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Inventory management under financial distress: an empirical analysis

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This study analyses inventory reductions as a means of short-term financing of firms under financial distress. We use quarterly panel data of U.S. manufacturing firms for the period from 1995 to 2007. We identify a sample of 198 distressed firms for which we analyse changes in relative inventory. Approximately 70% of distressed firms reduce their inventories until the end of their individual distress periods. This decrease corresponds to a mean reduction of 18.7 inventory days or 9.4%. Additional regression analyses show that differences in inventory adjustments depend on pre-distress inventory performance, firm size, and turnaround strategy. We also compile a sample of 142 firms that defaulted to analyse inventory actions of unsuccessful turnarounds. Our findings indicate that defaulting firms also reduce their inventories but that the reductions are lower than those of firms that resolve their financial distress. We conclude that distressed firms use short-term inventory adjustments to free up cash and to achieve long-term efficiency gains from inventory optimisation. Our findings suggest that inventory optimisation is an essential part of a complete and successful turnaround strategy and financially distressed firms should always consider this action as a means to prevent bankruptcy.

Keywords: inventory management; financial distress; quarterly inventory; econometrics; Z-Score; bankruptcy

1. Introduction

In 2012, 40,075 businesses filed bankruptcy in the United States under the different chapters of the Bankruptcy Code (Administrative Office of the U.S. Courts 2013). Among these filings were prominent firms like imaging pioneer Eastman Kodak, coal producer Patriot Coal Corp and aircraft manufacturer Hawker Beechcraft as highlighted by the Wall Street Journal (Fitzgerald and Beaudette 2012; Tadena 2012; Spector, Mattioli, and Brickley 2012). However, even before filing bankruptcy many more firms observe financial distress. Financial distress is a condition in which a firm has difficulty meeting or cannot meet mature financial obligations. It is widely experienced by firms in every industry at every point in time.

Distress can originate from factors that are either internal or external to the firm, management mistakes, excessive leverage, rising costs, uncontrolled growth and sluggish demand are typical causes of distress. External economic factors can include unfavourable industrial structures, governmental deregulation activities, rising interest rates, increasing competition and industry overcapacity (Altman and Hotchkiss 2006). Throughout this study, financial distress refers to a demonstrated threat to a firm's survival resulting from one or more of the previously cited causes. Because early warning signs of such threats are not easily detected (Bibeault 1982), empirical studies on financial distress rely on deteriorating financial ratios, which imply an absence of early adjustment actions (Hendricks and Singhal 2005). As financial distress progresses, firms become prone to illiquidity, which creates a stronger and more evident need for restructuring or turnaround actions. If firms fail to initiate appropriate restructuring processes, upcoming liquidity constraints will force them to file a Chapter under US bankruptcy law or even face liquidation (Altman and Hotchkiss 2006).

The turnaround literature presents several classification schemes for strategies that firms can use to overcome distress. Hofer (1980) identifies two generic categories of turnaround strategies: 'Strategic turnarounds' and 'operating turnarounds'. According to Hofer's definition, strategic turnarounds involve the renewal of a firm's business model, whereas operating turnarounds involve asset divestment, cost-cutting or revenue expansion in current markets. Hambrick and Schecter (1983) build a model based on Hofer's definition and distinguish between four strategies: (i) revenue generation, (ii) product/market refocusing, (iii) asset reduction and (iv) cost cutting. In the first strategy, firms aim to increase sales by launching new products or entering new markets, whereas in the second, the main objective is to expand revenues in current markets by refocusing on profitable products and market segments. The latter two strategies aim at improving efficiency and reduce cash outflows in periods of distress.

Academicians and practitioners are discussing the impact of financial distress and financing constraints on firm inventories (e.g. Hambrick and Schecter 1983; Carpenter et al. 1994; Guariglia 1999; BCG 2009). In their early study, Hambrick and

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Schecter (1983) show that inventory adjustments, which are our primary area of interest, are observable in clusters of firms that mainly employ the last three strategies, excluding only the revenue generation strategy. However, in practice, turnaround strategies may be combined, causing financial figures to become blurred (Hofer 1980). Therefore, we assume that in times of constrained liquidity, inventory reductions are generally applicable in every turnaround situation because they can rapidly generate cash (Carpenter et al. 1994), whereas inventory efficiency improvements are advantageous in the long term.

Transforming assets into cash is one of the key actions that ensures liquidity and may help a firm to avoid bankruptcy (Beaver, Correia, and McNichols 2010). However, divesting fixed assets may not be an easy task for distressed firms. Manufacturers with highly specialised assets can face problems selling their assets (Shleifer and Vishny 1992). The problem of asset specificity is less severe when transforming working capital into cash in times of distress. Firms are expected to be able to generate significant amounts of cash in the short term by adjusting inventories, accounts payables and accounts receivables (Sudarsanam and Lai 2001; Molina and Preve 2009). The Pecking Order Theory also suggests a preference for internal capital sources over the issuance of debt or equity due to the higher implied adjustment costs of external financing (Myers 1984). Consistent with financial theory and due to relatively low adjustment and liquidation costs (Carpenter et al. 1994), inventory adjustments seem to be adequate means to generate cash. To improve inventory efficiency and increase free cash flow, firms can choose from a variety of different options: short-term actions including optimising inventory policies, reducing obsolete stocks and improving forecasting approaches; and long-term actions, including redesigning manufacturing networks, reducing portfolio complexity and integrating suppliers. Reducing inventories within a short time period requires careful planning, but the resulting cash inflows and cost reductions during the first year are expected to pay off. If cash is scarce, the turnaround literature and practitioners also suggest reducing receivables and expanding payables (BCG 2009). Nevertheless, firms need to be aware of the trade-offs between short-term cost reductions that facilitate quick cash gains and long-term efficiency gains (Niemeyer and Simpson 2008; BCG 2009).

