination of the results shows significant impacts from the interaction between employment related exposure and all four response variables, indicating that when an employment related exposure occurs, management's response can make a significant impact on the outcome of business failure or survival. Similarly, we see significant interactions between lockdown exposure and cost-cutting and new product development. Liquidity shocks and digital transformation also show significance but not for digital transformation.

6. Discussion

In this paper we have analyzed business failure of US public manufacturing firms in detail for a period of over 20 years, including the economic downturn in the early 2000s, continuing through The Great Recession, and on through the current economic challenges created by the COVID-19 pandemic. Our analysis employs both machine learning techniques and traditional logistic regression. Unlike prior bankruptcy studies that simply focused on predicting bankruptcy, our analysis first develops an accurate model, and then analyzes the specific factors relating to business survival or failure in detail. We also deploy innovative text variable measurement techniques from unstructured data to analyze business exposures and management responses derived from rhetoric included in firms' 10-K management's discussion and analysis. Our analysis also includes interactions between exposures including natural disasters as well as other economic shocks and potential management responses to those events.

Our logistic regression models identify the most important variables in predicting business survival or failure. These include new product development, pretax earnings ratios, firm market value, current ratios, cash ratios, retained earnings ratios, and interest rates. Cost-cutting and firm market value, current ratio, cash ratio, and retained earnings to liabilities were also found to be important factors in predicting business failure using the balanced machine learning models, which had about 95% accuracy in predicting business failure.

When examining the relationships between exposures and management responses, our models show that community engagement, cost cutting, digital transformation, and new product development are all effective responses to ensure firm survival in times of disasters. With regard to the impact of other exposures and response combinations on business survival, we find that when employment related exposures occur, management's responses of community engagement, cost cutting, digital transformation, and new product development can all be significant factors in ensuring firm survival. Now that most businesses are back in operation, a significant challenge that manufacturers seem to be facing are supply chain disruptions. Unfortunately, our analysis did not find any response to supply chain exposure that affected business survival.

The application of machine learning to incorporate unstructured data into accounting research is an important development and growing field of research. Examining business survival in times of economic stress using a variety of data sources and analysis methods contributes to a better understanding of how management can better plan for a variety of risks. The fact that there have been three significant national economic downturns in the past 20 years, not including numerous more localized natural disasters, shows that improving firm resilience to withstand economic shocks can have an important long-term societal impact and could benefit the economic competitiveness and quality of life of communities across the U.S. Our study leverages the power of machine learning to create more informative decision making models that may be useful in future crises.

While much attention has been focused on how consumer service organizations coped during the pandemic, less focus has been given to manufacturing and B2B businesses. Due to strong consumer demand for physical products most manufacturers did not experience the demand shocks that service firms did. Furthermore, many manufacturers were considered essential and not subject to government mandated lockdowns. However, manufacturers were concerned about worker safety and many firms had to spend significant amounts to protect workers from exposure. Many workers with health concerns retired or changed to jobs that could be performed remotely. Labor shortages remain one of the current challenges that manufacturers face. One of the most important lessons learned from the pandemic is the need for on-going training in the workforce, as well as flexibility in terms of hours and venues of work. Current labor shortages in some sectors have resulted in some firms reconsidering their hiring requirements, and weighing the tradeoffs between formal education and on-the-job training.

For manufacturing, construction, and retail firms making or distributing physical products, one of the most difficult operational challenges recently has been addressing supply chain bottlenecks. While just-in-time manufacturing and low buffer inventories have been advocated for the past 3 decades, we now see that disruptions of the supply chain can lead to serious work stoppages and revenue losses in many industries. Diversification of the supply chain will become increasingly important going forward, particularly for critical components, and firms will need to seriously consider the tradeoffs between sourcing locally, from a cheaper foreign source, or storing larger inventories in case of logistical disruptions. Our analysis shows that the most effective response to supply disruptions is new product development.

Finally, firms will have to reconsider their financing strategy going forward. Low interest rates over many years have allowed firms to take on greater amounts of debt at low cost. However, increases in interest rates may mean that firms will need to rethink their financing strategies. Our analysis shows that debt service costs can play a significant role in firm failure. In future down cycles, there may not be government stimulus funding or financing in every sector. In that case, firms that want to survive may need to maintain a greater cushion of cash reserves to survive business cycles. That said, investment in new technology and equipment may be needed to meet the challenges of supply chain in-sourcing and to meet new competition, and financing for these investments must be adequately planned. While stock buybacks were common over the past five years, many firms may need to retain earnings to keep a higher level of cash reserves on hand. Investor relations personnel will need to make the case for these reserves, accepting that extra cash may reduce current profits and ROA but may ensure against failure risk during economic downturns.

7. Conclusions

The perennial question of how firms can improve their resilience to survive significant economic shocks as well as on-going competitive pressures and challenges is a key issue that deserves on-going attention. We examine how firms can better address this question using a variety of structured and unstructured data and machine learning analysis. Using non-traditional data sources and innovative analysis techniques, the goal of this research is to develop a better understanding of how to create more resilient businesses and economies using better business planning and forecasting to withstand severe and unanticipated economic stress.

Using machine learning, we can predict almost 95% of business failures. By using machine learning and more traditional data analysis tools, we also provide insights into how management's response can help firms cope with unexpected shocks.

APPENDIX A

Definitions of variables

A1. Firm's characteristics variables.

	Variable	Calculation	Definition
1	*logat*	log(at)	Log(Total Assets(t))
2	*logsale*	log(sale)	Log(total sales(t))
3	*actlct*	act/lct	Current Ratio = Current Assets(t)/Current Liabilities(t)
4	*cheat*	che/at	Cash and Short-term Investment(t)/Total Assets(t)
5	*chat*	ch/at	Cash(t)/Total Assets(t)
6	*chlct*	ch/lct	Cash(t)/Current Liabilities(t)
7	*lctchat*	(lct-ch)/at	(Current Liabilities(t) – Cash(t))/Total Asset(t)
8	*reat*	re/at	Retained Earnings(t)/Total Asset(t)
9	*relct*	re/lct	Retained Earnings(t)/Current Liabilities(t)
10	*dtat*	dt/at	Total Debt Including Current(t)/Total Assets(t)
11	*seqat*	seq/at	Total Stockholders' Equity(t)/Total Assets(t)
12	*wcapat*	wcap/at	Working Capital(t)/Total Assets(t)
13	*invtsale*	invt/sale	Inventories(t)/Sales(t)
14	*xintsale*	xint/sale	Total Interest and Related Expense (t)/Sales(t)
15	*atemp*	at/emp	Total Assets(t)/Employees(t)
16	*indinvt*	invt	An indicator equal to 1 if Inventories(t+1) - Inventories(t) is greater than zero, and 0 otherwise.

