Journal of the Academy of Marketing Science (2024) 52:1195–1215
https://doi.org/10.1007/s11747-023-00985-9

ORIGINAL EMPIRICAL RESEARCH

Marketing capability and the turnaround of financially distressed firms

Abhi Bhattacharya[1] · **Joseph Johnson**[2] · **Ashkan Faramarzi**[3] · **Niket Jindal**[4] · **Ross W. Johnson**[5]

Received: 2 March 2021 / Accepted: 9 October 2023 / Published online: 31 October 2023

Abstract

Financial distress befalls even well-managed firms, many of which find ways to turn around. Hence, it is pertinent to explore how distressed firms recover. Unfortunately, extant research sheds little light on the role of marketing in enabling distressed firms' turnaround. Using a longitudinal dataset of U.S. firms, we empirically show that when the source of distress is firm-specific, it is marketing capability (as opposed to R&D and operations capabilities) that enables a turnaround. However, when distress is industry-driven, R&D capability is also beneficial. Further, although operations capability and cost-reduction actions do help distressed firms survive, they do not help firms regain financial well-being. Overall, these results highlight the importance of capabilities in the context of distressed firms and have implications for both firm managers and shareholders.

Keywords Turnaround · Marketing capability · R&D capability · Operations capability · Financial distress

Introduction

A financially distressed firm is one whose cash inflow is inadequate to meet its future contractual obligations (Bhagat et al., 2005). Distressed firms end up in one of three states. Some recover[1] (D'Aveni, 1989), some remain distressed, and a third group succumbs to their financial distress and files for bankruptcy[2] (where legal protection from debtors is granted). Recovery involves arresting the decline and achieving a state of financial health while survival signifies staying afloat but not necessarily emerging from distress. Considering that a substantial percentage of distressed firms do not fail (in our dataset, 1303 out of 1488 distressed firms—i.e., 88%—survive), examining how distressed firms turn around[3] is important because employing incorrect recovery strategies can negatively affect stakeholders. Debtors incur losses, employees lose earnings and face uncertainty, and stockholders' holdings decrease (Smith & Graves, 2005).

Scholars show that distressed firms employ three turnaround strategies to recover from distress: (1) cost-cutting, (2) increasing revenues through additional spending and (3) risk-shifting. Exemplifying the first approach, Jensen (1989)

Frank Germann served as Area Editor for this article.

✉ Joseph Johnson
jjohnson@miami.edu

Abhi Bhattacharya
abhattacharya3@cba.ua.edu

Ashkan Faramarzi
afaramarzi@ucly.fr

Niket Jindal
niket.jindal@missouri.edu

Ross W. Johnson
ross.johnson@unt.edu

1 Culverhouse College of Business, University of Alabama, Tuscaloosa, AL, USA

2 University of Miami, Coral Gables, FL, USA

3 UCLy, ESDES, Lyon, France

4 Trulaske College of Business, University of Missouri, Columbia, MO, USA

5 G. Brint Ryan College of Business, University of North Texas, Denton, TX, USA

[1] We consider distressed firms to have recovered when they enter a state of financial health and solvency following a period of financial distress and their future risk of insolvency is minimal.

[2] Bankruptcy is a dichotomous event that occurs when a firm cannot repay its debtors and is either dissolved or reorganized. Distress refers to the poor financial health of a firm. A firm in distress need not file for bankruptcy and many firms fall into distress without ever experiencing bankruptcy.

[3] We use the term "turnaround" to mean "financial recovery," as the terms are used interchangeably in past literature (e.g., Pearce II & Robbins, 1993).

contends that financial distress forces management to cut expenses and develop a "leaner" firm with fewer assets or employees (Sudarsanam & Lai, 2001). Reducing marketing expenses such as advertising is often a part of such cost-cutting measures. Unfortunately, cost-cutting alone may not bring a firm out of distress, even though the stock market often rewards such measures (Denis & Kruse, 2000). For example, Wonder Bread America first tried to salvage its business by cost-cutting. It curtailed advertising and product development; even as consumers' tastes shifted to multigrain bread, the owners balked at the expense needed to introduce Wonder Bread's multigrain product offerings (Keller, 2014). As managers continued their excessive focus on cutting costs, customers migrated to competitors and Wonder Bread finally filed for bankruptcy in 2004.

A second way to recover from distress is to increase spending (as opposed to cost-cutting). Evidence for this approach indirectly comes from research on bankruptcy. Specifically, Jindal and McAlister (2015) show that more advertising reduces bankruptcy risk. However, the bankruptcies of companies like Toys "R" Us, despite substantial spending on advertising, seem to dispute the utility of this strategy. Notably, cost-cutting and increasing revenues through spending are conflicting strategies.

A third strategy that distressed firms employ to recover is risk-shifting, in which the firm takes on additional debt to increase cash flows while not necessarily making internal improvements. Managers often take on additional debt to delay an expected bankruptcy declaration (Khanna & Poulsen, 1995) or because they truly believe that the additional cash flow obtained from borrowing will enable them to recover (Sudarsanam & Lai, 2001). However, assuming additional debt does not seem to ensure a distressed firm's survival, as the Hertz bankruptcy in 2020 demonstrates. Hertz struggled to remain profitable and took on debt to continue operations but ultimately filed for bankruptcy (Gladstone & Naughton, 2020).

These conflicting recovery strategies for financial distress indicate that a more comprehensive explanation of how distressed firms recover is required. We propose that recovery from distress involves the efficient and effective use of assets. In our study, we define efficiency as the optimal use of resources required to achieve an outcome and effectiveness as the achievement of better results (in terms of the outcome sought, for instance, value to customers) given a certain set of resources. For example, TV advertising may be an efficient communication medium because it reaches a wide target market, but a sales force may be a more effective medium in achieving sales because of its high sales conversion rates (Zoltners et al., 2004). Efficiency is critical for distressed firms because such firms cannot afford expenses that increase debt and/or drain cash (Ofek, 1993). Further, without effectiveness, distressed firms cannot increase their revenues as desired. We thus argue that firm *capability*—how efficiently and effectively a firm deploys its assets (Morgan et al., 2009)—is essential to the recovery from financial distress. Moreover, we contend that dynamic capabilities,[4] which are the antecedent organizational and strategic routines by which managers alter their resource base and generate new strategies (Schilke et al., 2018), are instrumental in successfully turning around financially distressed firms. Dynamic capabilities help distressed firms in three ways. First, they reduce working capital needs by increasing efficiencies and effectiveness in investments. Second, they generate higher cash flows by making actions more effective. Third, dynamic capabilities, through redeployment, reconfiguration, retirement, and augmentation of existing processes and resources, catalyze strategic change (i.e., firms change how they compete, create, and capture value in the market).

Our analysis of 4464 firm-year observations over 27 years (1995–2021) of 1488 distressed manufacturing firms reveals that 1303 (88%) survived. We find that overall, marketing capability (MC), not R&D capability (RDC), aids in turning around distressed firms. Assuming that MC and RDC are on roughly the same scale, MC has 21 times the impact of RDC. In addition, we find that the impact of MC on recovery is more pronounced when the distress is firm-specific; in contrast, RDC impacts recovery only when the distress is industry-driven. Cost-cutting measures, such as asset stripping or decreasing dividends, do not drive recovery.

Our research makes two contributions to the literature on capabilities and one to the marketing-finance literature. First, we extend the capabilities literature to the context of distressed firms by showing that MC aids distressed firms' recovery when the source of distress is firm-specific and RDC aids recovery when the source of distress is industry-led. To the best of our knowledge, there is no research on the benefits of MC and RDC for distressed firms. Table 1, which provides an overview of the literature on firm recovery, shows that extant research focuses on the impact of cost-based strategies such as retrenchment and changes in top management personnel in effecting a turnaround. Since cost-based strategies are largely ineffective, the role of MC and RDC in aiding turnaround is an important extension of the literature (Table 2).

Second, our paper contributes to the literature by highlighting the value of proactive marketing under adverse conditions as well as the importance of MC in deploying cost-effective marketing strategies. How well marketing costs are managed is rarely discussed in MC literature compared to the revenue-generating aspect of marketing.

Our findings contribute to the marketing-finance interface literature by demonstrating that bankruptcy is not the

[4] Hereafter, "capabilities" refers to dynamic capabilities.

Table 1 Literature review- recovery and turnaround

Study	Strategies investigated	Findings
Barker & Mone, 1994	Retrenchment strategies	Retrenching firms do not have significantly higher performance than non-retrenching firms
Sudarsanam & Lai, 2001	Operational, asset and managerial restructuring	Recovery firms adopt growth-oriented and external-market focused strategies, non-recovery firms engage in fire-fighting strategies
Bruton et al., 2003	Retrenchment strategies	Asset retrenchment results in increases to firm performance
Morrow et al., 2004	Retrenchment strategies	Cost retrenchment results in increases in market and accounting performance in poorly performing firms in mature industries and accounting performance in declining industries
Boyne & Meier, 2009	Top Management changes	Insider succession is beneficial to turnaround
Ndofor et al., 2013	Retrenchment strategies	Layoffs (cost retrenchment), asset reduction (asset retrenchment), and asset reduction (product withdrawal from the market) are negatively related to performance turnaround for firms
Tangpong et al., 2015	Retrenchment strategies	Declining firms that implement retrenchment actions early have a higher likelihood of successful turnaround
Arora, 2016	Top management team changes	Efforts of financially linked independent directors, and not other director categories, matter for reemergence
Santana et al., 2018	Retrenchment and HR strategies	The use of downsizing with internal deficiencies may create further problems within the company while strategic negotiations help
Flammer & Ioannou, 2021	Retrenchment strategies	Companies are adversely affected when using a "two-pronged" approach of curtailing their workforce and capital expenditures
Rico et al., 2021	Intangible and tangible asset retrenchment	Deep cost retrenchment increase the likelihood of survival
This study	Dynamic capabilities and retrenchment strategies	Marketing capabilities help a firm recover especially if the cause of distress is firm specific. R&D capabilities help only when the cause of distress is industry-led. Operations capabilities and retrenchment strategies aid survival but not recovery

Table 2 Comparisons with the bankruptcy literature in marketing

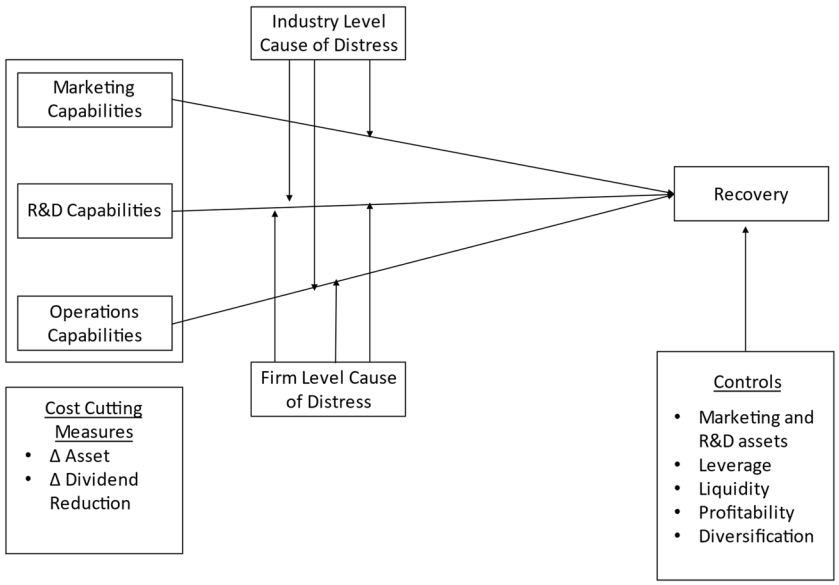
Source	Outcome	Firms considered	Marketing variables	Contingency
Jindal and McAlister (2015)	Bankruptcy filing	All	Marketing assets	Industry turbulence
Antia et al. (2017)	Bankruptcy filing	Franchisees and franchisors	Governance mechanisms	Ability- vs motivation-influencing
Jindal (2020)	Bankruptcy survival (vs liquidation)	Bankrupt firms	Marketing assets	Supplier influence
Current study	Financial distress recovery (vs bankruptcy)	Financially distressed firms	Marketing capabilities and assets	Firm- vs industry-led distress

inevitable outcome for a firm in financial distress. Therefore, instead of deploying strategies such as panic asset sales to stave off bankruptcy, managers may leverage and employ their MC (primarily) and RDC to achieve financial turnaround.