Below we will briefly present the example of Motorola Inc., a global manufacturer of communication and electronic equipment, that was split up into two separate companies in 2011. Motorola experienced a period of severe distress following the dot-com bubble burst in 2000 and is therefore a suitable example. From the first quarter of 2001 until mid-2002, Motorola accumulated approximately US$6.7 billion in net losses. At the same time, Motorola's sales decreased by 25%. In this difficult situation, the company had to find ways to stabilise its business activities while paying attention to preserve liquidity. Motorola's financial figures reflect the proposed transformation of its current assets into cash. Figure 1 shows the development of Motorola's inventory during the distress period from 2000 to 2004. The beginning and end of the distress period are indicated by a decrease in the Altman's Z-Score (Altman 1968) below a threshold level, which is presented at

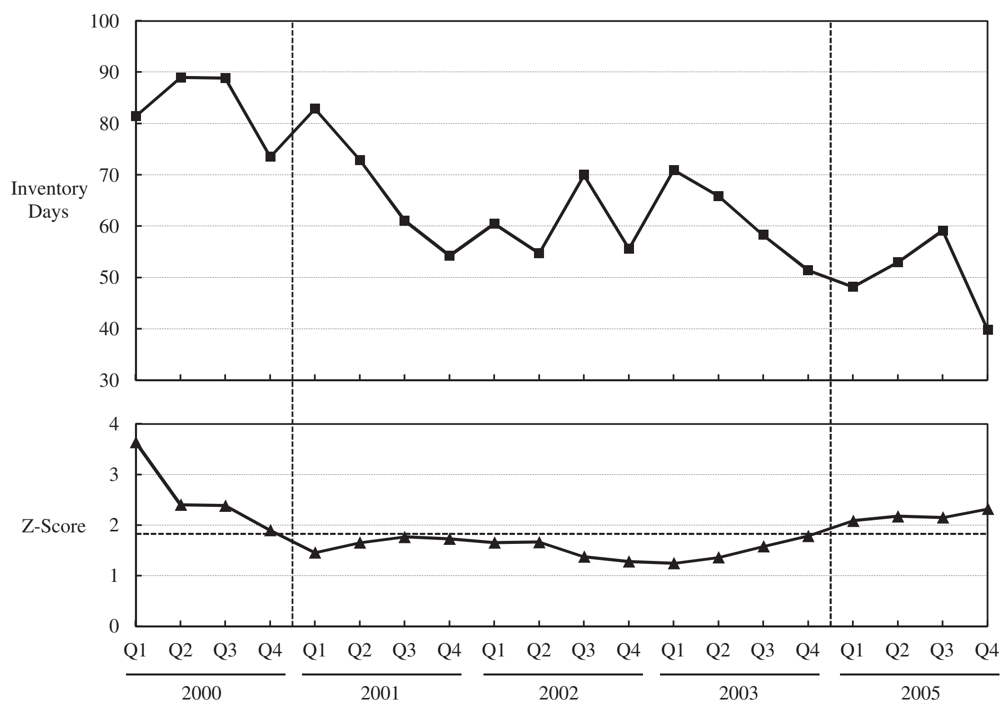

Figure 1. Inventory days and Z-score of Motorola Inc. (2000–2004).

the bottom of Figure 1. The dashed vertical lines mark the boundaries of the 12-quarter distress period that Motorola faced. Within this distress period, Motorola's quarterly inventory decreased from 73 to 48 days (a reduction of 34%). As expected, Motorola was also highly engaged in additional turnaround activities. During the downturn, the firm laid off 60,000 of its 150,000 employees (Corcoran 2004) and increased its liabilities-to-assets ratio by 4%, but a reduction in inventory days clearly accompanied Motorola's other efforts to resolve its distress.

Although recommendations and anecdotal evidence of inventory optimisation under conditions of financial distress seem intuitive, recent studies do not analyse the overall persistence and magnitude of inventory adjustments. Most studies from the turnaround literature and other previous research that analyses firm reactions to financial distress focus either on large asset restructuring efforts or on working capital adjustments without explicitly analysing inventories (Hambrick and Schecter 1983; Ofek 1993; Asquith, Gertner, and Scharfstein 1994; Opler and Titman 1994; Brown, James, and Mooradian 1994; Sudarsanam and Lai 2001; Molina and Preve 2009; Hill, Kelly, and Highfield 2010). To the best of our knowledge, there is only one previous research paper that thoroughly studies the link of inventory adjustments and internal financing constraints (Guariglia 1999). However, the paper's main objective is to analyse whether internal financing constraints, in particular during periods of recession and tight monetary policy, cause changes in inventory investments large enough to ultimately affect aggregate output. Other studies that link financial constraints to inventory investments also have a macroeconomic rather than a firm-level perspective (Carpenter et al. 1994; Carpenter, Fazzari, and Petersen 1998; Guariglia and Mateut 2010) and these studies do generally not measure the magnitude of inventory adjustments during firm-specific instances of financial distress or which firm characteristics mediate the inventory divestments. Further, none of the aforementioned studies has analysed whether inventory reduction efforts differ for distressed firms compared to later defaulting firms. Our paper bridges this gap in the contemporaneous operations management literature. The contribution of our study is threefold.

First, we quantify the inventory reduction effect in periods of financial distress. Using a sample of US public manufacturing firms with quarterly data from 1995 to 2007, we identify 198 firm distress periods based on a drop in firms' Z-Score (Altman 1968) that lasts between four and twelve consecutive quarters. We find that the mean (median) inventory reduction in 18.7 (8.4) inventory days. Our findings indicate a positive relationship between a firm's ability to convert inventories into cash and an overall successful turnaround. Most notably, financially distressed firms achieve the inventory reductions in relatively short time periods of less than six quarters. Most of the inventory reductions seem to take place in the early stages of the distress period. Our results indicate that inventory reductions in long distress periods of up to 12 quarters are not significantly different from shorter distress periods of only six quarters. We also find that the overall inventory effect persists for at least one year following a period of distress.