A2. Firm performance and its lagged variables.

	Variable	*Calculation*	*Definition*
1	*roa*	ni/at	Return on assets
2	*ebitat*	ebit/at	Earnings before interest and taxes on assets
3	*Q*	(prcc_f*csho + dltt + dlc + pstk)/at	Tobin's Q
4	*salegrowth*	[sale(t) -sale(t-1)]/sale(t-1)	Sales growth
5	*roalag1*	ni_bw1/at_bw1	Prior year ROA

6	*ebitatlag1*	ebit_bw1/at_bw1	Prior year EBIT
7	*Qlag1*	(prcc_f_bw1*csho_bw1 + dltt_bw1 + dlc_bw1 + pstk_bw1)/at_bw1	Prior year Q
8	*salegrowthlag1*	[sale(t-1) - sale(t-2)]/sale(t-2)	Prior year sales growth

A3. Exogenous shock variables measured from text analysis using Form 10-Ks and word dictionaries from Li et al. (2021).

	Variable	Calculation	Definition
1	*BO_exposure*	An indicator equal 1 if the rank of counts are above the sample mean of *BO_exposure*, and 0 otherwise. The rank of counts is developed by the word counts in the Appendix B among six exposure categories.	*Business Operations exposure*
2	*DM_exposure*	An indicator equal 1 if the rank of counts are above the sample mean of *DM_exposure*, and 0 otherwise. The rank of counts is developed by the word counts in the Appendix B among six exposure categories.	*Demands exposure*
3	*EM_exposure*	An indicator equal 1 if the rank of counts are above the sample mean of *EM_exposure*, and 0 otherwise. The rank of counts is developed by the word counts in the Appendix B among six exposure categories.	*Employees exposure*
4	*LQ_exposure*	An indicator equal 1 if the rank of counts are above the sample mean of *LQ_exposure*, and 0 otherwise. The rank of counts is developed by the word counts in the Appendix B among six exposure categories.	*Liquidity exposure*
5	*LD_exposure*	An indicator equal 1 if the rank of counts are above the sample mean of *LD_exposure*, and 0 otherwise. The rank of counts is developed by the word counts in the Appendix B among six exposure categories.	*Lockdown exposure*
6	*SC_exposure*	An indicator equal 1 if the rank of counts are above the sample mean of *SC_exposure*, and 0 otherwise. The rank of counts is developed by the word counts in the Appendix B among six exposure categories.	*Supply chain exposure*

A4. Firm response variables from Form 10-Ks text analysis (using dictionary from Li et al. 2021).

	Variable	Calculation	Definition
1	*CE_response*	An indicator equal 1 if the rank of counts are above the sample mean of *CE_response*, and 0 otherwise. The rank of counts is developed by the word counts in the Appendix B among four response categories.	*Community engagement*
2	*CC_response*	An indicator equal 1 if the rank of counts are above the sample mean of *CC_response*, and 0 otherwise. The rank of counts is developed by the word counts in the Appendix B among four response categories.	*Cost cutting*
3	*DT_response*	An indicator equal 1 if the rank of counts are above the sample mean of *DT_response*, and 0 otherwise. The rank of counts is developed by the word counts in the Appendix B among four response categories.	*Digital transformation*
4	*NP_response*	An indicator equal 1 if the rank of counts are above the sample mean of *NP_response*, and 0 otherwise. The rank of counts is developed by the word counts in the Appendix B among four response categories.	*New product development*

A5. Natural and industry exogenous variables.

	Variable	Calculation
1	*disaster*	Disaster word counts in the Appendix B. An indicator equal 1 if counts are greater than 3, and 0 otherwise. [3]
2	*hhi*	Herfindahl Index (HHI) = Sum of square of market shares of all firms within a particular 3-digit SIC industry in a particular year (t).
3	*interestrate*	US borrowing interest rate in year (t)
4	*gdpgrowth*	US Gross Domestic Product growth in year (t)
5	*inflation*	US inflation rate in year (t)

[3] We use 3 as the cutoff because financial statements may contain discussion about disasters but firms are not impacted. This cutoff is also the 75 percentile of disaster word counts.

A6. Firm actions/response variables – Long-term investing and financing conditions and strategies.

	Variable	Definition
1	*intcapx*	An indicator equal to 1 if Capital expenditure(t+1) - Capital expenditure(t) is greater than zero, and 0 otherwise.
2	*inddvc*	An indicator equal to 1 if Dividends Common, Ordinary(t+1) minus Dividends Common, Ordinary(t) is greater than zero, and 0 otherwise.
3	*indsiv*	An indicator equal to 1 if Sales of investment (t+1) - Sales of investment (t) is greater than zero, and 0 otherwise.
4	*indivch*	An indicator equal to 1 if Increase in Investments(t+1) - Increase in Investments(t) is greater than zero, and 0 otherwise.
5	*indsstk*	An indicator equal to 1 if Sale of Common and Preferred Stock(t+1) - Sale of Common and Preferred Stock(t) is greater than zero, and 0 otherwise.
6	*indprstkc*	An indicator equal to 1 if Purchase of Common and Preferred Stock(t+1) - Purchase of Common and Preferred Stock(t) is greater than zero, and 0 otherwise.
7	*indsppe*	An indicator equal to 1 if Sale of Property(t+1) - Sale of Property(t) is greater than zero, and 0 otherwise.
8	*indsppiv*	An indicator equal to 1 if Sale of Property, Plant and Equipment and Investments, (Gain) Loss(t+1) - Sale of Property, Plant and Equipment and Investments, (Gain) Loss(t) is greater than zero, and 0 otherwise.
9	*indaqc*	An indicator equal to 1 if Acquisitions(t+1) - Acquisitions(t) is greater than zero, and 0 otherwise.
10	*indivaco*	An indicator equal to 1 if Investing Activities, Other(t+1) - Investing Activities, Other(t) is greater than zero, and 0 otherwise.
11	*indfiao*	An indicator equal to 1 if Financing Activities, Other(t+1) - Financing Activities, Other(t) is greater than zero, and 0 otherwise.
12	*inddltis*	An indicator equal to 1 if Long-Term Debt, Issuance(t+1) - Long-Term Debt, Issuance(t) is greater than zero, and 0 otherwise.
13	*inddltr*	An indicator equal to 1 if Long-Term Debt, Reduction(t+1) - Long-Term Debt, Reduction(t) is greater than zero, and 0 otherwise.