Our results have two implications for firm managers and stakeholders. First, though the extant literature suggests that cost-cutting, spending, or risk-shifting measures may help a firm survive, such actions may not foster recovery from distress. Instead, our findings imply that investing in and maintaining firm capabilities, especially MC is critical. Our second implication is for downstream stakeholders. Debtholders can include capabilities into their credit risk models to ascertain which of their high-risk business customers is the least likely to slide into liquidation. Suppliers may also factor in customer firms' MC and RDC when deciding on whether to dial back exposure to distressed firms.

The rest of this paper is organized as follows. In "Theory and hypotheses" section, we discuss the literature on firm financial distress and the role of MC and RDC in such firms. We then describe the contrasting roles of MC and RDC depending on the source of distress. In "Empirical evidence" section, we empirically demonstrate the value of such capabilities in the context of recovery from distress as

Fig. 1 Conceptual framework



well as from bankruptcy. In "Results" section, we present the results of our empirical analyses and robustness checks. Finally, we discuss the findings, contributions, and implications of our research in "Discussion" section. Figure 1 provides an overview of our conceptual framework.

Theory and hypotheses

Antecedents of distress

Firms face distress due to a multitude of factors that can broadly relate to either the industry in which firms operate or the functioning of the firms themselves.

Industry-led sources of distress Industry-led distress can arise from a declining economy (i.e., a recession), reduced demand for extant products as customer needs change, or technological advances that make firms' products outdated. Under such conditions existing firms' offerings will not be able to meet customers' needs (Kohli & Jaworski, 1990), and existing value propositions may become less relevant for the industry. For example, Cemex, a cement manufacturer, struggled to service its debt during the 2008 recession, when demand for housing collapsed.

Firm-specific sources of distress Financial distress may also arise from individual firm-specific factors. Managerial missteps, unsustainable growth, and ill-conceived strategies are examples of firm-specific factors that can result in financial distress. Also, managers' investment choices may not always result in greater earnings and lead to higher volatility in earnings and thus a greater probability of financial distress. Thus, a firm may be unable to generate sufficient earnings, even though its parent industry remains healthy. The unsustainable sales growth targets of JDS Uniphase (Sterman et al., 2007) exemplify a firm that tried to grow rapidly by keeping its prices low to gain market share; however, the firm ended up in financial distress because other parts of the firm were not capable of sustaining that growth, leading to declines in both product quality and sales.

Prior theories on the recovery of distressed firms

Studies on organizational decline and turnaround (e.g., Smith & Graves, 2005) provide evidence that economically troubled firms can attempt recovery through strategies that are either efficiency-oriented (i.e., by reducing costs) or entrepreneurial-oriented (e.g., by introducing new products). Understanding whether a distressed firm has the potential to recover is important. Firms with the potential to recover should be able to (a) attract the funds necessary to realize recovery because lending decisions are based on such understandings, (b) achieve better negotiations with suppliers since they can showcase future profit potential, (c) avoid negative media mentions, and (d) generally be more confident of being able to move toward a better future. The literature (e.g., Ofek, 1993) indicates that distressed firms are identified by two particular characteristics: high leverage and low liquidity (i.e., high debt and low cash flow). These characteristics often drive firms to cut costs to increase cash flow (a part of which may be used to service debt), take on more debt, if possible, or attempt to invest out of distress by taking on high-risk ventures (Eisdorfer, 2008).

Dynamic capabilities in distressed firm recovery

Following Peteraf and Barney (2003), we define capability as the ability of a firm's functional department to achieve the desired outcomes (e.g., sales growth) to the maximum possible extent by using inputs and resources (e.g., R&D budget). Capabilities are an outcome of the skills and knowledge embedded in organizational processes or routines (Helfat & Peteraf, 2003). Dynamic capabilities and their components—such as the strategic routines they are composed of—may change over time, enabling a firm to build successive temporary advantages by effectively responding to successive internal and external environmental shocks (Eisenhardt & Martin, 2000). The value of dynamic capabilities is based on their marginal contribution to a firm's rents, by either increasing revenues or decreasing costs. Marketing, operations, and R&D capabilities are all considered dynamic (Day, 1994).

Dynamic capabilities are crucial for distressed firms. They increase both the efficiency and effectiveness of marketing investments (i.e., both revenue-enhancing and cost-reducing), making them critically valuable for the survival of firms with curtailed financial flexibility (Day, 1994). Distressed firms face rising costs of continuing operations. Therefore, process efficiencies and effectiveness (doing more with less) are essential to ensuring the availability of sufficient working capital in addition to enacting strategic change. Understanding how dynamic capabilities increase efficiency and effectiveness is essential. For a distressed firm, the attractiveness of extant markets or products has likely declined. As extant markets and products become less important, a firm must build and seek new opportunities that require timely investments and novel strategies. Dynamic capabilities help firms configure, orchestrate, manage, and transform their resources, as well as reallocate funds to respond as necessary to opportunities and corresponding challenges in both the internal and external environment (Day, 2014; Lovallo et al., 2020). This may involve changes in positioning, moving into new markets, adapting new technologies, removing or changing certain managerial roles, and so on. Without adjustments, the initial resource allocation across expenditure categories can become suboptimal, resulting in continued poor performance or further decline (Heaton et al., 2023). Such adjustments go beyond cost savings or simply doing more of the same (e.g., spending on advertising in ineffective categories). Overall, we argue that dynamic capabilities—specifically, R&D and marketing—are vital for this strategic change.

RDC and distressed firm recovery

Building on the discussion of dynamic capabilities, we define RDC as the ability to build, maintain, and reconfigure cross-functional skills in technology scanning, idea generation, product design, prototyping, product testing, manufacturing, and commercialization. It reflects the efficiency and effectiveness with which R&D expenditures are converted into research outputs (Lumpkin & Dess, 1996). Beyond product innovations, in-house R&D helps firms with process and manufacturing innovations. At their core, R&D processes are explorative, involving themes such as search, variation, risk-taking, experimentation, play, flexibility, and discovery (March, 1991).

We argue that RDC is beneficial to recovery from industry-led distress for two reasons. First, distress at the industry level suggests that an industry has lost its value proposition, as extant products generally no longer meet customer needs. As a result, the path to recovery is through innovation that may help establish new markets or attract new customers. R&D-led innovations also have the potential to make customers re-evaluate their preferences and behavior (van Heerde et al., 2004). We argue that for a firm suffering from industry-led distress, it is more plausible for the firm to shift preferences through innovation, as opposed to better marketing its currently underperforming product or service. An example is that of Lego, which was financially struggling and nearing bankruptcy as toy sales stagnated. However, it innovated its product lines, releasing more complex, high-tech toys that are attractive to older children and adults. The company introduced Lego Mindstorms—programmable Lego bricks equipped with sensors that allow consumers to create movable Lego designs and robots—which were a resounding success. They also adopted a (then novel) outside-in innovation approach, allowing users to design their own Lego models, upload them to the company's website and order them for delivery (Lego Design by Me) (Ashcroft, 2014).

Second, as the current market and associated product offerings are less favorable, being able and willing to enter new markets and release new products unrelated to current offerings is likely to help recovery. Greater RDC (rather than MC) thus increases firms' interest and ability to explore new customer groups and products where customer wants are less known, in turn making these firms less market-led (Lukas & Ferrell, 2000).

Distressed firms facing industry-wide challenges may still succeed in their current market; however, to do so, they must either adapt technologically or differentiate sufficiently to compete in a separate niche. Here again, RDC may help firms achieve discontinuous innovations in products and production processes as well as enable them to adapt to new technology, which may determine their longer-term viability in the industry. Samsung adapted quickly to the open-source Android operating system, which led to faster processing speeds in its cell phones. In contrast, Nokia failed to adapt and continued with a struggling Symbian OS, ultimately

bowing out of the cell phone market altogether. Fuji Film's R&D enabled the company to successfully establish a niche. In a failing photo film market due to the rise of digital photography, Fuji Film secured a niche in health care, imaging, and materials (Gavetti et al., 2007). RDC may also help a firm realize process innovations, thereby lessening overt reliance on a more expensive raw material whose higher prices might be afflicting the industry. Although not financially distressed, Unilever used its RDC to innovate its soap manufacturing process and allow it to switch between animal and vegetable fat when prices of either raw material moved adversely (Jones, 2005). Given the above arguments, we hypothesize the following:

H1 Greater RDC increases the probability of recovery for distressed firms when the source of distress is at the industry level.

MC and distressed firm recovery

MC reflects the efficiency and effectiveness with which the marketing function generates revenue and profit using marketing inputs (resources and expenses). MC pertains to the ability to build, maintain, and reconfigure skills in marketing areas such as media planning, pricing, brand differentiation, gathering competitive intelligence, customer relationship management, sales management, and strategy selection. Compared with the exploratory nature of RDC, MC primarily exploits current markets and customers (Mizik & Jacobson, 2003). In addition, MC is more malleable than RDC and therefore allows for changing marketing tactics with shorter time delays and lower cost outlays compared to R&D. For example, digital promotions and advertisements allow for quick design changes and rapid execution to suit market changes. The dynamic alteration of online banner ads and promotions through A/B testing and techniques such as multi-armed bandits demonstrate the speed with which marketing actions can be changed.

We argue that MC is more advantageous in mitigating financial distress when the distress is firm-specific and does not afflict most firms in the industry. This means that solutions which meet customer needs exist and the distressed firm does not necessarily need to overcome industry deficiencies; rather, it must align and redeploy its resources to better match its extant market. In this scenario, MC can reduce distress through strategies such as better differentiating its offerings and protecting its competitive space, without the need for a radical change in its product offerings.

The differentiation itself can be customer-led and customer-focused, as category demand is not declining and customers are likely engaging with and buying from other firms in the industry. In addition, although higher MC may not easily transform a weak marketing asset (such as a weak brand) into a strong one, MC may help better leverage extant assets and make marketing expenditures more effective in garnering revenue (e.g., Becchetti & Sierra, 2003). For example, when market sensing and competitive intelligence gathering—both facets of MC—are greater, advertising and promotions may lead to even greater future cash flows (e.g., Slotegraaf & Dickson, 2004). Greater MC also provides firms with a heightened ability to select the most suitable marketing actions to implement and the best segments to target. A higher MC may enable a clearer vision of the market potential of a project, such as a marketing campaign or a product release, and a better ability to ensure that a given project is executed optimally so that it relates to extant customer needs and wants.

We do not assume that a firm can function optimally by employing only its MC or RDC. The use of both capabilities is beneficial to firms. Further, firms can face distress due to simultaneous firm-specific and industry-level causes. However, for firm-specific causes of distress, we argue that MC may be more beneficial than RDC in financial recovery. Given the above reasoning, we hypothesize the following:

H2 Greater MC increases the probability of recovery for distressed firms when the source of distress is at the firm level.