Second, we identify firm characteristics before the distress period that lead to different inventory adjustment decisions. Having lean inventory prior to distress reduces a firm's likelihood of transforming its inventory into cash without harming the on-going business. Further, we find that inventory adjustments are stronger for small firms than for large ones.

Third, we compare the inventory decisions between firms that are able to get out of financial distress with defaulting firms. We analyse a sample of 142 firms that eventually defaulted, which we identified from the UCLA-LoPucki Bankruptcy Research Database (LoPucki 2011). Our results indicate that these firms reduce their inventory days only by an average of approximately 5.3 days.

The remainder of this paper is structured as follows. In Section 2, we develop a set of seven hypotheses that relates to inventory management during financial distress. In Section 3, we summarise the data-set, provide definitions of relevant metrics and describe the development of two subsamples of distressed or defaulted firms. Section 4 describes our methodology and the result of the empirical analysis for each hypothesis. In Section 5, we present several robustness checks with alternative indicators of financial distress to validate our findings. Section 6 summarises our main findings and concludes with managerial implications.

2. Hypothesis development

The above discussion raises three key questions. First, do financially distressed firms follow the recommendation to reduce their inventories in times of scarce liquidity? Second, are inventory reductions still significant after controlling for average industry performance or when compared to the inventory behaviour of defaulting firms? Third, which are the firm characteristics that lead to different inventory adjustments under distress? Below, we develop seven testable hypotheses to address these questions.

We assert that firms prefer internal financing over external funds (Myers 1984) and that working capital reductions are often related to successful turnarounds (Hambrick and Schecter 1983). The results by Petersen and Rajan (1997) support this notion as firms make intensive use of trade credit if their access to debt markets is constrained. Other studies do also provide empirical evidence of asset reductions for companies that face liquidity constraints or that are financially distressed

(Asquith, Gertner, and Scharfstein 1994; Opler and Titman 1994; Sudarsanam and Lai 2001). However, these studies do not explicitly measure the inventory divestments associated with asset reductions in more general terms.

Given results from earlier studies, it seems plausible that inventories are a valuable source of 'quick' liquidity that can be transformed into cash during periods of distress. In contrast to assets in general, and in particular fixed assets, inventory divestments require only limited adjustment costs. In this context, it is noteworthy that firms do not have to actively sell off inventories; even 'freezing' of outstanding raw material orders enables a reduction in inventory over time if raw materials are steadily consumed during the production process (Carpenter et al. 1994).

Given the argumentation above, we expect that distressed firms will adjust current assets, particularly their inventories, before turning to external sources of cash. To test the impact and existence of inventory adjustments, we analyse changes in inventory days during firm-specific distress periods. Our first hypothesis is as follows:

Hypothesis 1 *Firms in financial distress significantly reduce inventories.*

Firms can use short- and long-term actions to reduce their inventories. Although restructuring efforts and other long-term initiatives may reduce inventories in the long-run, we believe that short-term inventory reductions are most likely to occur before large asset sales (Shleifer and Vishny 1992) or other turnaround actions. For example, manufacturing redesign, product design harmonisation or inventory system alignment can help to reduce inventories in the long-run. However, these long-term actions are harder to implement and depend on individual firm characteristics. In addition, long-term initiatives often involve large monetary investments which are not feasible for firms that are already financially constrained. Due to the significant burden of financial distress and the resulting liquidity constraints, managers should seek activities that can be implemented in a short period of time to secure firm survival (Arpi and Wejke 1999). Within the sample used by Ofek (1993), the most common operational action undertaken by firms is asset restructuring, with 23% of sample firms following this option. Similarly, Sudarsanam and Lai (2001) report asset reductions for more than one-third of their sample during the first year of distress. In line with these findings, we expect that companies will start divesting assets – and in particular current assets and inventories – shortly after the onset of the financial distress. Any complementary long-term actions that firms may undertake in response to financial distress will take more time to become effective and long-run efficiency gains in inventory management (i.e. leaner inventories) will emerge only gradually. We therefore hypothesise that the largest fraction of inventory reductions occurs shortly after the firm becomes financially distressed and that only small incremental inventory reductions will be observed after a prolonged time of financial distress. Our second hypothesis is therefore:

Hypothesis 2 *The largest inventory reductions will be observed in the first quarters of financial distress and no incremental inventory reductions are observed for firms that remain in distress for longer periods.*

Although we expect a large fraction of the inventory reductions to stem from short-term actions, we believe that the inventory improvements (i.e. leaner inventories) are permanent and beneficial in the long-run. For instance, selling slow-moving or obsolete inventories provides a quick cash inflow, but firms should have no need to increase their respective inventory holdings if sales increase again. Furthermore, after a crisis and successful turn-around, firms will probably attempt to keep inventories lean and avoid a reversal back to outdated calculation models for safety stocks or forecasts. This distinction differentiates inventory actions from suggested short-term actions for accounts payables and accounts receivables. Such actions partly squeeze suppliers or customers for cash, eventually harming the overall performance of the supply chain (Hofmann and Kotzab 2010). However, after a distress period, trade credit policies can be relaxed to encourage customers to buy higher quantities, or customer discounts can be offered again. Furthermore, while suppliers are probably willing to help their customers during periods of financial distress, they might not be willing to extent trade credits forever, once the firm has recovered economically. Therefore, accounts payable and accounts receivables are likely to revert to their pre-distress levels (see practitioner interviews in Pesch (2012)). However, unlike accounts payable and accounts receivable, which both involve external parties (i.e. suppliers and customers, respectively), inventories are under the sole control of the company and firms will likely attempt to keep inventories as lean as possible. We argue that when a company is able, in response to financial distress, to reduce its inventories substantially and without harming ongoing operations, then the company is unlikely to return to pre-distress inventory levels. Our third hypothesis is therefore:

Hypothesis 3 *Inventory reductions during distressed periods are permanent and will lead to lower post-distress inventories.*

Given our argumentation above, we claim that inventory reductions are an integral part of a successful turn-around strategy for companies in financial distress, because inventory reductions are a relatively easy means of immediate cash inflows. A question that naturally arises in this context is how important inventory reductions are for a successful turnaround action and to what extent successful and unsuccessful companies (i.e. defaulting firms) differ with respect to inventory performance. In order to address this question and to analyse the importance of inventory adjustments, we compare the behaviour of distressed firms that achieved successful turnarounds to those that later defaulted. We generally expect that distressed firms, both surviving and later defaulting firms, try to exploit working capital resources (i.e. reduce inventories) to generate liquidity and to avoid a filing for bankruptcy. This notion is in line with the findings by Asquith, Gertner, and Scharfstein (1994) who show that distressed firms generally sell assets to avoid bankruptcy, but the authors do not provide insights whether firms that later default do so to a greater or lesser extent compared to firms that successfully recover from distress. DeAngelo, DeAngelo, and Wruck (2002) describe the case of L.A. Gear and show that rough inventory divestments delayed the firm's bankruptcy filing although the firm ultimately went bankrupt. This example shows that firms adjust their inventories regardless of whether they eventually default. However, the key question is whether firms that successfully avoid bankruptcy reduce their inventories by a larger or smaller amount than defaulting firms. We argue that only companies with (i) satisfactory supply chain capabilities and (ii) a viable business model will be able to liquidate their inventories effectively to free up sufficiently cash in a short period of time. For instance, companies with better downstream supply chain competencies may quickly find new distribution channels, negotiate temporarily better sales terms with their customers or clear in-transit inventories effectively. Similarly, firms that have good upstream supply chain competencies will likely be able to reduce raw material inventories without jeopardising ongoing production processes. In more general terms, firms that are financially distressed due to fundamental business problems (e.g. obsolete production technology or products) have a higher probability to default. At the same time, those companies will most likely not be able to reduce their inventories as efficiently as competitors with less severe problems. For instance, a company that accumulated excess inventories due to obsolete products will certainly have difficulties selling those outdated products and will hence not be able to reduce inventories to free up cash quickly. We therefore claim that defaulting firms will not be able to reduce their inventories by the same amount as companies that recover from financial distress.

Hypothesis 4 *Defaulting firms reduce their inventories by a smaller amount compared to non-defaulting firms.*

Previous research has shown that US manufacturing firms have reduced their relative inventory levels over the last decade regardless of whether they experienced distress (Chen, Frank, and Owen 2005). Firms with initially low inventory days relative to their industry competitors are likely to already use lean inventory strategies. We expect that under conditions of financial distress, these firms will have less potential to further reduce their inventories without harming their production flows or service levels (Eroglu and Hofer 2011). Additionally, further optimisation potential will be associated with higher marginal costs (Carpenter et al. 1994). In contrast, high inventory days indicate that firms may have excessive inaccessible capital on their balance sheets which they might liquidate to free up cash during periods of financial distress.

Hypothesis 5 *Firms with higher inventory levels in the pre-distress period reduce their inventories more significantly than firms with lower pre-distress inventory levels.*

Sluggish sales are one of the major causes of financial distress. Small firms are particularly vulnerable to serious decreases in sales, which suggests that asset adjustments might be more pronounced and prominent for smaller firms (Opler and Titman 1994). Small firms typically have less access to capital markets and should therefore have a greater need for tighter working capital management (Hill, Kelly, and Highfield 2010). In addition, smaller companies usually do not have access to equity markets (i.e. stock exchanges) and rely on bank loans as the preferred source of external financing. However, banks are not likely to extend credit lines for firms that are in financial distress, making inventory divestment even more relevant as an additional source of financing. In contrast, large firms typically have better access to external sources of liquidity.

Carpenter et al. (1994) find that small firms are more affected by financial constraints than large firms, which generates greater inventory investment volatility for small firms than for large ones. This observation supports our expectation that small firms will make greater inventory reductions. Large companies also appear to hold proportionally less inventory than small firms due to their greater scale and size effects (Rumyantsev and Netessine 2007). Hendricks and Singhal (2009) observe that excess inventory announcements, as a proxy for demand and supply mismatches, generate fewer negative abnormal returns for large firms than for small firms.

Furthermore, large firms usually have more diversified business lines than small firms. Thus, large firms are more likely to be able to transform their inventories into cash by discontinuing entire business or product lines altogether (Ofek 1993). Small firms do not have such opportunities because their business models are more focused and they typically have more limited product lines (Hendricks and Singhal (2005, 2009).

Hypothesis 6 *Smaller firms reduce their inventories more than large firms in response to financial distress.*

We hypothesise that the observed inventory reductions likely depend on individual firm choices regarding appropriate turnaround actions (Hofer 1980). Consistent with previous recommendations from the literature, we assert that inventory reductions will have a significant effect if firms aggressively engage in cost or asset reductions. Other turnaround strategies, particularly revenue expansions, are not likely to be associated with inventory adjustments (Hambrick and Schecter 1983). Such turnaround strategies aim to increase market share (Hofer 1980) and should therefore be less related to inventory

Table 1. Expected change of inventory days for focused turnaround strategies.

Turnaround strategy	Hypothesized sign
Revenue increase	+
Product/Market refocus	±
Cost cutting	−
Asset reduction	−

reduction efforts. The turnaround literature proposes the identification of turnaround strategies based on financial ratios (Barker III and Duhaime 1997; Boyne and Meier 2009). Such an approach allows us to prove the dependence of inventory adjustments on the turnaround actions chosen by firms. Table 1 summarises the hypothesised signs of inventory performance during distress for the previously introduced turnaround actions.