A7. Firm action/response variables – Short-term advertising and R&D.

	Variable	*Calculation*	*Definition*
1	*indxrd*	[xrd(t+1) - xrd(t)] > 0	An indicator equal to 1 if Research and Development Expense(t+1) minus Research and Development Expense(t) is greater than zero, and 0 otherwise.
2	*indxad*	[xad(t+1) - xad(t)] > 0	An indicator equal to 1 if Advertising Expense(t+1) minus Advertising Expense(t) is greater than zero, and 0 otherwise.

APPENDIX B

B1. Disasters word lists

airburst
apocalypse
ash fall
avalanche
avalanche
blizzard
calamity
cataclysm
catastrophe
catastrophes
cold wave
convective storm
cyclone
cyclones
debacle
derecho
devastating
disaster
disasters
drought
dust storm
earthquake
earthquakes
El Nino
extra-tropical storm
extreme heat
extreme temperature
extreme weather
fire
flood
flooding
floods
fog
fogs
forest fire
freeze
gale
glacial lake outburst
hail
hailstorm
hazard
heat wave
hurricane
hurricanes
hydrological hazard
landslide
lava flow
lightning
mass movement
mudslide
natural disasters
rainstorm
rock fall
rogue wave
sand storm
seiche
severe storm
severe winter conditions
storm
storms
tension
thunderstorm
tornado
tornados
tremor
tropical cyclone
tsunami
twister
typhoon
volcanic activity
volcanic eruption
volcano
volcanos
whirlpool
wildfire
windstorm
windstorms
winter storm

B2. Exposure word lists (Li et al., 2021)

Business Operations	**Demand**	**Employees**	**Liquidity**
implementation	record	location	generate
agreement	report	staff	flexibility
installation	trade	safe	balance sheet
final	income	include	cares act
progress	represent	meeting	capital expenditure
activity	slide	remotely	balance
track	compare	follow	dividend
unusual	share	field	pay
award	impact covid-19	Employees	bank
receive	earnings	measure	fund
timeline	decrease	protocol	draw
building	increase	event	capital
process	sale	social distancing	liquidity
delay	revenue	operation	remain
anticipate	adjust	client	prudent
phase	global	safety	cash
completion	basis point	practice	maintain
discussion	reflect	workforce	strong
transaction	decline	office	provide
construction	market	implement	suspend
complete	result	operate	access
program	exclude	facility	addition
pause	gross margin	travel	cash flow
project	year-over-year	transition	share
timing	volume	government	debt
schedule	include	remote	leverage
permit	total	virtual	funding
plan	price	require	additional
continue	volatility	ensure	program
contract	offset	essential	raise

B3. Exposures word lists (Li et al., 2021) (continue)

Lockdown	Supply Chain
franchisee	manufacture
school	operation
comp	supply
student	product
closure	supplier
business	material
shelter	chinese
open up	shipment
store	volume
decision	component
lockdown	closely
store closure	supply chain
start	demand
country	production
traffic	disruption
activity	produce
location	factory
stay-at-home	shut down
geography	equipment
return	shutdown
local	industrial
restriction	inventory
city	business
door	source
reopen	manufacturing
lift	plant
restaurant	ramp
shelter-in-place	ship
online	backlog
	capacity

B4. Responses/actions word lists (Li et al., 2021)

Community Engagement	**Cost Cutting**	**Digital Transformation**	**New Product Development**
	cost structure		
commitment	savings	innovation	marketplace
continue	furlough	create	exist
focus	labor	network	larger
provide	sg&a	scale	purchase
family	incur	offer	partner
community	adjust	tool	add
crisis	incremental	offering	expand
challenging time	variable	focus	sell
associate	associate	digital transformation	build
serve	covid-related	challenge	shift
team	spending	include	sale
support	additional	capability	online
respond	action	continue	competitor
entire	benefit	service	category
priority	reduce	customer	opportunity
commit	cost	technology	product
protect	expense	provide	center
challenge	hire	business	relationship
remain	pay	solution	brand
deliver	include	enable	consumer
partner	travel	deliver	launch
critical	reduction	application	retailer
global	temporary	design	partnership
ensure	cut	access	pipeline
organization	relate	unique	space
health	operating	leverage	excite
effort	expense	engage	food
time	productivity	platform	channel
essential	manage	accelerate	dealer
employee	spend	infrastructure	retail

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Figure 1. Number of firm failures by year.