Operations capability (OC) and distressed firm recovery

OC is the ability of the firm to build, maintain, and reconfigure skills that enable the efficient use of resources, the minimization of costs while meeting objective quality standards. It is reflected in the effectiveness and efficiency with which a firm uses its available resources to deliver its products of the required quality better than its rivals do (Krasnikov & Jayachandran, 2008). In the popular press, OC is often associated with announcements of plant closures (asset retrenchment) and employee layoffs, indicating that managers commonly use these tactics to reduce distress (e.g., Morrow et al., 2004). Compared to general asset reductions, which can range from physical asset offloading to employee layoffs, greater OC might help reduce costs more sustainably and strategically.

For a financially distressed firm, efficiency is key to lowering the costs of production when employing resources. However, although OC is important, it may be competed away and not provide sustained competitive advantage (Helfat, 2007). Further, highly firm-specific operational processes may require substantial organizational adaptation and a distressed firm may not have sufficient time or resources to incorporate such changes. Processes that are faster and easier to implement might also be easier to imitate, thus

minimizing the resulting cost advantages over a firm's competitors (Hayes & Upton, 1998).

Similarly, asset retrenchment may provide a viable flow of capital in the short term but might not produce new or differentiated cash flows that are protected enough to maintain a viable recovery. As the literature offers no insights into whether differences might exist based on firm- or industry-led causes of distress, we do not delve into such contextual differences (although we account for them in our empirical model[5]) and instead offer the following falsifiable hypothesis:

H3 Greater OC increases the probability of recovery for distressed firms.

Empirical evidence

Data

We posit that distressed firms face one of three likely outcomes: (a) they may do enough to survive but not escape their distressed state, (b) they may succumb to financial pressures and slide into bankruptcy, or (c) they may overcome their distress and enter a state of financial health. Our analyses and data reflect these possibilities.

We employ a dataset that combines data on financial health and information on bankruptcy filings for all large public U.S. companies (those having a book value of assets that exceeded $185 million in 1995 dollars based on the U.S. Consumer Price Index) from 1995 to 2021. Information on whether and when a firm filed for bankruptcy comes from the Bankruptcy Research Database of Lynn M. LoPucki at the University of California, Los Angeles. The necessary accounting information comes from the annual Compustat Fundamentals database, with a conversion to 1995 dollars using the U.S. Consumer Price Index from the Department of Labor's Bureau of Labor Statistics.

We use Altman's (1968) Z-score to identify distressed firms, similar to Sudarsanam and Lai (2001) and Koh et al. (2015). Altman's Z-score is a widely accepted proxy for a publicly traded manufacturing company's likelihood of bankruptcy and has been validated as a strong predictor of financial distress and bankruptcy (Altman et al., 2017). It is based on five financial ratios (profitability, leverage, liquidity, solvency, and activity) that can be calculated from data appearing in annual reports. The risk index, or Z-score, is defined as $Z = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + X5$. X1 refers to the liquidity ratio of working capital/total assets. X2 represents the leverage ratio of retained earnings/total assets. X3 is the profitability ratio and is calculated as earnings before interest and taxes (EBIT)/total assets, X4 refers to the solvency ratio of market value equity/book value of total debt, and X5 represents the activity ratio of sales/total assets.

We use Z-scores to create thresholds for classifying firms' bankruptcy risk. A Z-score below 1.81 signifies a "distressed" firm with a high chance of becoming bankrupt. Z-scores from 1.81 to 2.99 are considered to be in the "gray" zone, where bankruptcy prediction is difficult to make. Finally, a Z-score above 2.99 signifies a firm's relative safety from financial distress. We use Z-scores below 1.81 to classify firms (during that year) as being in financial distress and scores above 2.99 (for firms that were once in distress) to indicate financial recovery. These cutoffs are consistent with the original work of Altman (1968) in which the model was generated and tested and has been consistently used in literature (e.g., Li & Rahgozar, 2012). We restrict our sample to only manufacturing firms for two reasons: (a) the Z-score is known to apply mainly to manufacturing firms and (b) the conceptualization of RDC for service firms is not well developed in the literature.

The LoPucki dataset includes 185 manufacturing firms that went bankrupt between 1995 and 2021. Among them, 169, or approximately 91% of the LoPucki sample, were financially distressed. This indicates that the vast majority of bankrupt firms were first financially distressed. However, we also find that 1303 other distressed manufacturing firms[6] during the same period did not file for bankruptcy, indicating that financial distress need not inevitably lead to bankruptcy. Consistent with previous studies (e.g., Jindal & McAlister, 2015), we utilize two-year-lagged explanatory variables. Firms tend to not report financial information a year before filing for bankruptcy, and a two-year lag maximizes the data available for analysis, as opposed to longer lags. Altman (2013) also reports that the Z-score model is best for predicting bankruptcy for up to two years.

Among the sample firms, there were 404 recoveries within two years, 185 bankruptcies, and 867 distressed firms that remained distressed and did not recover within the two-year window but also did not file for bankruptcy.[7] In addition

[5] We also test for the impact of cost-reduction strategies such as asset reductions and dividend reductions. We do not explicitly hypothesize for them to maintain the scope of comparison among various capabilities.

[6] Because the LoPucki database records only firms having a book value of assets that exceeded $185 million in 1995 dollars, we used the same criteria for the inclusion of other distressed firms.

[7] On average, firms remained in distress for 7.5 years. The average continuous period over which firms remained in distress was six years.

to the 404 recoveries, 25 firms had two separate recoveries (i.e., a recovery followed by a period of distress again at some point) and seven firms had three separate recoveries (when tracked over extended time periods not included in our analyses). We did not find any instances of four or more recoveries in our sample. When considering a longer time frame of 10 years, we observe 792 total recoveries and 92 additional bankruptcies. Thus, 387 firms seemed to remain in a continual state of distress during the sample period. In our empirical analyses, if we use a longer window (for instance, a four-year window) to map recoveries,[8] approximately 100 more firms recovered, although the substantive results are similar. These firms represented 104 Standard Industry Classification (SIC) four-digit industries (constrained between 2000 and 3999, which represent manufacturing industries), with the average firm having $2.3 billion in assets, $204 million in profits, and $3540 million in sales annually. Industries with the highest number of distressed firms in our sample include SIC 2834 (pharmaceuticals) with 92 firms, SIC 2860 (organic chemicals) with 44 firms, and SIC 2631 (paper mills) with 35 firms. The median industry in our sample had 11 firms in distress at any given point. Panels A and B of Table 3 provide descriptive statistics and correlations for the dataset.

Dependent variables

Recovery We use a categorical indicator for firm recovery when a distressed firm crosses over from the distress zone to the safe zone, as indicated by its Z-score.

Bankruptcy Corporate bankruptcy refers to the legal procedure through which a company declares that it is unable to pay its debts and seeks financial relief. In the United States, bankruptcies of public firms take the form of either Chapter 7 or Chapter 11.[9] As more than 95% of the firms in our sample filed for Chapter 11 bankruptcy initially (and we consider only the first instance of a bankruptcy filing), we omit Chapter 7 bankruptcies from our analyses. We set the bankruptcy indicator, $BANK_{iy}$, to 1 when firm i files for Chapter 11 bankruptcy in year y and 0 otherwise.

Independent variables

Marketing Capability (MC) To operationalize MC, we follow the approach of Kalaignanam et al. (2013). Drawing on the resource-based view of a firm, they theorize that firms with higher levels of MC use their resources (as inputs) more efficiently than less capable firms to maximize sales (as outputs). Resources available to firms are included in sales, general, and administrative expenditures (SG&A). Given that SG&A includes several items unrelated to marketing, using the variable as is would produce biases (e.g., Ptok et al., 2018). We follow Lim et al. (2020)[10] in constructing a cleaner measure by using Compustat's built-in text analysis package to parse out the expenses associated with marketing. Web Appendix 7 provides a sample of firms that we evaluated through this technique.

Using stochastic frontier estimation (SFE), we then estimate the maximum dollar value of sales that a firm can achieve given its available resources within a particular industry.[11] Using an SFE, we can directly measure each firm's ability to convert the input resources of varied marketing expenditures into output (i.e., MC), compared to firms with similar inputs and outputs. The smaller the difference between a firm's actual sales and maximum sales, the greater its MC. Any shortfall in actual sales indicates inefficiencies. The SFE approach allows us to estimate the degree of efficiency, which we use as a measure of MC.[12] We first estimate the residual from the following equation:

$$\begin{aligned} ln\left(Sales_{it}\right) =& \beta_1 ln\left(CapitalExpenses_{it}\right) + \beta_2 ln\left(R\&DStock_{it}\right) \\ &+ \beta_3 ln\left(Employees_{it}\right) + Ind + \varepsilon'_{it}, \end{aligned} \quad (1)$$

where $Sales_{it}$, $Capital\ Expenses_{it}$, $R\&D\ Stock_{it}$, and $Employees_{it}$ represent the sales, capital expenses, stock of R&D expenses,[13] and the number of employees, respectively, for firm i in year t. *Ind* and *Year* are industry dummies that control for industry

[8] We do not use a long(er) time frame to avoid additional confounds with longer time frames such as board composition changes and partial takeovers by private equity firms.

[9] We only consider Chapter 11 bankruptcy in this study. In Chapter 11 bankruptcy, the debtor negotiates with creditors to alter the terms of the loan without having to liquidate assets. All other cases of bankruptcy are eliminated, partly because the vast majority of bankruptcy cases in the database (>95%) are (at least initially) Chapter 11 bankruptcies.

[10] It is beyond the scope of this article to completely delineate how this task was performed. For comprehensive details on the process, please refer to Lim et al. (2020). If marketing expenses are not denoted separately in an annual report (as was the case for a moderate number of firms in our sample), we subtract any expense denoted separately as part of SG&A that does not constitute a marketing expense (e.g., engineering expense or bad debt expense).

[11] To create the frontier to measure capabilities, we consider all firms in the Compustat universe within a particular industry. We define industries in line with Hoberg and Phillips (2018), who measure product market similarity using annual reports to define industry boundaries. However, we conduct the core analyses on distressed firms only.

[12] Some operationalizations of MC use patents as input. We do not do so because patents are typically a result of R&D efforts and we want to avoid confounding MC and RDC.

[13] We provide the derivation in "RDC and distressed firm recovery" section, which discusses the measure of RDC.