However, our interviewees (Pesch 2012) stress the importance of combining several turnaround actions, which indicates that companies usually chose a mix of different actions making it harder to obtain a clear-cut cluster of generic strategies for our sample companies. Given this complication, we decided to test only extreme cases for specific turnaround actions, and we propose the following hypothesis:

Hypothesis 7 *Significant inventory reductions will be observed for firms that engage in aggressive cost cutting or asset reductions as part of their turnaround strategy.*

We will introduce our data and methodology in the next section before we present the empirical results in Section 4.

3. Data selection and sample generation

In this section, we describe the data-set and the relevant metrics used throughout this study. In addition, we describe the sample generation procedure for the samples of financially distressed and defaulted firms. All of the analyses of the data-set are performed using the statistical software package Stata (version 12.1).

3.1 *Data and metrics*

The data set consists of US manufacturing firms collected from the Standard & Poor's Compustat database. The analysis is based on quarterly financial data covering the period 1995–2007, which allows us to capture even short-term changes in firms' inventory levels (Guariglia 1999). The full data-set includes a total of 5,126 firms, with an average of 19 quarterly observations per firm. We restrict ourselves to manufacturing companies due to the important role of inventories in this sector. We use the codes from 311 to 339 of the North American Industry Classification System 2007 (NAICS) to identify manufacturing segments, while Compustat's GVKEY is used as individual firm identifier.

Firm observations with negative values for total assets, cost of goods sold, inventories and any remaining duplicates are excluded from our analysis. Additionally, we exclude firms reporting less than one million US$ in sales to avoid the distorting effect of including very small companies.

We investigate inventory performance based on quarterly inventory days ($\mathrm{ID}_{\mathrm{istq}}$), which are calculated by dividing ending inventory (I_{istq}) by the cost of goods sold ($\mathrm{COGS}_{\mathrm{istq}}$). Subscript i denotes a firm observation, s is each firm's 3-digit NAICS industry and tq denotes the time-series years and quarters, respectively, leading to the following definition of inventory days (see Chen, Frank, and Owen 2005):

$$\mathrm{ID}_{\mathrm{istq}} = \frac{\mathrm{Inv}_{\mathrm{istq}} \times 90}{\mathrm{COGS}_{\mathrm{istq}}} \tag{1}$$

Using $\mathrm{ID}_{\mathrm{istq}}$ allows us to compare the inventory performance for firms of different sizes. Additionally, the relative inventory $\mathrm{ID}_{\mathrm{istq}}$ does not improve if decreasing sales volumes cause equal decreases in inventory and cost of goods sold. Besides inventory, we already emphasised the importance of related working capital components to enhance liquidity in periods of financial distress. Therefore, we include days of accounts receivables (DSO) and days of accounts payables (DPO) in our analysis. The calculations of these two metrics are based on accounts receivables (AR) and accounts payables (AP) and are analogous to the definition of inventory days (cf. Randall 2009; Hofmann et al. 2011):

$$\mathrm{DSO}_{\mathrm{istq}} = \frac{AR_{\mathrm{istq}} \times 90}{\mathrm{Sales}_{\mathrm{istq}}} \quad (2)$$

$$\mathrm{DPO}_{\mathrm{istq}} = \frac{AP_{\mathrm{istq}} \times 90}{\mathrm{COGS}_{\mathrm{istq}}} \quad (3)$$

The cash conversion cycle (CCC) aggregates these financial ratios as follows:

$$\mathrm{CCC}_{\mathrm{istq}} = \mathrm{ID}_{\mathrm{istq}} + \mathrm{DSO}_{\mathrm{istq}} - \mathrm{DPO}_{\mathrm{istq}} \quad (4)$$

To control for outliers the ratios defined above are winsorised at the one per cent level. Because we observe skewed distributions for the variables, we report mean and median values.

Previous research has shown that optimal and average inventory levels differ by manufacturing sectors (Rumyantsev and Netessine 2007; Eroglu and Hofer 2011). Additionally, Chen, Frank, and Owen (2005) find an overall decline in the inventories of US manufacturing firms from 1981 to 2000. To control for these effects, we tested the observed changes in inventory days in our samples against the changes in peer industries. We use two methods to measure industry peer group effects. First, we compute a simple mean of firm i's 3-digit NAICS industry (s) for each period tq, given as $\overline{\mathrm{ID}_{\mathrm{stq}}}$. The second metric builds upon this peer group mean and calculates the abnormal inventory $\mathrm{AbI}_{\mathrm{istq}}$ (Chen, Frank, and Owen 2005), where σ_{stq} is the standard deviation of the peer group:

$$\mathrm{AbI}_{\mathrm{istq}} = \frac{\mathrm{ID}_{\mathrm{istq}} - \overline{\mathrm{ID}_{\mathrm{stq}}}}{\sigma_{\mathrm{stq}}} \quad (5)$$

If $\mathrm{AbI}_{\mathrm{istq}}$ is below zero, the firm has a lower relative inventory than the control group, whereas a value above zero indicates higher relative inventory compared to peers. We compared $\mathrm{AbI}_{\mathrm{istq}}$ to more restrictive firm matches by further controlling for size or return on assets performance (see Opler and Titman 1994; Barber and Lyon 1996). We find that the means and quartiles only change slightly. Hence, we continue using $\mathrm{AbI}_{\mathrm{istq}}$ and $\overline{\mathrm{ID}_{\mathrm{stq}}}$ in the subsequent analysis.