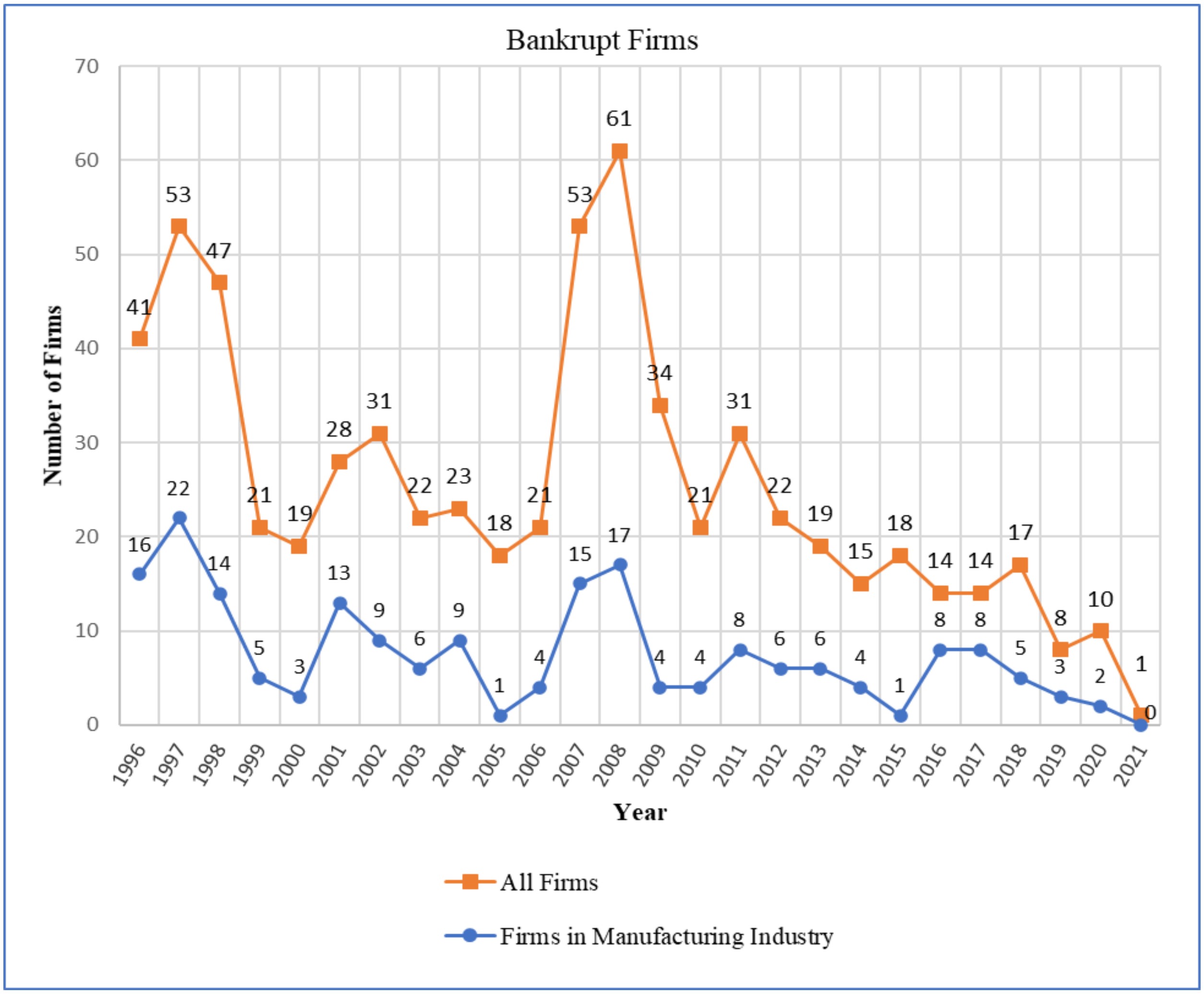
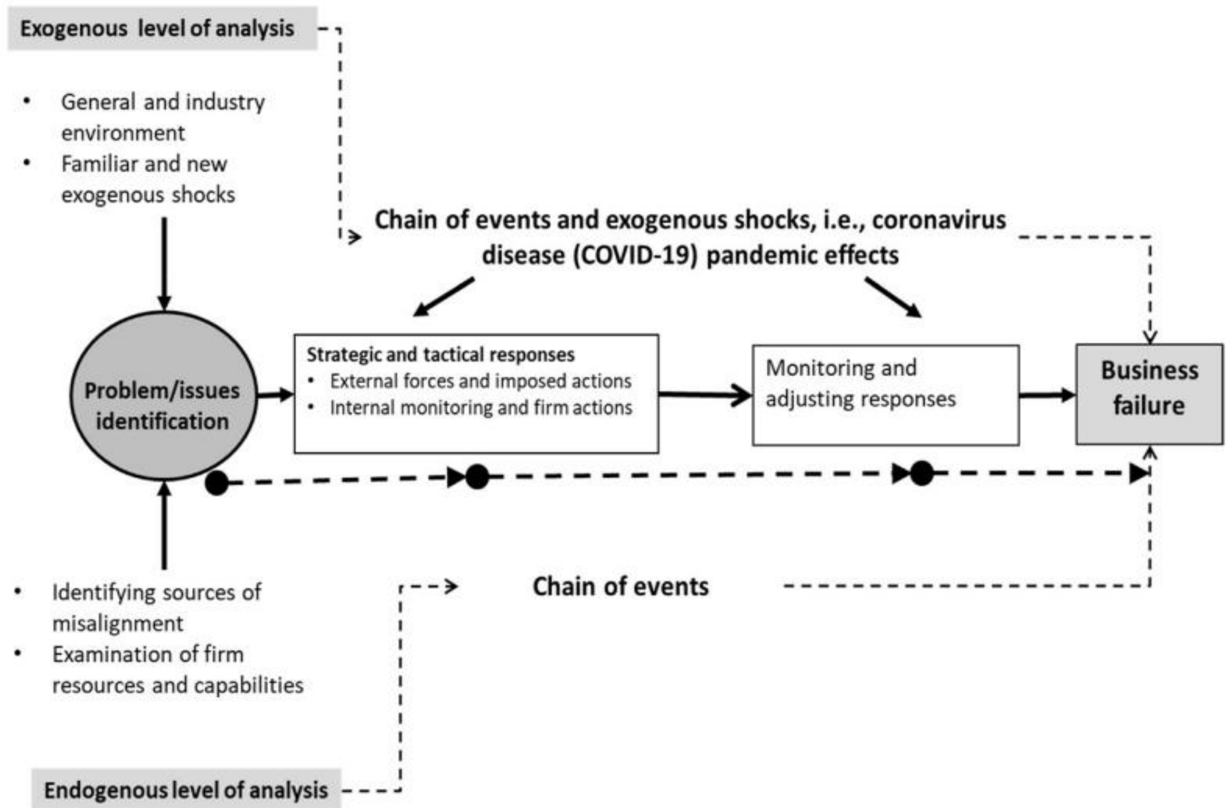


Figure 2. Business failure framework.