Table 3 Descriptive statistics

A: Summary statistics						
Variables	Mean	SD	Min	Max	Skew	Kurt
Bankruptcy	0.005	0.072	0	1	13.68	188.30
Recovery	0.013	0.056	0	1	15.84	66.96
Marketing capabilities	0.622	0.102	0.057	0.904	−1.23	5.87
R&D capabilities	0.587	0.269	0	0.981	−0.313	2.24
Operations capabilities	0.625	0.235	0	0.985	−0.444	2.46
Dividends	145.5	650.3	0	19,043	11.92	199.68
Diversification	0.105	0.038	0.027	0.455	2.32	12.85
Industry Distress Proxy	−1.90	0.776	−3.201	0.053	−0.152	2.38
Firm Distress Proxy	−0.068	0.346	−−5.253	1.337	−0.037	12.26
Liquidity	0.295	0.201	−2.366	0.909	0.107	6.92
Profitability	0.121	0.126	−3.078	1.937	−3.334	66.34
Leverage	0.225	0.204	0	2.615	1.811	11.83
Firm size	2.275	10.267	0.003	212.94	9.25	113.45
Marketing assets	0.524	0.535	0.034	7.329	3.35	36.03
R&D assets	0.146	0.255	0.0	2.912	9.749	319.58

B: Matrix of correlations															
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Bankruptcy	1.000														
(2) Recovery	−0.056	1.000													
(3) Marketing capabilities	−0.004	0.041	1.000												
(4) R&D capabilities	0.006	0.015	0.039	1.000											
(5) Operational capabilities	−0.014	−−0.021	0.018	0.141	1.000										
(6) Industry Distress Proxy	0.013	−0.046	−0.049	0.086	0.127	1.000									
(7) Firm Distress Proxy	0.016	−0.033	0.066	−0.040	−0.057	−0.367	1.000								
(8) Dividends	−0.005	0.001	0.296	−0.025	−0.007	−0.046	0.001	1.000							
(9) Diversification	−0.017	0.012	0.038	0.073	−0.125	0.176	−0.084	0.135	1.000						
(10) Liquidity	−0.032	−0.013	−0.036	−0.025	0.038	−0.153	0.119	−0.176	−0.089	1.000					
(11) Profitability	−0.030	0.028	0.056	0.061	0.042	0.003	−0.110	0.097	0.107	0.094	1.000				
(12) Leverage	0.017	−0.017	0.028	0.050	−0.010	0.019	−0.091	0.017	0.153	−0.374	−0.039	1.000			
(13) Firm size	−0.007	−0.005	0.070	0.054	0.072	0.014	0.014	0.590	0.200	−0.211	0.047	0.019	1.000		
(14) Marketing assets	−0.007	−0.004	0.039	−0.046	−0.002	−0.057	0.010	0.401	0.128	−0.193	0.014	0.037	0.276	1.000	
(15) R&D assets	−0.030	−0.003	−0.015	0.036	−0.016	−0.089	0.124	0.011	0.101	0.207	0.184	−0.004	0.034	0.031	1.000

effects. β_1, β_2, and β_3 are coefficients to be estimated, and ε'_{it} is the random error. This first step takes into account major drivers of sales excluding marketing as well as industry-level effects as different industries may have varying levels of maximum possible efficiencies owing to structural factors. Following Kalaignanam et al. (2013), we then specify the sales frontier as follows:

$$\ln\left(SalesRes_{it}\right) = \beta_0 + \beta_1 \ln\left(MKTStock_{it}\right) + \mu_i + \nu_{it}, -\eta_i - u_{it}, \tag{2}$$

where $SalesRes_{it}$ is the residual estimated from Eq. (1) and $MKT\ Stock_{it}$ is the stock of marketing expenses for firm i in year t. Marketing stock is a proxy for the amount a firm spends on market research, sales efforts, trade, and other marketing activities. β_0 and β_1 are coefficients to be estimated. η_i and u_{it} respectively represent the time-specific and time-varying inefficiency terms. μ_i and ν_{it}, are firm effects and noise, respectively.

We are only concerned with the time-varying inefficiency term, as capabilities are dynamic in our context. We follow Kumbhakar et al. (2015) (see Web Appendix 3.1 for details) to compute the inefficiency. The inverse of the inefficiency is the firm's MC. Consistent with the literature, we assume that the random error term is normally distributed, the inefficiency term is positively skewed with a half-normal distribution, and the random and inefficiency terms are independent.

We calculate the stock of marketing expenses $MKT\ Stock_{it}$ for firm i in year t by considering the carryover effect of marketing effort (SG&A) and employing a Koyck lag structure (Kalaignanam et al., 2013):

$$\begin{aligned} MKTStock_{it} =& MKTExp_{it} + \lambda_i MKTExp_{it-1} \\ &+ \lambda_i{}^2 MKTExp_{it-2} + \lambda_i{}^3 MKTExp_{it-3} \ldots, \end{aligned} \tag{3}$$

where $MKT\ Exp_{it}$, … $MKT\ Exp_{it-3}$… represent annual marketing expenditures (SG&A) of a firm for the previous six years (unless the firm ceases to exist or was not publicly traded during that time). We estimate the firm-specific decay factor (λ_i) using the following equation:

$$Sales_{it} = \nu_{i0}\left(1-\lambda_i\right) + \nu_{i1}\left(1-\lambda_i\right) MKTExp_{it} + \lambda_i Sales_{it-1} + \psi_{it}, \tag{4}$$

where $Sales_{it}$ and $MKT\ Exp_{it}$ are the respective sales and marketing expenses of firm i in year t. $\nu_{i\,0}$ is the intercept, ν_{i1} is the contemporaneous effect of marketing on sales, and ψ_{it} is the random error.

R&D Capabilities (RDC) To measure RDC, we follow Dutta et al. (1999) and use SFE to estimate the technological output that a firm can achieve given its available R&D resources. We measure technological output using patent counts weighted by citations. We first calculate the average number of citations received by all the patents belonging to all firms in a given industry in a given year. The weight assigned to a particular firm is obtained by dividing the number of citations the firm's patents received by the industry average. After using a first step similar to Eq. (1) in "Dynamic capabilities in distressed firm recovery" section for MC (wherein we regress patents on factors marketing stock, capital expenses, and the number of employees and then generate the residual), we use the following specification for the frontier:

$$\ln\left(PatentRes_{it}\right) = \beta_0 + \beta_1 \times \ln\left(R\&DStock_{it}\right) + \mu_i + \nu_{it}, -\eta_i - u_{it}, \tag{5}$$

where $PatentRes_{it}$ and $R\&D\ Stock_{it}$ are the number of patents and the R&D stock of firm i in year t, respectively. η_i and u_{it} are the respective time-specific and time-varying inefficiency terms. μ_i and ν_{it}, are firm effects and noise, respectively, and β_0 and β_1 are coefficients to be estimated. We use a similar Koyck lag structure as in Eq. (3) to obtain R&D stock.

Independent variables associated with cost-efficiency-based turnaround: Operations capability (OC)

We use the cost of goods sold (COGS) as the outcome (a proxy for costs of production) and the number of employees (EMP) and capital expenses (CAPX) as the inputs (proxies for cost of labor and capital) in a similar SFE framework, akin to Feng et al. (2017). Thus, the frontier is as follows:

$$\begin{aligned} ln\left(COGS_{it}\right) =& \beta_0 + \beta_1 \times ln\left(EmpStock_{it}\right) + \beta_2 \\ &\times ln\left(CAPXStock_{it}\right) + \mu_i + \nu_{it}, -\eta_i - u_{it}, \end{aligned} \tag{6}$$

where $COGS_{it}$, $Emp\ Stock_{it}$, and $CAPX\ Stock_{it}$ are the cost of goods sold, employee stock, and the capital stock respectively for firm i in year t. β_0, β_1, and β_2 are the coefficients to be estimated. η_i and u_{it} are the time-specific and time-varying inefficiency terms while μ_i and ν_{it}, are firm effects and noise. We use a similar Koyck lag structure as in Eq. (3) to obtain the stock variables and a similar first step to control for other major drivers of sales as in Eq. (1). OC employs a minimization function (i.e., a lower cost of goods is better) as opposed to a maximization function used in measuring MC and RDC.

Independent variables associated with retrenchment-based turnaround

Firm size We calculate firm size as the book value of a firm's assets (in units of $10 billion). As maintaining assets is costly and the sale of assets may help raise funds, we include the difference in the firm's assets as representative of asset divestment.

Dividends Firms that reduce dividends benefit by preserving available cash that can be utilized to maintain firm operations. We use the difference in dividends (DVT), which we obtain directly from Compustat, as indicative of shareholder divestment.

Independent variables associated with risk-shifting and investment-based turnaround

Marketing and R&D assets These are resources built through investments in marketing and R&D. Previous studies show that assets built through advertising and R&D reduce bankruptcy risk (Jindal & McAlister, 2015). Irrespective of their levels of capabilities, firms may choose to increase their investments in advertising and R&D to generate desperately needed cash flows, even if the effectiveness and efficiency of such investments have declined. We calculate firms' R&D assets by considering the carryover effect of R&D expenses and employing a Koyck lag structure (Kalaignanam et al., 2013). For marketing assets, we use the modified SG&A measure mentioned in "Dynamic capabilities in distressed firm recovery" section as a proxy for marketing investments and calculate it using a similar Koyck lag structure. Both are scaled by firm size.

Leverage Firms may also take on additional debt and increase their leverage since bondholders bear the costs if a firm declares bankruptcy. In particular, incumbent creditors as claimants will often agree to provide further debt to avoid a costly liquidation, irrespective of a company's state of distress (Noe & Wang, 2000). While increasing leverage may certainly help distressed firms achieve performance improvements if appropriately invested, it is more likely that such additional debt will be used to finance operational needs or risk-increasing negative-NPV projects since managers reap the benefits if things go well (Eisdorfer, 2008). However, neither strategy is likely to yield a path to recovery. We thus include leverage as a covariate and calculate it as total debt divided by the book value of assets.

Moderators

Industry-level causes of distress We first measure decline as the change in Z-score during the year a firm enters the distress zone. For example, if a firm enters a state of distress in year t, our measure is $Z_{(t-1)} - Z_t$. We then regress a variety of industry-level variables that may lead to firm decline: recession, market growth, competition, and turbulence. We define *recession* as any year in which the gross GDP decreased over two successive quarters (e.g., NBER) and indicate it with a dummy variable.

Industry turbulence measures the extent to which industry demand changes rapidly and unpredictably (Fang et al., 2008). Distressed firm recovery can in part depend on industry turbulence. We measure industry turbulence by dividing the standard deviation of sales in the firm's product industry over the preceding four years by the mean value of industry sales for the year (Fang et al., 2008).

Market growth is the extent to which demand in a specific industry increases (Bahadir et al., 2008). In a high-growth market, firms can easily increase revenue because there is enough space for everyone, thereby reducing competitive pressure. We operationalize high growth as the ratio of the difference between the total industry sales in year t and $(t-1)$ to the total industry sales in year $(t-1)$ (Homburg et al., 2015).

Greater *competition* can lead to lower demand for the focal firm's products and ultimately to firm distress. We measure competition using the Herfindahl–Hirschman Index (HHI). $\text{HHI} = \sum_i s_i^2$ where s_i is the market share of firm i. Finally, we incorporate industry dummies to capture any fixed industry effects. The fitted (i.e., predicted) value of the regression is the amount of decline explained by industry-level causes and serves as our proxy for industry-level causes of distress. Web Appendix 4 provides the regression results.

Firm-level cause of distress We argue that any unexplained variance in firm distress is due to firm-specific factors (as opposed to industry-led factors). We thus use the residual from the aforementioned regression as a proxy for firm-specific decline. As residuals can be positive or negative and only negative residuals indicate under-explained distress,[14] we use a dummy variable to capture whether the residuals are negative and multiply it with the residual term.

Controls

Liquidity This measures the velocity with which a firm's assets can be bought or sold on the market. Lack of liquidity can also have a significant effect on the continuation of

[14] If the residual is positive, it indicates that there is some firm-level factor that is buffering the firm from the industry-led distress conditions. Hence, we only use negative residuals (under-explained variance in distress) to proxy firm-specific causes of distress.

Table 4 Model-free evidence

	Distressed	*Not distressed*	*Recovered from distress*	*Distressed and went bankrupt*
Average marketing capabilities	62.17%	70.01%	65.79%	62.69%
Average R&D capabilities	58.68%	56.14%	59.79%	58.31%
Average operations capabilities	62.49%	56.83%	63.33%	63.90%
	T-test of distressed vs not	T-test of recovered vs distressed		
Marketing capabilities	12.43, $p<0.001$	5.87, $p<0.001$		
R&D capabilities	−2.20, $p<0.05$	1.98, $p<0.05$		
Operations capabilities	−6.79, $p<0.001$	0.084, $p<0.1$		

The percentages should be interpreted as levels of capabilities and not as the % of firms that were distressed etc

distress. We calculate liquidity as the ratio of working capital to total assets.