We postulate that inventory reductions are generally applicable in every turnaround situation. However, to test Hypothesis 7, we must identify firms that clearly employ one of the generic strategies presented in Table 1. We argue that revenue-increasing strategies cause substantial increases in market share, sales and assets, with market share given as $\mathrm{Sales}_{\mathrm{istq}}/\overline{\mathrm{Sales}_{\mathrm{stq}}}$ (Molina and Preve 2009). In contrast, asset reductions can be identified by extreme declines in assets. As stated in Table 1, refocus strategies do not have a clear sign for inventory reductions. Such strategies could either enhance sales to key customers, or cause the firm's market share to decrease because it withdraws from markets. Finally, cost reductions are identified by decreases in firm's sales, general and administrative expenses (SGA) and the respective ratio $\mathrm{SGA}_{\mathrm{istq}}/\mathrm{Sales}_{\mathrm{istq}}$ (SGATS).

Based on the full manufacturing firm data-set, we derive two samples. The first sample, Panel A, consists of 198 identified firm distress events, whereas the second sample, Panel B, consists of firms that filed for bankruptcy during the sample period. Table 2 presents the summary statistics for all three panels. The substantial differences between the lower and upper quartiles in inventory days are consistent with our expectation that there would be large differences between firms and industries.

3.2 *Predicting distressed firms*

To identify financially distressed firms, we use Altman's Z-Score (Altman 1968), which was originally derived using discriminant analysis on a sample of 66 firms (33 defaulting and 33 surviving firms). The Z-Score aggregates five financial ratios into one metric that can be used to predict financial distress and bankruptcy risk. The Z-Score and its variants and extensions have been widely used by researchers in the past decades (e.g. Swamidass 2007; Cleary 2007; Ha 2013) and it was found that (i) discriminant analysis did equally well in predicting bankruptcy risk as more sophisticated techniques like neural networks (Altman, Giancarlo, and Franco 1994) and (ii) the Altman Z-Score is still useful in identifying financially distressed firms (June and Reza 2012). The Z-Score as proposed by Altman (1968) is calculated as follows:

$$\text{Z-Score} = 1.2\ X_1 + 1.4\ X_2 + 3.3\ X_3 + 0.6\ X_4 + 1.0\ X_5 \quad (6)$$

with X_1 = Working Capital/Total Assets, X_2 = Retained Earnings/Total Assets, X_3 = Earnings before Interest and Taxes/Total Assets, X_4 = Market Value of Equity/Book Value of Total Liabilities, X_5 = Sales/Total Assets.

We compute the Z-Score for every firm-quarter and flag a quarter as distressed if the Z-Score falls below Altman's calculated threshold of 1.81. We choose the Z-Score as a measure for distressed firm quarters for two main reasons. First, the computation is relatively simple and requires few input variables. This is an advantage when dealing with quarterly data, since a high amount of variables have not always been tracked on a quarterly basis . Second, the model coefficients apply to

Table 2. Summary statistics of sample firms.

Metric	Mean	St. Dev.	1st quartile	Median	3rd quartile
Full compustat data ($N = 5, 126$)					
Total assets	2494.0	13433.9	38.0	158.0	778.0
Sales	637.5	3307.5	9.7	42.4	205.0
Inventory	253.3	1054.5	5.9	24.5	112.5
Return on assets (%)	2.1	5.4	0.9	3.0	4.8
Gross margin (%)	33.5	26.7	22.2	34.0	48.2
Inventory days	104.5	81.5	51.7	83.6	132.3
Receivables days	61.2	30.8	43.1	56.8	72.5
Payables days	53.8	43.6	29.1	42.2	62.6
CCC	111.9	85.2	57.4	97.1	148.8
Panel A: distressed firms ($N = 198$)					
Total assets	2453.0	9412.1	37.1	138.1	763.7
Sales	604.5	2300.5	10.9	36.0	172.9
Inventory	304.4	1113.8	6.6	21.9	103.4
Return on assets (%)	2.3	4.5	1.0	3.0	4.5
Gross margin (%)	37.4	21.3	27.3	37.3	50.0
Inventory days	109.9	80.6	58.6	89.7	137.0
Receivables days	63.6	29.0	47.0	59.2	74.0
Payables days	53.6	37.9	32.1	44.7	61.5
CCC	120.2	89.7	65.2	102.7	156.7
Panel B: defaulted firms ($N = 142$)					
Total assets	1381.5	2238.2	383.9	665.1	1,416.1
Sales	351.8	705.5	100.7	169.7	347.4
Inventory	193.2	252.9	60.5	104.3	198.6
Return on assets (%)	1.6	2.8	0.6	1.9	3.0
Gross margin (%)	17.7	17.4	11.4	18.2	27.0
Inventory days	77.1	47.3	45.3	69.0	95.6
Receivables days	52.9	25.4	36.2	50.7	64.0
Payables days	45.1	25.9	28.9	40.1	55.1
CCC	84.7	56.3	48.0	76.1	112.6

manufacturing firms because Altman (1968) derived the original model on basis of a manufacturing firm sample. Hence, we expect the model to be a reliable predictor of distress for our sample of manufacturing firms.

However, our classification scheme may suffer from two limitations of the Z-Score. First, Altman and Hotchkiss (2006) revised the failure rate of the Z-Score for the 1997–1999 period, which falls within our sample period, and find that the Z-Score still correctly predicts more than 80% of all default cases occurring one year later. At the same time, the error rate of falsely predicting default increases to over 25%. However, because we are interested in predicting distress rather than default, the Z-Score remains a good choice. Second, there is an interdependency between the Z-Score and the inventory level of a firm due the inclusion of working capital in X_1.

To address both concerns, we will run several robustness tests in Section 5. More specifically, we will run a sensitivity analysis on the original Altman Z-Score. This sensitivity analysis of the original Altman Z-Score shows that the Z-Score is relatively invariant to changes in inventories alone. We will subsequently also run a discriminant analysis to re-estimate the coefficients of the Z-Score using our own sample which we construct from the UCLA-LoPucki Bankruptcy Research Database (BRD) (LoPucki 2011) and the North America Compustat database. Using this ‘updated’ Z-Score allows us to assess whether the variables that enter the Z-Score are still appropriate to identify distressed companies and whether results are robust when we use the updated Z-Score to classify distressed firms. Moreover, to address the potential concern of endogeneity of the Z-Score and inventories, we will use a modified variant of the Z-Score that we calculate by netting out inventory from all variables that enter the Z-Score.