Source: Amankwah-Amoah et al. (2021).

Figure 3. The modified business failure framework.

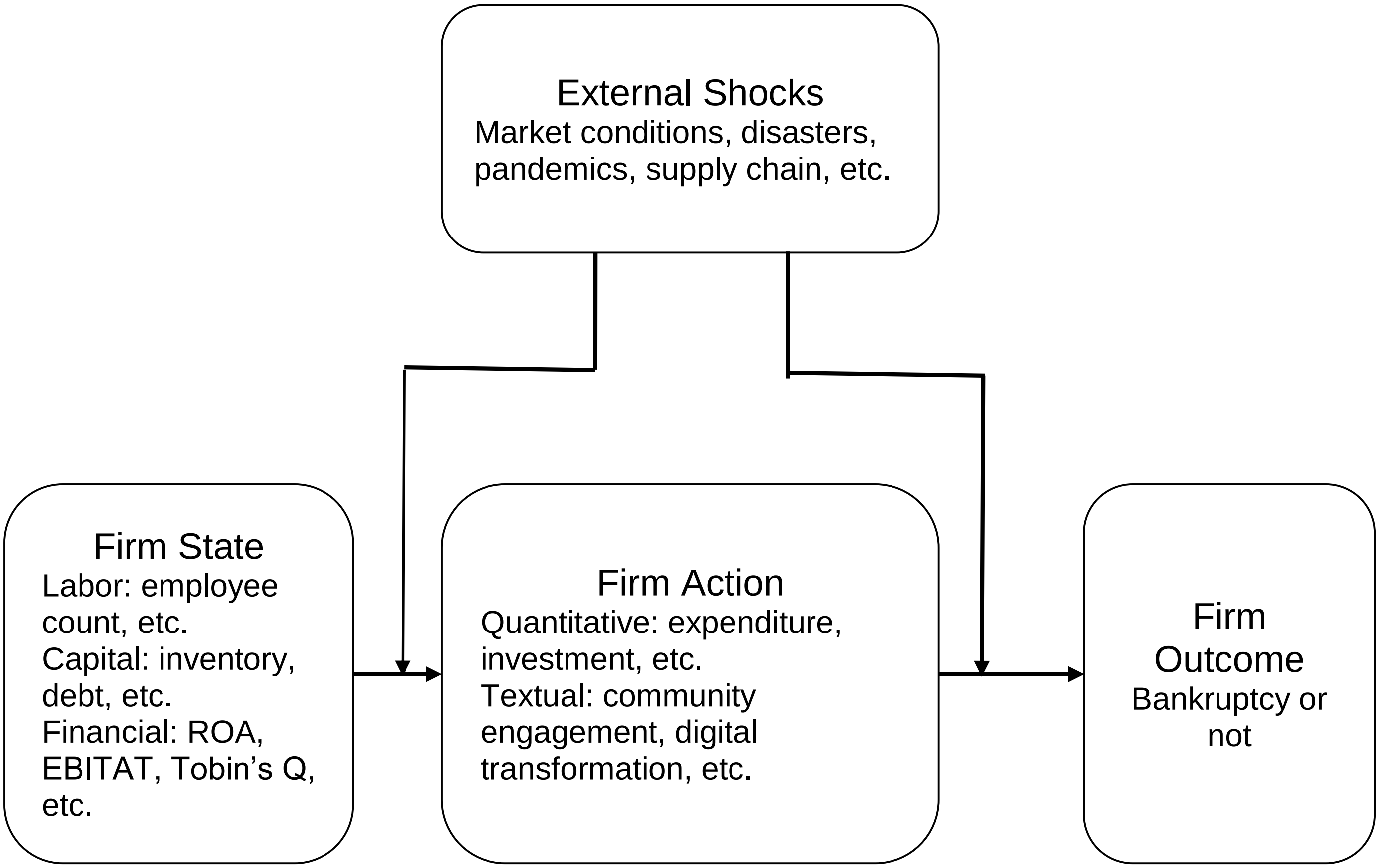


Figure 4. The heatmap of the Spearman correlation between independent variables.