Profitability Research has shown that firms with relatively high rates of profitability are less likely to fail and thus have a lower risk of bankruptcy (Shumway, 2001). We calculate profitability as the ratio of EBIT to total assets.

Diversification Firms that diversify might be more capable of hedging risks and hence ensuring income stability. We measure diversification as the HHI of sales share (i.e., sales in segment/total sales) across all business segments in which a firm operates.[15]

Web Appendix 2 provides an overview of the measures of our study. Web Appendix 3.2 provides face validity for our focal measures for MC and RDC.

Model-free evidence

Table 4 details the average MC and RDC values of firms in distress and shows that firms that survive and recover have greater MC and RDC than those that go bankrupt. It also shows that firms that recover have lower OC than firms that do not survive.

Empirical model (firm recovery)

In this study, distressed firms have three different possible outcomes: recovery, bankruptcy, and remaining distressed. Traditional hazard models treat the cases in which the firm goes bankrupt (i.e., a competing hazard) as censored, which biases the results of those models. Therefore, a competing risks model that accounts for the fact that bankruptcy is a competing outcome that prevents distressed firms from recovering is appropriate. The recovery sub-distribution hazard function is expressed as follows:

$$h_{it} = \lim_{\Delta t \to 0} \{P_r(t < T_{i,recovery} \leq t + \Delta t \Big| T_{i,recovery} > tUT_{i,recovery}, \leq t)/(\Delta t)\},$$

where t is the length of time since entering bankruptcy, $T_{i,\text{ recovery}}$ is a random variable for the length of time to financial recovery, and $T_{i,\text{ recovery}'}$ is a random variable for the length of time to a competing event (i.e., bankruptcy) for firm i. Therefore, h_{it} gives the instantaneous rate of financial recovery for firm i at time t, given that the firm has not become bankrupt. To avoid issues associated with skewness, we employ a log–log discrete time hazard function.

A firm that views marketing as a discretionary expenditure may cut back in that area as it approaches acute financial insolvency. To resolve this endogeneity issue, we use a control function approach with two stages. In the first stage, we use an auxiliary regression and regress the endogenous variable on all variables in the model that are not correlated with the error term (i.e., the exogenous variables) and an additional instrumental variable (IV). The IV must meet the instrument relevance criterion (i.e., the IV predicts the endogenous variable) and the exclusion restriction (i.e., the IV does not correlate with the error term) (Germann et al., 2015). After fitting the first-stage regression, we compute the fitted residuals (see Web Appendix 5 for all first-stage estimates). In the second stage, we include the fitted residuals as an additional regressor in the main model to control for the endogenous regressor.

To account for the endogeneity between MC and RDC, strong and valid instruments are necessary. We use historical market-average MC and RDC (with a three-year window for historical market average) as the instruments in the equation. The instruments are relevant because the

[15] We use SIC and not Hoberg–Philips-based segments here as the corresponding database (Compustat Segments) for obtaining segment-level sales.

correlations between the instruments with their associated endogenous regressors are high (MC: 0.39, $p < 0.001$; RDC: 0.53, $p < 0.001$; OC: 0.56, $p < 0.001$). In addition, the coefficient estimates for the associated instruments in each of the first-stage regressions are significant (MC: 0.845, $p < 0.01$; RDC: 0.904, $p < 0.01$; OC: 0.808, $p < 0.001$). Therefore, the IVs satisfy the relevance criterion.

Our IVs also meet the exclusion restriction, as they are uncorrelated with the omitted variables that affect the focal firm's bankruptcy risk and return. Historical market-average capabilities are unlikely to be related to an individual firm's bankruptcy risk and return two years later, after we control for other firm- and industry-level predictors. For a similar instrument, Germann et al. (2015) note that it is unlikely that such an instrument would relate to a focal firm's omitted variables (i.e., those that affect the focal firm's financial performance) because the market (and other firms in the market collectively) either cannot observe or measure the focal firm's omitted variables or cannot act on those variables strategically. Finally, we use a bootstrap approach to approximate the correct standard errors. As mentioned before, we use a dynamic measure of markets (as in Hoberg & Phillips, 2018). Thus, firms can enter and exit markets, which prevents serial correlation of the peer instrument. These market definitions allow for firms to belong to different markets in different years, thereby providing dynamic exogeneity.

Our attempt at ruling out endogeneity thus far involves using instruments for each of our key variables. Further, firm recovery is a discrete event modeled in the future; thus, reverse causality should not be an issue. However, one may argue that firms become distressed due to a lack of capabilities and that it is obvious that increasing capabilities would then bring firms out of distress. Since distressed firms may be systematically different from non-distressed firms, we utilize a Heckman probit model to model the selected firms in distress as a function of selected firm-level explanatory variables that may serve to protect against distress. First, we calculate the inverse Mills ratio (IMR), as shown in Web Appendix 6. Next, we use the IMR as an additional covariate. We use non-debt tax shields and capital expense intensity as additional variables that satisfy the exclusion criterion. These affect the likelihood of firms being treated (i.e., whether firms are in the non-distressed or the distressed sample), although they are unrelated to financial recovery. Non-debt tax shields are measured following Titman and Wessels (1988), who use the ratio of depreciation and amortization to total assets. Boyer and Marin (2013) and Mangena et al. (2020) use this approach when modeling firm distress.

Thus, the resulting equation for estimating firm recovery is as follows:

$$
\begin{aligned}
h_{it} &= Pr\left(T_i = t | T_i \geq t, x_{it}\right) = \frac{e^{\alpha_t + x_{it}\beta}}{1 + e^{\alpha_t + x_{it}\beta}}, ln\left(-ln\left(1 - h_{i,t+2}\right)\right) \\
&= \alpha_t + \beta_1 MC_{it} + \beta_2 RDC_{it} + \beta_3 OC_{it} + \beta_4 Ind.Distress_{it} \\
&+ \beta_5 FirmDistress_{it} XDummy_{it} + \beta_6 Ind.Distress_{it} XMC_{it} \\
&+ \beta_7 Firm.Distress_{it} XDummy_{it} XMC_{it} + \beta_8 Ind.Distress_{it} XRDC_{it} \\
&+ \beta_9 FirmDistress_{it} XDummy_{it} XRDC_{it} + \beta_{10} Ind.Distress_{it} XOC_{it} \\
&+ \beta_{11} FirmDistress_{it} XDummy_{it} XOC_{it} + \sum_{i=12}^{20} \beta_i CONTROL_{it} \\
&+ \beta_{21} \lambda^{mcap}{}_{it} + \beta_{22} \lambda^{rdcap}{}_{it} + IND + u_i + \varepsilon^{BRH}{}_{it},
\end{aligned} \tag{7}
$$

where $h_{i,t+2}$ is the probability of recovery for firm i in year $(t+2)$, MC_{it} represents marketing capability, RDC_{it} represents R&D capability, and OC_{it} represents operations capability, dummy represents a 1/0 dummy variable that captures whether the residuals are negative (1) or positive (0). $\lambda^{mccap}{}_{it}$ and $\lambda^{rdcap}{}_{it}$ are control functions addressing the endogeneity problem. $CONTROL_{it}$ are covariates. IND are industry dummies. u_i is a firm-specific effect to control for unobserved firm heterogeneity. $\varepsilon^{BRH}{}_{it}$ is the independent and identically distributed error.

Regarding α_t, the baseline hazard, we use a non-parametric baseline hazard. This approach avoids inconsistent estimation of covariate coefficients due to a misspecified baseline hazard (Meyer, 1990). Therefore,

$$
\alpha_t = \alpha_0 + YEAR_i, \tag{8}
$$

where α_0 is an intercept term and $YEAR_i$ represents the year dummy variables, which control for unobserved macroeconomic events and provide a non-parametric control for duration dependence. We use a fixed-effects estimator to account for any remaining unobserved firm heterogeneity and cluster-robust standard errors to account for heteroscedasticity (Jindal & McAlister, 2015). We use a maximum likelihood estimation for the full model.

Results

Table 5 shows that only MC (and not RDC or OC) increases the probability of the recovery of distressed firms (MC: $\beta = 1.479$, $p < 0.001$; RDC: $\beta = 0.069$, $p > 0.1$; OC: $\beta = -0.056$, $p > 0.1$). Table 5 also shows that RDC increases the chances of firm recovery when the distress stems from industry-level causes ($\beta = 0.365$, $p < 0.05$), although MC is more valuable when the distress stems from firm-specific causes ($\beta = 2.890$, $p < 0.05$). We also observe that OC does not help firms recover from financial distress irrespective of the underlying cause(s) ($\beta = -0.616$, $p > 0.1$ for industry-level causes; $\beta = 0.174$, $p > 0.1$ for firm-level causes). Retrenchment strategies

Table 5 The effect of capabilities on distressed firms' recovery

	$Recovery_{t+2}$	$Recovery_{t+2}$
$Marketing\ Capability_t$	1.479^{***}	3.656^{*}
	(0.403)	(1.771)
$R\&D\ Capability_t$	0.069	0.071
	(0.075)	(0.075)
$Operations\ Capability_t$	−0.056	−0.056
	(0.058)	(0.058)
$Industry\ Distress\ Proxy_t$	-0.945^{***}	-1.099^{*}
	(0.278)	(0.501)
$Firm\ Distress\ Proxy_t$ X Residual Dummy	-2.059^{*}	−3.401
	(0.998)	(1.902)
$Marketing\ Capability_t$ X $Industry\ Distress_t$		0.199
		(0.576)
$R\&D\ Capability_t$ X $Industry\ Distress_t$		0.365^{*}
		(0.179)
$Operations\ Capability_t$ X $Industry\ Distress_t$		−0.616
		(0.384)
$Marketing\ Capability_t$ X $Firm\ Distress_t$X Residual Dummy		2.890^{*}
		(1.168)
$R\&D\ Capability_t$ X $Firm\ Distress_t$X Residual Dummy		−1.639
		(0.965)
$Operations\ Capability_t$ X $Firm\ Distress_t$X Residual Dummy		0.174
		(0.102)
Diversification	0.078	0.091
	(0.198)	(0.210)
ΔDividends	0.040	0.037
	(0.037)	(0.037)
$Leverage_t$	-0.250^{***}	-0.255^{***}
	(0.073)	(0.073)
$Liquidity_t$	0.133^{*}	0.129^{*}
	(0.065)	(0.065)
$Profitability_t$	0.078	0.076
	(0.107)	(0.107)
$\Delta Firm\ Size_t$	0.907	0.971
	(0.488)	(0.512)
$Marketing\ Assets_t$	0.011	0.026
	(0.028)	(0.057)
$R\&D\ Assets_t$	0.069	0.016
	(0.075)	(0.031)
$Inverse\ Mills\ Ratio_t$	-0.374^{*}	-0.364^{*}
	(0.181)	(0.181)
Constant	4.570	8.411
	(5.930)	(10.394)
$Control\ Function\ Marketing\ Capability_t$	0.041 (0.104)	0.072 (0.081)
$Control\ Function\ R\&D\ Capability_t$	0.040 (0.039)	0.048 (0.039)
$Control\ Function\ Operations\ Capability_t$	0.011 (0.024)	0.029 (0.025)
AIC	3973.7	3782.5
-LL	1973.8	1930.1
Pseudo R^2	33.61	35.91

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. Residual Dummy is a dummy capturing negative residuals (i.e. distress underpredicted by industry level variables). Δimplies "the difference in variable x year on year". IMR is Inverse Mills Ratio. Market and Year Dummies are included. 4464 observations. Standard errors are in parentheses. Control Function indicates control function residuals

such as asset stripping ($\beta = 0.907$, $p > 0.1$) and dividend reductions ($\beta = 0.040$, $p > 0.1$) also do not appear to impact firm recovery. Thus, it seems that firms require strategic initiatives rather than operational or market restructuring to effect a successful recovery. These results support H1 and H2 but not H3.