Firms’ distress periods are aggregated based on a time-series operator that generates firm-specific distress events. Consecutive quarters of financial distress, as indicated by below threshold Z-Score values, mark our events. The transition

Table 3. Panel A descriptive statistics before and after financial distress.

	Four quarters before distress period Q_{-4}		One quarter before distress period Q_{-1}		One quarter after distress period Q_{-1}		Four quarters after distress period Q_{+4}	
Metric	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Total assets	2154.0	125.0	2286.9	126.3	2599.7	114.4	2688.6	139.6
Sales	513.6	31.4	541.1	27.4	595.0	33.8	656.5	37.2
Inventory	259.2	19.0	266.6	23.4	264.9	19.8	276.2	21.9
Return on assets	2.3	3.0	0.8	2.3	2.9	3.4	3.1	3.2
Gross margin	36.9	37.8	34.8	35.9	38.0	37.4	39.3	37.8
Inventory days	115.0	93.9	125.1	101.5	100.2	83.9	102.2	83.1
Abnormal inventory	0.1	–0.2	0.2	–0.1	–0.1	–0.3	–0.1	–0.3
Receivables days	66.4	60.4	71.3	62.9	59.2	56.6	60.4	57.4
Payables days	54.1	45.9	59.0	48.6	51.0	43.8	49.5	44.1
CCC	128.1	102.6	138.1	119.3	108.8	90.9	113.1	95.9

from a non-distress quarter to a distress quarter gives the starting point for the distress period and is denoted as Q_{start}. We select distress cases for Panel A only if a firm experiences no distress quarters one year before and one year after a distress period. We allow the duration of distress periods to vary between four and twelve quarters in order to capture short-term and long-term firm actions under distress. The inclusion of a maximum of 12 distress quarters is consistent with the time frames mentioned in recent practitioner studies (BCG 2009) and in the turnaround literature (Hambrick and Schecter 1983). By using this definition we ensure to exclude long-term poor performers, which are not in the focus of the study. Quarterly data are prone to seasonal fluctuations within the observations. We therefore exclude distress periods of less than four quarters to lower the probability of including distress events that only occur due to these seasonal variations. For the same reason, we mark single recovery quarters as distressed, if the previous and subsequent quarters are both identified as distressed.

The first quarter during which a firm is in distress, as indicated by the Z-Score, is assumed to represent a structural break in each firm observation. We are interested in the differences between inventory before, during and after financially distressed quarters. Building on our notation, we refer to this first quarter of distress as Q_{start}, we denote quarters before the period of distress as Q_{-p} and a firm's final distress quarter as Q_{end}. Q_p refers to the quarters within the distress period. Additionally, we examine firm performance up to four quarters after the end of distress, because turnaround actions can be reversed or relaxed if overall firm performance improves again. The quarters following the last quarter in the distressed period are denoted as Q_{+p}. Thus, the fourth quarter before the first indication of financial distress is stated as Q_{-4}, the fourth quarter in the distress period is stated as Q_4 and the fourth quarter following the end of a distress period is given as Q_{+4}. We refer to the period from Q_{start} to Q_{end} as the event window. Our study can therefore be considered as an event study and is conceptually similar to the studies by Hendricks and Singhal (2005, 2008) or Hendricks and Singhal (2009) – albeit our event windows are much longer than in these studies.

The final Panel A consists of 198 firms that meet the criteria described above. The distribution of years in which the distress starts is stated in the Appendix (Table A1). Notably, approximately 19% of the distress starting points are observed in 1998, two years before the recession of the early 2000s. During 1998, computer manufacturers were negatively impacted by the Asian financial crisis (Roberts 1998). Firms within the computer and electronics product manufacturing industry (334 of 3-digit NAICS) account for 19 of 37 distress sample cases in 1998. Table 3 presents detailed summary statistics for single quarters before and after the occurrence of distress. We analyse inventory changes between the beginning and the end of a distress period. Based on the introduced notation, we develop a set of performance metrics that is used to control for random inventory fluctuations in single quarters. Figure 2 provides an overview of the definitions. Single quarter changes are calculated as differences between the first quarter after the end and the last quarter before the start of a distress period. To control for quarterly fluctuations, we use two moving averages. The first moving average, MA 2, extends the single quarter definition and includes the first distress quarter and the ending distress quarter. The second moving average, MA 4, incorporates 4 quarters around the start and the end of a distress period. Our last measure, the annual metric, is the average of 4 quarters before or 4 quarters after a firm's distress period. Building absolute and relative differences of these metrics allows us to compare values that are observed around firm-specific distress events.

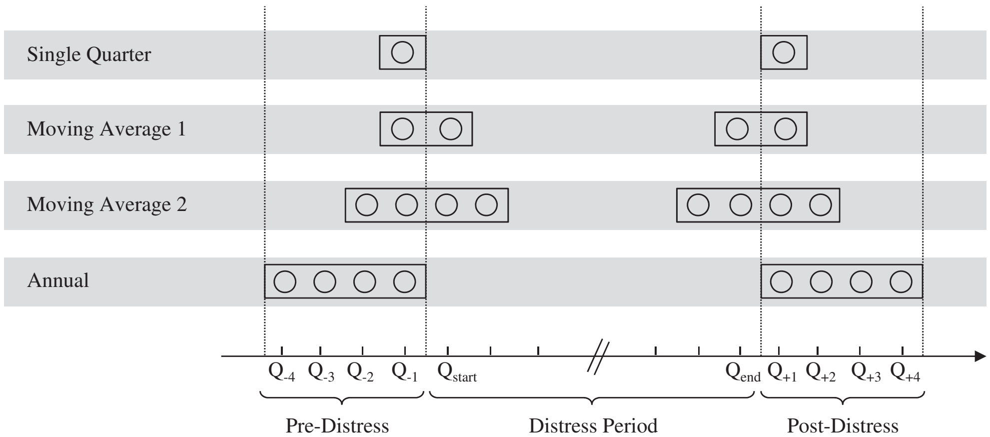

Figure 2. Definition of change performance metrics around distress period.