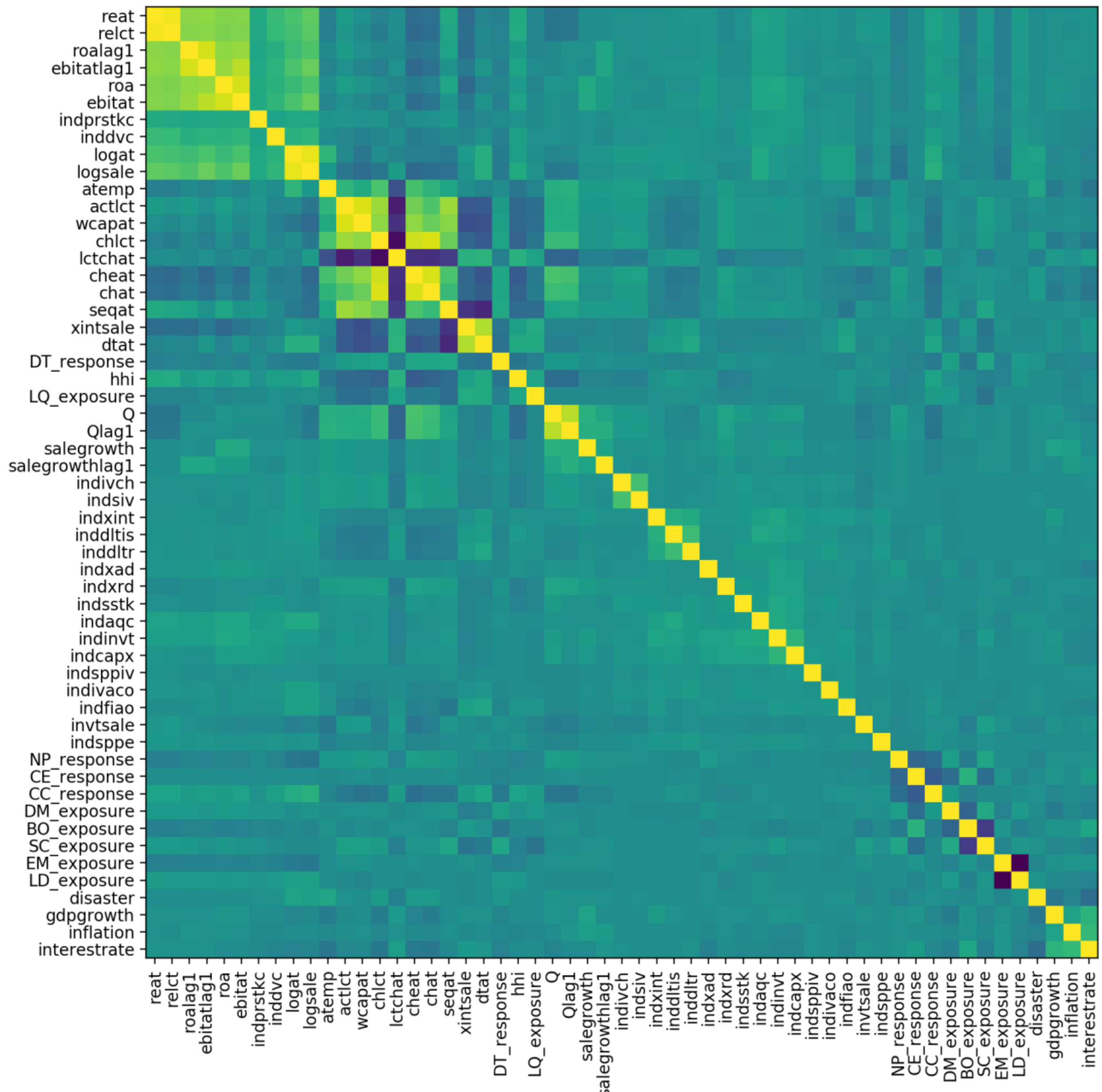


Figure 5. The dendrogram that illustrates the clustering of independent variables.

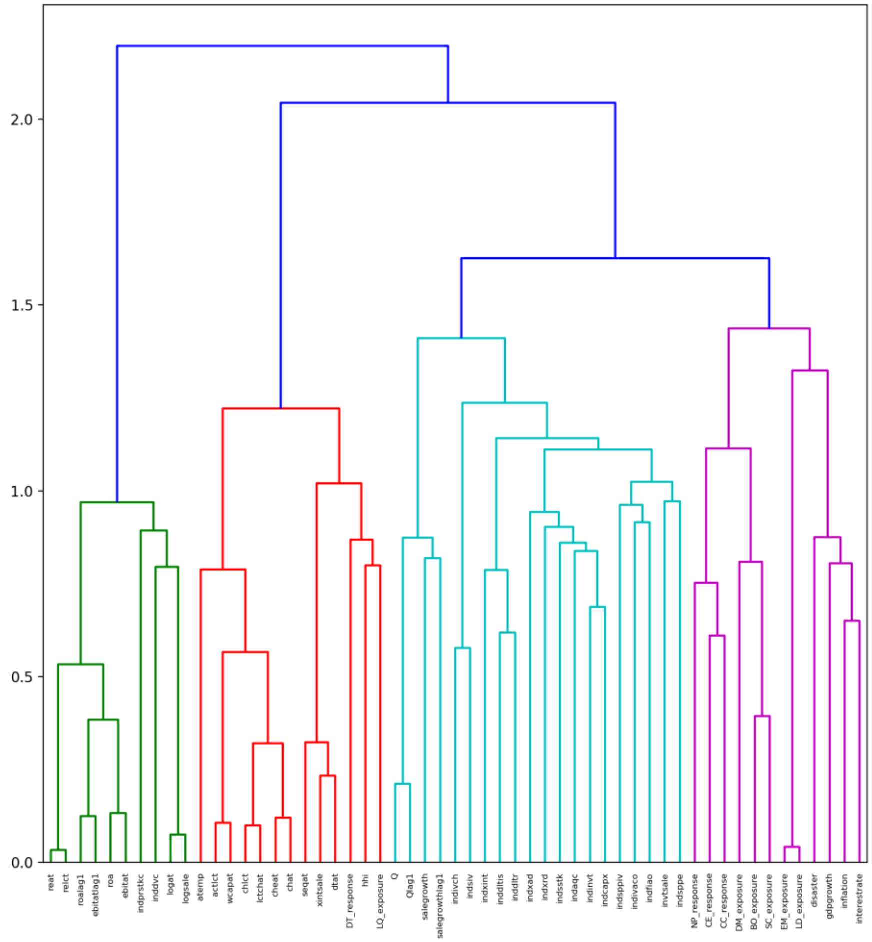


Figure 6. Permutation importance of variables in the 45-variable model.