Additional results: The impact of capabilities on firm survival

Extant research (e.g., Jindal, 2020; Jindal & McAlister, 2015) shows the importance of marketing and R&D (assets) in reducing bankruptcy risk and re-emerging after a Chapter 11 reorganization effort. However, the results from these studies cannot simply be extended to the context of distressed firm recovery. First, the decision to file for Chapter 11 versus Chapter 7, which forces the firm to liquidate, is subject to creditor votes and depends on the bankruptcy court's decision (Jindal, 2020). Conversely, managers have more control over firm recovery. Second, a firm may "survive" by simply not becoming bankrupt and remaining in financial distress. This is not the same as recovery, which indicates a firm regains its financial health and overcomes even the gray zone of potential distress. To creditors, a recovered firm is, technically, no different from other healthy firms; hence, such firms may start using debt and retained earnings to foster growth instead of simply looking to cover expenses, as most financially distressed firms do. Table 2 and Web Appendix 1 show how our study differs from marketing studies on bankruptcy.

Empirically, our results also reveal differences in the effectiveness of attrition-based strategies. We invert the competing hazard model and use bankruptcy as our outcome of interest and recovery as a competing phenomenon while keeping the variables consistent (see Appendix Table 6). The results are generally consistent with those of firm recovery but we do not find any difference in the effectiveness of MC and RDC when the cause of distress is either firm-specific or industry-led. We do find that the effect of OC on bankruptcy risk for a distressed firm is marginally significant in general ($\beta = -0.349$, $p < 0.1$) and if the cause of distress is firm-specific ($\beta = -0.180$, $p < 0.1$). Further, a reduction in assets also significantly decreases the probability of bankruptcy ($\beta = -0.755$, $p < 0.05$). Although we do not find evidence of cost efficiency and attrition strategies in the case of corporate turnarounds, such strategies seem to be somewhat valuable in helping a distressed firm survive.

Robustness checks

We employ patents as one outcome measure for calibrating RDC. Patents may take some time to yield tangible sales and often serve to protect firm technologies rather than lead to successful commercial products. We thus use sales as an alternate outcome to measure RDC. Web Appendix 8 indicates that results largely remain consistent.

To avoid double counting, we do not include industry-level causes of distress as potential controls. However, these variables may still impact the probability of recovery. Web Appendix 9 shows that the results remain consistent, even with additional controls.

We also investigate whether MC and RDC inhibit firm decline in general. Web Appendix 10 shows that distressed firms' Z-scores increase along expected lines. However, for healthy firms, we find that all three capabilities increase Z-scores. It appears that for distressed firms, developing MC is critical, while for healthy firms, all three capabilities protect against financial decline.

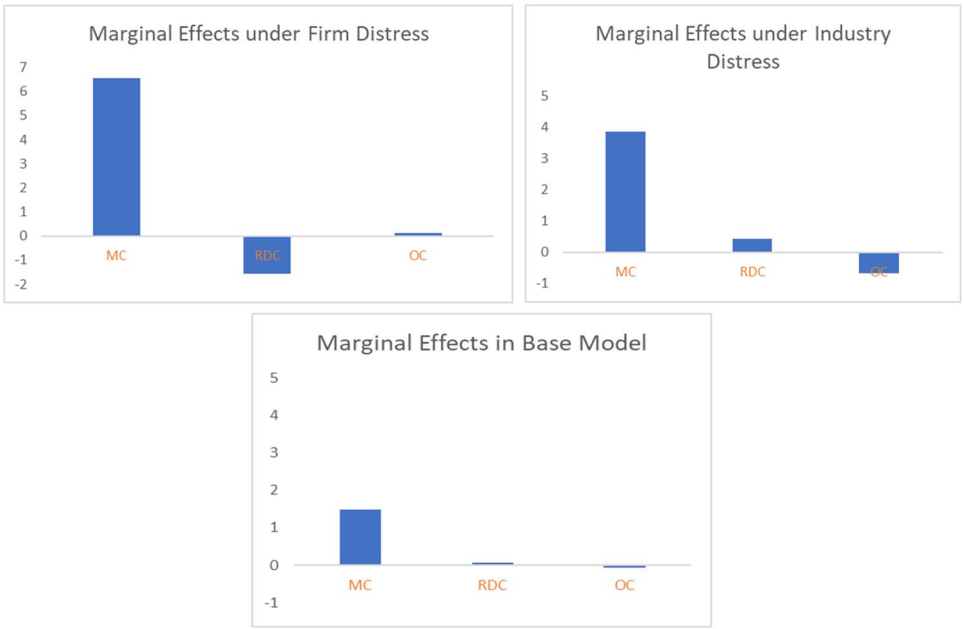
Discussion

Many financially distressed firms turn around their fortunes (88% in our data set), making distress turnaround an economically significant phenomenon to examine. The literature suggests that firms recover from distress using one or a combination of three strategies: cost-cutting, increasing spending on marketing, and risk-shifting by taking on debt. However, cost-cutting and increasing spending present conflicting strategies. Therefore, a clearer explanation of what aids turnaround is essential. In addition, we need to ascertain contextual boundaries within which different turnaround strategies work. In this paper, we propose and empirically show, using a competing hazard model,[16] that capabilities, in particular MC and RDC, provide one explanation for how firms recover from distress. Our results show that, in general, MC is superior in increasing a firm's probability of recovery. This role of MC, never discussed in the context of distressed firm recovery, is a key strategic resource that distressed firms can use for recovery. Overall, although MC trumps RDC (the marginal effects are equivalent to the beta coefficients in a log–log model), RDC is helpful in recovery when the cause of distress is industry-led. Figure 2 graphs these marginal effects.

We find in our sample that upon the onset of distress, firms cut costs in operations (mean ΔCOGS = \$ − 744 M), advertising (mean ΔAdvertising = \$ − 2.65 M), and R&D (mean ΔR&D = \$ − 23.56 M). Typically, to conserve cash, managers often resort to investing less in long-term

[16] Most studies concerning distressed firms are in finance, where it is typical to use only financial ratios to predict distress and the probability of recovery. However, such ratios are only symptoms of malaise and do not give any indication as to what a firm should do to recover.

Fig. 2 Marginal effects



brand-building, research, and advertising (Grullon et al., 2006). At the firm level, managers often engage in asset sales and workforce reductions to increase working capital. Post hoc analyses reveal that a decision to cut costs has an impact on firm survival ($\beta = 1.24$, $p < 0.05$) but not recovery ($\beta = 0.34$, $p > 0.1$). This is in line with our main findings which show that although cost-reduction strategies and OC increase survival probability, they are not as effective as MC and RDC in effecting a financial turnaround. Increasing MC helps firms enact strategic changes to better target customers and position their product offerings while ensuring that the costs of doing so are within bounds (Helfat & Peteraf, 2003). We note that the outcomes of MC, RDC, and OC are different (sales, patents, and cost of goods, respectively), which may bias the results. However, the cost of goods relates directly to revenues retained (i.e., bottom line) and we find the results to be substantively unchanged when we consider sales as an outcome for RDC in the frontier function.

Our main findings may, however, raise the following question: Why does RDC not have a direct effect on distress turnaround? We provide two reasons to explain this lack of direct effect. First, despite the increased efficiency and effectiveness that RDC brings to the conversion of R&D expenses into new products, the immediate success of such (new) products and the size of resulting gains are uncertain. Therefore, while RDC might provide high cash flows but such cash flows are typically more uncertain and slower (Srinivasan et al., 2011). As distressed firms are cash-constrained, obtaining reliable short-term cash is essential for reducing distress.[17]

Since R&D activities are cross-functionally embedded within a firm, starting, ending, or changing extant projects proves challenging. Further, changing R&D processes may require purchasing or re-purposing equipment and space as well as hiring personnel, all of which require money and time (e.g., Howells, 2008). However, despite these downsides, RDC may still be valuable when the distress is largely industry-led. The inherent riskiness of new product introductions due to demand uncertainty may not apply in cases of changing customer needs and tastes (and hence an increased preference for newer and different products). Although the risks of new product failure still exist, the ability to introduce divergent (i.e., unrelated to extant offerings) innovations and increased technical competence to match the competition may overcome such risks.

The role of MC versus RDC in recovering from distress depends on the origins of the distress. Financial distress may originate from industry-level factors, such as gradual changes in the competitive landscape or sudden environmental shocks (Short et al., 2007), as well as firm-specific

[17] This is empirically shown in our analyses. The length of time the firm stays in distress reduces the likelihood of recovery ($\beta = -0.069$, $p < 0.05$) and strongly increases the likelihood of bankruptcy ($\beta = -0.406$, $p < 0.001$). Thus, while returns to R&D may be higher as time accumulates, the gains are washed out since a financially distressed firm will find itself in a more precarious position.

factors, such as ineffective revenue generation (Morrow et al., 2007). Although returns from RDC take longer to materialize and are more volatile (e.g., Aziz et al., 1988), our research shows that these inherent disadvantages may be overcome by the benefits that RDC confers when the distress is industry-led. Greater RDC helps a firm's products stand out from typical offerings in the industry through the provision of less market-led products, which are likely new products (e.g., Zhou et al., 2005). When the cause of distress is firm-specific, the firm may benefit from targeting different segments, re-positioning existing products, and down-scoping product portfolios to eliminate unprofitable products (Pearce II & Robbins, 1993). Greater MC increases the value of existing products and services and aligns them to target more profitable segments (Ketokivi & Schroeder, 2004).

Our results may be interpreted both across firms and within firms. Firms with greater MC have a higher chance of recovery and firms with lower MC would benefit from improving this capability to achieve a turnaround.[18] The literature suggests how firms can strengthen their MC and RDC. Jaworski and Lurie (2019) provide a set of recommendations on how to improve MC. They involve figuring out the best methods and the right data for each marketing choice, designing a process and IT system that enables people to use those methods and data, and finding people with the appropriate skills to exploit the information garnered and produce tangible results. Similarly, Lee and Kelley (2008) list how to improve RDC through better process management tools, loose cultures, and processes that avoid organizational rigidities, close inter- and intra-functional coordination, and tolerance for unfamiliarity.

Theoretical implications

Our findings have two theoretical implications. First, our results imply that the role of capabilities extends beyond the context of financially healthy firms to financially distressed firms. In contrast to financially healthy firms, in which capabilities enhance profits, capabilities, especially MC, help distressed firms arrest and reverse financial decline. Two aspects of capabilities help distressed firms recover. First, distressed firms, being financially constrained, benefit from the efficiency-enhancing role of capabilities in demand-generating tasks. Second, capabilities help distressed firms recover through strategic regeneration via redeployment, replication, renewal, or recombination of their existing resources (e.g., Helfat, 2007).

Second, the differential value of MC and RDC depends on the origins of distress, implying that R&D and marketing are very different organizational functions. Although most extant research (e.g., Feng et al., 2017) offers insights into how the two capabilities complement each other, the circumstances under which each capability offers more value are, to the best of our knowledge, rarely discussed. Further, our analyses show a clear superiority of marketing when a firm is mired in firm-specific crises.

Managerial implications

Our study has several managerial implications. Distressed firms should not rely on cost-cutting alone to recover. Often such cost-cutting comes at the expense of marketing and R&D expenses, thereby hurting the firm. Instead, distressed firms should deploy and invest in MC (and in appropriate circumstances, RDC) to recover from distress.