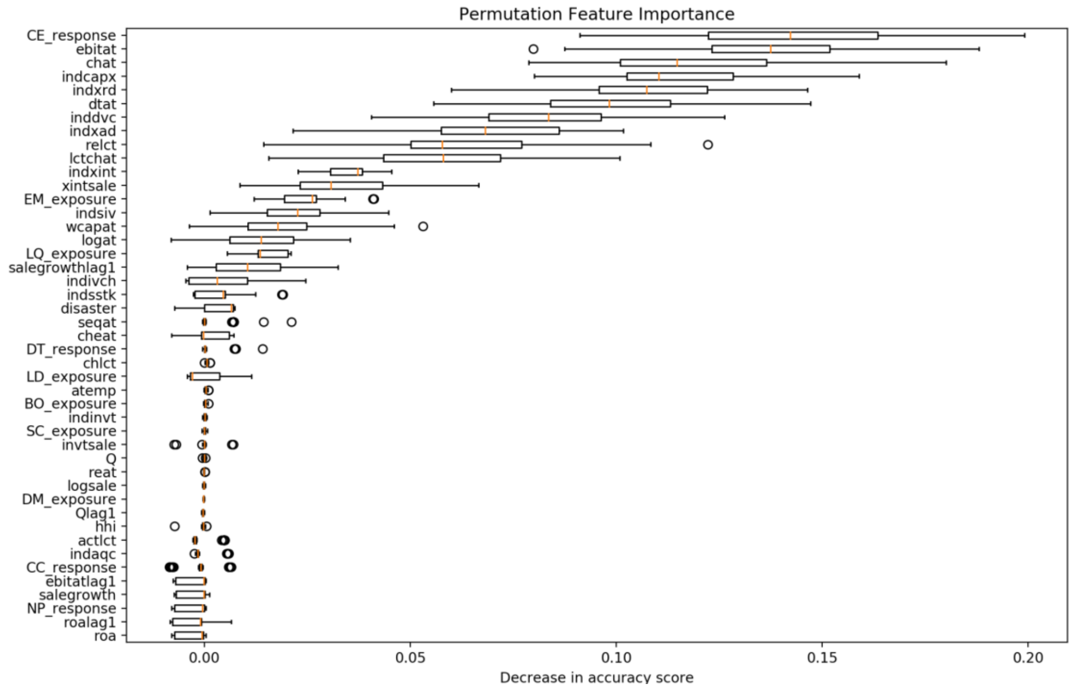


Figure 7. Permutation importance of variables in the 34-variable model.

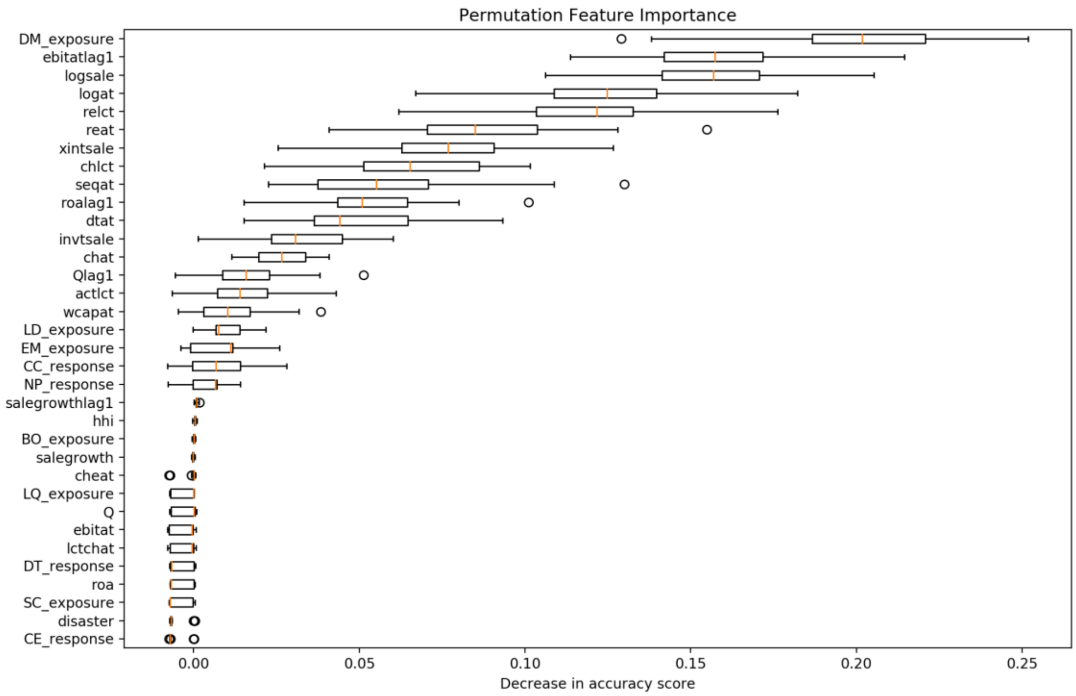


Exhibit 1. Confusion matrix of balanced logistic regression.

Balanced Logistic Regression		Predicted	
		Surviving	Failed
Actual	Surviving	10,755	793
	Failed	1	69

Exhibit 2. Confusion matrix of classic logistic regression.

Classic Logistic Regression		Predicted	
		Surviving	Failed
Actual	Surviving	11,544	4
	Failed	62	8

TABLE 1
Summary Statistics (n=11,618)

Variable	Mean	25th	Median	75th
hhi	0.334	0.129	0.243	0.449
disaster	0.633	0	1	1
roa	-0.123	-0.138	0.010	0.062
ebitat	-0.057	-0.068	0.044	0.101
Q	1.860	0.800	1.217	2.097
salegrowth	0.154	-0.073	0.056	0.206
roalag1	-0.113	-0.131	0.011	0.063
ebitatlag1	-0.050	-0.068	0.047	0.104
Qlag1	1.921	0.816	1.239	2.135
salegrowthlag1	0.193	-0.064	0.065	0.231
actlct	3.284	1.586	2.384	3.847
cheat	0.228	0.034	0.137	0.349
chat	0.152	0.029	0.096	0.215
chlct	0.964	0.113	0.440	1.131
invtsale	0.167	0.081	0.135	0.206
xintsale	0.070	0.003	0.013	0.032
lctchat	0.125	-0.021	0.107	0.230
logat	5.397	4.065	5.368	6.698
logsale	5.135	3.876	5.237	6.584
reat	-1.321	-0.973	-0.009	0.290
relct	-4.002	-4.233	-0.043	1.410
dtat	0.222	0.006	0.151	0.335
seqat	0.438	0.300	0.518	0.719
wcapat	0.299	0.150	0.306	0.493
atemp	431.216	154.166	267.683	502.091
indinvt	0.458	0.000	0.000	1.000
indcapx	0.425	0.000	0.000	1.000
indaqc	0.179	0.000	0.000	0.000
inddvc	0.141	0.000	0.000	0.000
indxad	0.146	0.000	0.000	0.000
indxrd	0.180	0.000	0.000	0.000
indxint	0.361	0.000	0.000	1.000
indivch	0.107	0.000	0.000	0.000
indsiv	0.110	0.000	0.000	0.000
indsstk	0.353	0.000	0.000	1.000
indprstkc	0.184	0.000	0.000	0.000
indsppe	0.163	0.000	0.000	0.000
indsppiv	0.281	0.000	0.000	1.000
indivaco	0.296	0.000	0.000	1.000
inddltis	0.234	0.000	0.000	0.000
inddltr	0.339	0.000	0.000	1.000
indfiao	0.223	0.000	0.000	0.000
BO_exposure	0.480	0	0	1
DM_exposure	0.719	0	1	1
EM_exposure	0.867	1	1	1
LQ_exposure	0.338	0	0	1
LD_exposure	0.143	0	0	0
SC_exposure	0.703	0	1	1
CE_response	0.273	0	0	1
CC_response	0.602	0	1	1
DT_response	0.520	0	1	1
NP_response	0.527	0	1	1
gdpgrowth	2.417	1.742	2.564	3.799
inflation	2.354	1.640	2.443	3.226
interestrate	3.534	2.061	2.981	4.786

TABLE 2
The Logistic Model Using all the Variables

Variable	coefficients	p-values
hhi	-0.0453	0.934
disaster	-0.1294	0.674
roa	-0.3280	0.477
ebitat	-1.6284**	0.020
Q	-0.4335**	0.018
salegrowth	-0.0982	0.663
roalag1	-0.6411	0.360
ebitatlag1	-0.5230	0.580
Qlag1	-0.1215	0.393
salegrowthlag1	0.0192	0.912
actlct	-1.2305***	0.000
cheat	0.9907	0.573
chat	-7.1596***	0.007
chlct	1.8825***	0.000
invtsale	0.4494	0.594
xintsale	-0.3947	0.453
lctchat	0.0028	0.998
logat	-0.3636	0.242
logsale	0.4379	0.143
reat	0.0719	0.163
relct	-0.0331**	0.044
dtat	2.7196***	0.000
seqat	0.0405	0.918
wcapat	1.9017	0.100
atemp	0.0000	0.989
indinvt	-4.0121	0.384
indcapx	-3.2921	0.571
indaqc	-1.6324	0.834
inddvc	-1.3528	0.828
indxad	-1.9778	0.747
indxrd	-2.8425	0.550
indxint	-3.9433	0.481
indivch	-1.0608	0.896
indsiv	-1.9999	0.771
indsstk	-3.8220	0.482
indprstkc	-2.1779	0.660
indsppe	-2.5996	0.669
indsppiv	-4.2181	0.379
indivaco	-3.2569	0.567
inddltis	-2.0535	0.765
inddltr	-4.8481	0.308
indfiao	-3.5378	0.482
BO_exposure	0.1626	0.670
DM_exposure	0.0940	0.783
EM_exposure	-1.0021	0.447
LQ_exposure	-0.5707*	0.060
LD_exposure	-6.3764	0.163
SC_exposure	0.5981	0.132
CC_response	-0.2964	0.465
CE_response	-0.0903	0.831
NP_response	-1.1088***	0.004
DT_response	-0.2376	0.464
gdpgrowth	-0.1432	0.120
inflation	-0.0131	0.927
interestrate	-0.2019**	0.043

***, **, * Denote significance at the 1, 5, and 10 percent levels, respectively. All variables are defined in Appendix A. All continuous variables are winsorized at 1st and 99th percentile.

TABLE 3

The Logistic Model with Natural Disaster and Firm Responses Interactions

Variable	coefficients	p-values
disaster*indinvt	-3.7014	0.515
disaster*indcapx	-3.6040	0.549
disaster*indaqc	-1.6422	0.861
disaster*inddvc	-2.2442	0.677
disaster*indxad	-1.8225	0.781
disaster*indxrd	-2.6358	0.643
disaster*indxint	-3.5165	0.565
disaster*indivch	-1.8139	0.817
disaster*indsiv	-2.2090	0.757
disaster*indsstk	-3.4351	0.560
disaster*indprstkc	-2.3951	0.680
disaster*indsppe	-2.6001	0.652
disaster*indsppiv	-3.9198	0.475
disaster*indivaco	-3.4913	0.547
disaster*inddltis	-2.2485	0.713
disaster*inddltr	-3.6601	0.508
disaster*indfiao	-3.4121	0.539
disaster*CE_response	-2.1866***	0.000
disaster*CC_response	-2.2862***	0.004
disaster*DT_response	-0.8007***	0.000
disaster*NP_response	-2.3133***	0.000

***, **, * Denote significance at the 1, 5, and 10 percent levels, respectively. All variables are defined in Appendix A. All continuous variables are winsorized at 1^{st} and 99^{th} percentile.

TABLE 4

The Logistic Model with Exposure Shocks and Firm Response Interactions

Variable	coefficients	p-values
BO_exposure*CE_response	-0.5704	0.349
BO_exposure*CC_response	-0.0876	0.862
BO_exposure*DT_response	0.5153	0.370
BO_exposure*NP_response	-0.7339	0.150
DM_exposure*CE_response	-0.2647	0.605
DM_exposure*CC_response	0.1710	0.692
DM_exposure*DT_response	0.2843	0.582
DM_exposure*NP_response	-0.4212	0.363
EM_exposure*CE_response	-3.1209***	0.000
EM_exposure*CC_response	-3.4717***	0.000
EM_exposure*DT_response	-1.7083**	0.047
EM_exposure*NP_response	-3.2577***	0.000
LQ_exposure*CE_response	-0.4197	0.432
LQ_exposure*CC_response	-0.5194	0.173
LQ_exposure*DT_response	0.8719*	0.068
LQ_exposure*NP_response	-0.1339	0.788
LD_exposure*CE_response	-5.6586	0.125
LD_exposure*CC_response	-7.3984	0.044
LD_exposure*DT_response	-4.6572	0.588
LD_exposure*NP_response	-6.5161*	0.070
SC_exposure*CE_response	0.4026	0.473
SC_exposure*CC_response	-0.2332	0.654
SC_exposure*DT_response	0.1224	0.845
SC_exposure*NP_response	-0.0610	0.927

***, **, * Denote significance at the 1, 5, and 10 percent levels, respectively. All variables are defined in Appendix A. All continuous variables are winsorized at 1^{st} and 99^{th} percentile.