For instance, Toys "R" Us failed to recover from distress by emphasizing "lower merchandise acquisition costs and lower operating expenses" (Toys "R" Us 10-K, 2016). Similarly, Hertz focused on minimizing costs by "creating time and cost efficiencies, providing solutions to reduce fleet operating cost, reducing costs of operating IT systems and minimizing staffing costs" (Hertz 10-K, 2019) and failed to recover. These two firms failed despite adopting cost-driven and spending-driven recovery strategies. Therefore, other factors must be considered to explain their failures. One explanation is that their low MC made investments both inefficient and ineffective (MC for Toys "R" Us, relative to its industry was 64.3% in 2016; MC for Hertz, relative to its industry was 63.1% in 2018) and the companies needed to adapt to changing customer needs. Toys "R" Us stores were too big, jammed full of inventory, poorly merchandised, and customer service was virtually nonexistent. Instead of having a greater online presence and diversifying to more profitable categories such as PC and console games, the firm continued to spend its marketing budget on traditional advertising through legacy media—i.e. catalog, radio, and TV marketing (Basiouny, 2018). Similarly, Hertz was not willing or able to change their aging fleet of vehicles that customers complained about, and when it did, it mostly bought sedans as opposed to SUVs that customers were migrating toward. It failed to identify and adapt to changing customer needs. Thus, even when travel and car rentals were thriving, Hertz struggled to be profitable and took on debt to continue operations and ultimately filed for bankruptcy (Gladstone & Naughton, 2020).

[18] A probit or logit model provides only pseudo R^2s; thus, it is not easy to distinguish between-, within-, and across-firm variance. However, replacing recovery with a continuous variable such as Z-scores or S&P ratings shows that the across-firm variance explained (approximately 19%) is less than the within-firm variance explained (29%).

The role of RDC in achieving turnaround when the origin of distress is industry-led is illustrated by 3D Systems Corporation, which engages in 3D printing and earns approximately half a billion dollars in revenue each year. Financially stable (Z-scores of > 3) until 2000, the company progressively slid into distress in 2001 (Z = 2.03), 2002 (Z = 0.91), and 2003 (Z = 1.12). However, it turned around and achieved a complete recovery in 2004 (Z = 3.69). An analysis of its annual reports shows that the firm acknowledged that the market for its capital equipment had been impacted by overall economic conditions in 2000 and 2001. In response, it reduced its cost structure by cutting its workforce by approximately 10%. Then, during the third quarter of 2002, it closed multiple facilities and reduced its workforce by an additional 20%. Unfortunately, such cost-cutting strategies did not help in achieving a turnaround. In 2003, it began incorporating changes led by its high RDC capabilities (RDC = 98.62%). The 2004 annual report has multiple sections that report the hiring of personnel as well as strategies for restructuring and repositioning for growth. The firm embarked on several product development campaigns, resulting in 17 new products, enabling it to rapidly regain industry leadership. In sum, the company was negatively impacted by the 2000 recession and initially enacted ineffective cost-cutting strategies before finally relying on RDC to recover.

As stated before, MC enables a firm to change its marketing strategies (e.g., positioning and pricing) as well as provides the ability to select appropriate marketing actions to implement and segments to target. The role of MC in aiding recovery from firm-led distress is exemplified by Pabst Blue Ribbon (PBR). By 2001, sales of PBR beer had been declining for decades, and were 90% below their 1975 peak, leading the company to financial distress. An unexceptional and declining brand, Pabst reinvented itself as the coolest of brews, targeting a completely different segment from its traditional 45 to 60-year-old adults who were overwhelmingly blue-collar workers. PBR never set out explicitly to target artsy, young urbanites or hipsters, but once the company discovered that a new audience in Portland, Oregon had taken a liking to its beer, it boldly realigned its strategies nationally to focus on this more profitable segment. It began sponsoring bike polo tournaments, art galleries, and indie publishers. PBR, which hardly invested in marketing at all before, now started investing in smaller community events that aligned with its demographics' tastes, such as music events, without inundating them with typical national advertising campaigns that would have caused them to discard it as a sellout (McClelland, 2011; Klara, 2019). Overall, this re-positioning resulted in a 5% increase in sales within one year. PBR also saw a 30% increase in sales in 2009 from 2008, while other beer brands lost customers (Kowitt, 2009). In Web Appendix 11 we detail the case of Campbell soup as another example of the role of MC in the recovery from firm-specific distress.

Finally, this paper also offers some recommendations for analysts, bondholders, and equity investors. Financially distressed firms often enter into negotiations with their bondholders to ask for more funds and delays in payments. Bondholders are likely to favor firms with a higher probability of recovery with new funds. Bondholders may also look to loan on more favorable terms to firms with appropriately high capabilities than is justified by their credit ratings. For suppliers, at-risk firms with high marketing and R&D capabilities may present less of a risk and thus such firms would be less likely to suffer supply chain disruptions or need to enter renegotiations, both of which would impede a firm's ability to recover.

Many firms in distress are taken private (e.g., Hertz). Private equity firms can use our measures of capabilities of the distressed firm to ascertain the probability of recovery. Our results imply that recovery prediction models should incorporate MC and RDC to obtain more accurate recovery predictions. We show that these capabilities enable *ex-post* discrimination between at-risk firms that survive and those that fail.

Limitations and future research

The limitations of the study present several opportunities for future research. First, in this study, we examine recoveries two years in the future. However, firms may take longer to recover. Future studies can investigate what strategies are helpful when the period of distress is longer (distress length) or when the firm's level of distress is high, as characterized by lower Z-scores (distress depth). Second, our sample comprises mainly of large publicly listed firms. Future research can ascertain if our findings hold for smaller firms which are often at greater risk of continued distress (e.g., Bruderl & Schussler, 1990).

Appendix

Table 6 The effect of capabilities on distressed firms' survival

	$Bankruptcy_{t+2}$	$Bankruptcy_{t+2}$
$Marketing\ Capability_t$	−3.033*	−5.504
	(1.176)	(2.617)*
$R\&D\ Capability_t$	0.862	0.839
	(0.601)	(1.363)
$Operations\ Capability_t$	−0.349[a]	0.381
	(0.179)	(0.545)
$Industry\ Distress\ Proxy_t$	0.548	0.720
	(0.326)	(0.489)
$Firm\ Distress\ Proxy_t$ X Residual Dummy	0.106	1.748
	(0.066)	(2.847)
$Marketing\ Capability_t$ X $Industry\ Distress_t$		−0.230
		(0.306)
$R\&D\ Capability_t$ X $Industry\ Distress_t$		−0.200
		(0.576)
$Operations\ Capability_t$ X $Industry\ Distress_t$		−0.588
		(1.174)
$Marketing\ Capability_t$ X $Firm\ Distress_t$X Residual Dummy		−0.189
		(0.310)
$R\&D\ Capabilitys_t$ X $Firm\ Distress_t$X Residual Dummy		0.211
		(0.304)
$Operations\ Capability_t$ X $Firm\ Distress_t$X Residual Dummy		−0.180[a]
		(0.101)
Diversification	−2.395**	−3.548**
	(0.791)	(1.303)
ΔDividends	−0.036	−0.058
	(0.132)	(0.089)
$Leverage_t$	1.415*	2.102
	(0.568)	(0.943)*
$Liquidity_t$	0.273	−0.207
	(0.236)	(0.354)
$Profitability_t$	−0.530*	−0.884*
	(0.205)	(0.409)
$\Delta Firm\ Size_t$	−0.755*	−0.526*
	(0.358)	(0.240)
$Marketing\ Assets_t$	−0.389*	−0.256
	(0.170)	(0.317)
$R\&D\ Assets_t$	−0.414**	−0.060
	(0.163)	(0.184)
$Inverse\ Mills\ Ratio_t$	−2.088	−0.654
	(1.291)	(1.461)
Constant	−4.290	−3.071
	(2.289)	(3.394)
$Control\ Function\ Marketing\ Capability_t$	0.063** (0.020)	0.062* (0.029)
$Control\ Function\ R\&D\ Capability_t$	0.021 (0.030)	0.022 (0.029)
$Control\ Function\ Operations\ Capability_t$	0.011 (0.013)	0.034 (0.025)
AIC	134.66	92.77
-LL	55.33	35.21
Pseudo R^2	37.39	38.78

*$p<0.05$; **$p<0.01$; ***$p<0.001$. For $p<0.1$, we denote the symbol a. Residual Dummy is a dummy capturing negative residuals (i.e. distress underpredicted by industry level variables). Δ implies "the difference in variable x year on year". IMR is Inverse Mills Ratio. Market and Year Dummies are included. 4464 observations. Standard errors are in parentheses. Control Function indicates control function residuals

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11747-023-00985-9.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

Altman, E. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance, 23*(4), 589–609.

Altman, E. I. (2013). Predicting financial distress of companies: revisiting the Z-score and ZETA® models. In *Handbook of research ethods and applications in empirical finance*. Edward Elgar Publishing.

Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K., & Suvas, A. (2017). Financial distress prediction in an international context: A review and empirical analysis of Altman's Z-score model. *Journal of International Financial Management & Accounting, 28*(2), 131–171.

Antia, K. D., Mani, S., & Wathne, K. H. (2017). Franchisor–franchisee bankruptcy and the efficacy of franchisee governance. *Journal of Marketing Research, 54*(6), 952–967.

Arora, P. (2016). Financially linked independent directors and bankruptcy reemergence: The role of director effort. *Journal of Management, 44*(7), 2665–2689.

Ashcroft, J. (2014). *The Lego Case Study*. John Ashcroft and Company.

Aziz, A., Emanuel, D. C., & Lawson, G. H. (1988). Bankruptcy prediction - An investigation of cash flow based models. *Journal of Management Studies, 25*(5), 419–437.

Bahadir, S. C., Bharadwaj, S. G., & Srivastava, R. K. (2008). Financial value of brands in mergers and acquisitions: Is value in the eye of the beholder? *Journal of Marketing, 72*(6), 49–64.

Barker, V. L., & Mone, M. A. (1994). Retrenchment: Cause of turnaround or consequence of decline? *Strategic Management Journal, 15*(5), 395–405.

Basiouny, A. (2018). What went wrong: The demise of toys R us. *Knowledge at Wharton*. www.knowledge.wharton.upenn.edu/podcast/knowledge-at-wharton-podcast/the-demise-of-toys-r-us/. Accessed 21 Apr 2023.

Becchetti, L., & Sierra, J. (2003). Bankruptcy risk and productive efficiency in manufacturing firms. *Journal of Banking & Finance, 27*(11), 2099–2120.

Bhagat, S., Moyen, N., & Suh, I. (2005). Investment and internal funds of distressed firms. *Journal of Corporate Finance, 11*(3), 449–472.

Boyer, M. M., & Marin, M. (2013). Financial distress risk and the hedging of foreign currency exposure. *The Quarterly Journal of Finance, 03*(01), 1350002.

Boyne, G. A., & Meier, K. J. (2009). Environmental change, human resources and organizational turnaround. *Journal of Management Studies, 46*(5), 835–863.

Bruderl, J., & Schussler, R. (1990). Organizational mortality: The liabilities of newness and adolescence. *Administrative Science Quarterly, 35*(3), 530–547.

Bruton, G. D., Ahlstrom, D., & Wan, J. C. C. (2003). Turnaround in East Asian firms: Evidence from ethnic Overseas Chinese communities. *Strategic Management Journal, 24*(6), 519–540.

D'Aveni, R. A. (1989). The aftermath of organizational decline: A longitudinal study of the strategic and managerial characteristics of declining firms. *The Academy of Management Journal, 32*(3), 577–605.

Day, G. S. (1994). The capabilities of market-driven organizations. *Journal of Marketing, 58*(4), 37–52.

Day, G. S. (2014). An outside-in approach to resource-based theories. *Journal of the Academy of Marketing Science, 42*(1), 27–28.

Denis, D. J., & Kruse, T. A. (2000). Managerial discipline and corporate restructuring following performance declines. *Journal of Financial Economics, 55*(3), 391–424.

Dutta, S., Narasimhan, O., & Rajiv, S. (1999). Success in high-technology markets: Is marketing capability critical? *Marketing Science, 18*(4), 547–568.

Eisdorfer, A. (2008). Empirical evidence of risk shifting in financially distressed firms. *The Journal of Finance, 63*(2), 609–637.

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal, 21*(10–11), 1105–1121.

Fang, E. (Er), Palmatier, R. W., & Steenkamp, J.-B. E. M. (2008). Effect of service transition strategies on firm value. *Journal of Marketing*, *72*(5), 1–14.

Feng, H., Morgan, N. A., & Rego, L. L. (2017). Firm capabilities and growth: The moderating role of market conditions. *Journal of the Academy of Marketing Science, 45*(1), 76–92.

Flammer, C., & Ioannou, I. (2021). Strategic management during the financial crisis: How firms adjust their strategic investments in response to credit market disruptions. *Strategic Management Journal, 42*(7), 1275–1298.

Gavetti, G., Aoshima, Y. & Tripsas, M. (2007). Fujifilm: A second foundation. *Harvard Business Review*.

Germann, F., Ebbes, P., & Grewal, R. (2015). The chief marketing officer matters! *Journal of Marketing, 79*(3), 1–22.

Gladstone, A., & Naughton, N. (2020). Rental-car company Hertz files for bankruptcy. *The Wall Street Journal*. www.wsj.com/articles/hertz-preparing-bankruptcy-filing-as-soon-as-friday-night-sources-say-11590182538. Accessed 21 Apr 2023.

Grullon, G., Kanatas, G., & Kumar, P. (2006). The impact of capital structure on advertising competition: An empirical study. *The Journal of Business, 79*(6), 3101–3124.

Hayes, R. H., & Upton, D. M. (1998). Operations-based strategy. *California Management Review, 40*(4), 8–25.

Heaton, S., David, T., Agronin, E. (2023). Dynamic capabilities and governance: An empirical investigation of financial performance of the higher education sector. *Strategic Management Journal*, *44*(2), 520–548.

Helfat, C. E. (2007). Stylized facts, empirical research and theory development in management. *Strategic Organization, 5*(2), 185–192.

Helfat, C. E., & Peteraf, M. A. (2003). The dynamic resource-based view: Capability lifecycles. *Strategic Management Journal, 24*(10), 997–1010.

Hoberg, G., & Phillips, G. (2018). Conglomerate industry choice and product language. *Management Science, 64*(8), 3735–3755.

Homburg, C., Vollmayr, J., & Hahn, A. (2015). Firm value creation through major channel expansions: Evidence from an event study in the United States, Germany, and China. *Journal of Marketing, 78*(3), 38–61.

Howells, J. (2008). New directions in R&D: Current and prospective challenges. *R&D Management, 38*(3), 241–252.

Jaworski, B. J., & Lurie, R. S. (2019). Building marketing capabilities: Principles from the field. *AMS Review, 9*(3), 372–380.

Jensen, M. C. (1989). Active investors, LBOs, and the privatization of bankruptcy. *Journal of Applied Corporate Finance, 2*(1), 35–44.

Jindal, N. (2020). The impact of advertising and R&D on bankruptcy survival: A double-edged sword. *Journal of Marketing, 84*(5), 22–40.

Jindal, N., & McAlister, L. (2015). The impacts of advertising assets and R&D assets on reducing bankruptcy risk. *Marketing Science, 34*(4), 555–572.

Jones, G. (2005). *Renewing Unilever: Transformation and Tradition*. OUP Oxford.

Kalaignanam, K., Kushwaha, T., Steenkamp, J.-B.E.M., & Tuli, K. R. (2013). The effect of CRM outsourcing on shareholder value: A contingency perspective. *Management Science, 59*(3), 748–769.

Keller, K. L. (2014). Designing and implementing brand architecture strategies. *Journal of Brand Management, 21*(9), 702–715.

Ketokivi, M., & Schroeder, R. (2004). Manufacturing practices, strategic fit and performance: A routine-based view. *International Journal of Operations and Production Management, 24*(2), 171–191.

Khanna, N., & Poulsen, A. B. (1995). Managers of financially distressed firms: Villains or scapegoats? *The Journal of Finance, 50*(3), 919–940.
Klara, R. (2019) How a bunch of urban hipsters saved Pabst Blue Ribbon. *Adweek*. www.adweek.com/brand-marketing/how-a-bunch-of-urban-hipsters-saved-pabst-blue-ribbon/. Accessed 21 Apr 2023.
Koh, S., Durand, R. B., Dai, L., & Chang, M. (2015). Financial distress: Lifecycle and corporate restructuring. *Journal of Corporate Finance, 33*, 19–33.
Kohli, A. K., & Jaworski, B. J. (1990). Market orientation: The construct, research propositions, and managerial implications. *Journal of Marketing, 54*(2), 1–18.
Kowitt, B. (2009). Let's hear it for hipster beer. *CNNMoney*. https://money.cnn.com/2009/12/10/news/companies/pbr_pabst_blue_ribbon.fortune/index.htm. Accessed 21 Apr 2023.
Krasnikov, A., & Jayachandran, S. (2008). The relative impact of marketing, research-and-development, and operations capabilities on firm performance. *Journal of Marketing, 72*(4), 1–11.
Kumbhakar, S. C., Wang, H., & Horncastle, A. P. (2015). *A practitioner's guide to stochastic frontier analysis using Stata*. Cambridge University Press.
Lee, H., & Kelley, D. (2008). Building dynamic capabilities for innovation: An exploratory study of key management practices. *R&D Management, 38*(2), 155–168.
Li, J., & Rahgozar, R. (2012). Application of the Z-score model with consideration of total assets volatility in predicting corporate financial failures from 2000–2010. *Journal of Accounting and Finance, 12*(2), 11–19.
Lim, L. G., Tuli, K. R., & Grewal, R. (2020). Customer satisfaction and its impact on the future costs of selling. *Journal of Marketing, 84*(4), 23–44.
Lovallo, D., Brown, A. L., Teece, D. J., & Bardolet, D. (2020). Resource re-allocation capabilities in internal capital markets: The value of overcoming inertia. *Strategic Management Journal, 41*(8), 1365–1380.
Lukas, B. A., & Ferrell, O. C. (2000). The effect of market orientation on product innovation. *Journal of the Academy of Marketing Science, 28*(2), 239–247.
Lumpkin, G. T., & Dess, G. G. (1996). Clarifying the entrepreneurial orientation construct and linking it to performance. *Academy of Management Review, 21*(1), 135–172.
Mangena, M., Priego, A. M., & Manzaneque, M. (2020). Bank power, block ownership, boards and financial distress likelihood: An investigation of Spanish listed firms. *Journal of Corporate Finance, 64*, 101636.
March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science, 2*(1), 71–87.
McClelland, E. (2011). And the next Great American Beer Will Be...? *Salon*. www.salon.com/2008/08/11/pabst_blue_ribbon/. Accessed 21 Apr 2023.
Meyer, B. (1990). Unemployment insurance and unemployment spells. *Econometrica, 58*(4), 757–782.
Mizik, N., & Jacobson, R. (2003). Trading off between value creation and value appropriation. *Journal of Marketing, 67*(1), 63–76.
Morgan, N. A., Slotegraaf, R. J., & Vorhies, D. W. (2009). Linking marketing capabilities with profit growth. *International Journal of Research in Marketing, 26*(4), 284–293.
Morrow, J. L., Johnson, R. A., & Busenitz, L. W. (2004). The effects of cost and asset retrenchment on firm performance: The overlooked role of a firm's competitive environment. *Journal of Management, 30*(2), 189–208.
Morrow, J. L., Sirmon, D. G., Hitt, M. A., & Holcomb, T. R. (2007). Creating value in the face of declining performance: Firm strategies and organizational recovery. *Strategic Management Journal, 28*(3), 271–283.
Ndofor, H. A., Vanevenhoven, J., & Barker, V. L., III. (2013). Software firm turnarounds in the 1990s: An analysis of reversing decline in a growing, dynamic industry. *Strategic Management Journal, 34*(9), 1123–1133.
Noe, T. H., & Wang, J. (2000). Strategic debt restructuring. *The Review of Financial Studies, 13*(4), 985–1015.
Ofek, E. (1993). Capital structure and firm response to poor performance: An empirical analysis. *Journal of Financial Economics, 34*(1), 3–30.
Pearce, J. A., II., & Robbins, K. (1993). Toward improved theory and research on business turnaround. *Journal of Management, 19*(3), 613–636.
Peteraf, M. A., & Barney, J. B. (2003). Unraveling the resource-based tangle. *Managerial and Decision Economics, 24*(4), 309–323.
Ptok, A., Jindal, R. P., & Reinartz, W. J. (2018). Selling, general, and administrative expense (SGA)-based metrics in marketing: Conceptual and measurement challenges. *Journal of the Academy of Marketing Science, 46*(6), 987–1011.
Rico, M., Pandit, N. R., & Puig, F. (2021). SME insolvency, bankruptcy, and survival: An examination of retrenchment strategies. *Small Business Economics, 57*(1), 111–126.
Santana, M., Valle Cabrera, R., & Galán González, J.-L. (2018). Sources of decline, turnaround strategy and HR strategies and practices: The case of Iberia Airlines. *Economic and Industrial Democracy, 40*(3), 583–610.
Schilke, O., Hu, S., & Helfat, C. E. (2018). Quo vadis, dynamic capabilities? A content-analytic review of the current state of knowledge and recommendations for future research. *Academy of Management Annals, 12*(1), 390–439.
Short, J. C., Ketchen, D. J., Jr., Palmer, T. B., & Hult, G. T. M. (2007). Firm, strategic group, and industry influences on performance. *Strategic Management Journal, 28*(2), 147–167.
Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *The Journal of Business, 74*(1), 101–124.
Slotegraaf, R. J., & Dickson, P. R. (2004). The paradox of a marketing planning capability. *Journal of the Academy of Marketing Science, 32*(4), 371–385.
Smith, M., & Graves, C. (2005). Corporate turnaround and financial distress. *Managerial Auditing Journal, 20*(3), 304–320.
Srinivasan, R., Lilien, G. L., & Sridhar, S. (2011). Should firms spend more on research and development and advertising during recessions? *Journal of Marketing, 75*(3), 49–65.
Sterman, J. D., Henderson, R., Beinhocker, E. D., & Newman, L. I. (2007). Getting big too fast: Strategic dynamics with increasing returns and bounded rationality. *Management Science, 53*(4), 683–696.
Sudarsanam, S., & Lai, J. (2001). Corporate financial distress and turnaround strategies: An empirical analysis. *British Journal of Management, 12*(3), 183–199.
Tangpong, C., Abebe, M., & Li, Z. (2015). A temporal approach to retrenchment and successful turnaround in declining firms. *Journal of Management Studies, 52*(5), 647–677.
Titman, S., & Wessels, R. (1988). The determinants of capital structure choice. *The Journal of Finance, 43*(1), 1–19.
van Heerde, H. J., Mela, C. F., & Manchanda, P. (2004). The dynamic effect of innovation on market structure. *Journal of Marketing Research, 41*(2), 166–183.
Zhou, K. Z., Yim, C. K. (Bennett), & Tse, D. K. (2005). The effects of strategic orientations on technology- and market-based breakthrough innovations. *Journal of Marketing*, *69*(2), 42–60.
Zoltners, A. A., Sinha, P., & Lorimer, S. E. (2004). *Sales force design for strategic advantage*. Palgrave Macmillan.