Table 4. Panel B descriptive statistics before default.

	Twelve quarters before default Q_{-12}		Eight quarters before default Q_{-8}		Four quarters before default Q_{-4}		Quarter of default Q_0	
Metrics	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Total assets	1,396.3	732.8	1,408.0	682.7	1,334.6	650.7	1,498.2	594.4
Sales	354.9	171.7	364.7	174.3	341.7	169.2	376.7	160.2
Inventory	202.0	104.2	194.6	102.7	188.9	105.1	187.7	87.4
Return on assets	2.4	2.7	2.0	2.3	1.1	1.4	0.3	0.9
Gross margin	21.5	20.8	20.5	20.2	13.8	17.7	11.7	12.2
Inventory days	79.0	68.0	77.7	69.9	74.6	68.4	72.2	62.0
Abnormal inventory	– 0.2	– 0.3	– 0.2	– 0.4	– 0.2	– 0.4	– 0.3	– 0.4
Receivables days	52.1	49.4	52.2	51.9	52.2	51.2	59.5	51.5
Payables days	43.8	40.1	46.5	41.5	46.5	39.9	24.5	19.2
CCC	86.3	74.9	83.3	74.8	80.2	75.2	107.5	88.2

3.3 *Identifying defaulted firms*

The UCLA-LoPucki BRD (LoPucki 2011) provides data on an extensive collection of bankruptcy cases and allows us to identify cases of default within the full data-set. The inventory adjustments of these defaulted firms are relevant to our evaluation of Hypothesis 4, as our goal is to analyse the differences between the inventory behaviour of firms that achieve successful turnarounds and those that do not. The database provides Compustat's GVKEY as firm identifier, which we use to match defaulting firms with firms in Computat. We ultimately identify 142 bankrupt firms, which we refer to in Panel B. Of these firms, 8 filed for bankruptcy twice, and one filed three times during the observation period. The chapter filings in Panel B are concentrated around the recession period in 2001, as presented in Table A1. The Panel B values, presented in Table 2, differ from the median values in Panel A. This effect results because the BRD only contains data for public firm chapter filings by firms with total assets of more than US$100 million (measured in 1980 dollars). For subsequent comparison, it is important to note that Panel B does not include any firms in Panel A and vice versa.

We analyse the changes in inventory days in the 8 and 12 quarters prior to the default quarter of every firm in Panel B. These time spans should capture effects of the suggested short-term and long-term actions, with 12 quarters corresponding to the maximum duration of distress periods within Panel B. Defaulting firms, at a certain stage need to file for bankruptcy protection. Therefore, we use the quarter in which a chapter filing occurred as an event date in Panel B. As in Panel A, we refer to this quarter as $Q_{Default}$. Quarters before this event are denoted as Q_{-p}. Unlike in Panel A, any differences following a default are not examined for two main reasons. First, the number of observations diminishes significantly and many companies do not report financial numbers after the default event anymore. Second, observations following a default

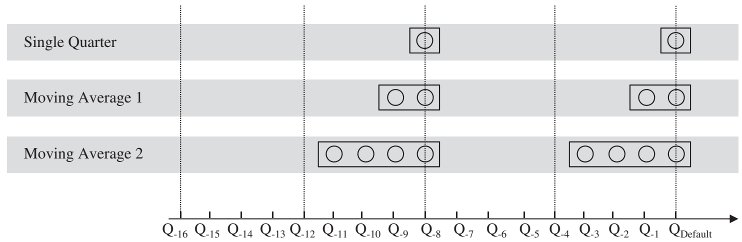

Figure 3. Definition of performance metrics prior to default.

differ substantially from pre-default values, given that bankruptcy protection entails a completely different reorganisation process (see Wruck 1990).

Figure 3 presents the changes in inventory for the proposed performance metrics for Panel B. Again, we use a single quarter comparison and two moving averages. Note that most defaulting firms do not report any data after the default. Accordingly, we cannot include post-default observations and we exclude the annual change metric. It would be an adapted version of MA 4. Within Figure 3, we only present the set-up for Q_{-8}, because observations at Q_{-12} are just the fourth lags of this definition.

The summary statistics for different quarters prior to default are presented in Table 4. As in the descriptive statistics for Panel B, we observe a decline in inventory days. From Q_{-8} until Q_0, defaulting firms reduce their inventory days by an average of 5.5 days (median −7.9 days). Interestingly, the days accounts receivables do not decline, but firms reduce their average days of accounts payables by 22 days during the same period (median −22.3 days). In contrast to the previous findings for distressed firms, the $\mathrm{AbI}_{\mathrm{istq}}$ remain negative with no sign change, indicating inventory levels below the industry average.

4. Results

We use different statistical tests and regression analysis to test our hypotheses presented in Section 3. As mentioned previously, our study is conceptually similar to the event studies by Hendricks and Singhal (2005, 2008, 2009). We therefore use a similar methodology and apply t-tests, median tests (Wilcoxon Singrank) and binomial sign tests as in Hendricks and Singhal (2005).

The previously stated hypotheses are mainly tested using data from Panel A. We report $\mathrm{ID}_{\mathrm{istq}}$ for the change performance metrics, as introduced earlier in Figure 2. More specifically, we conduct one sample t-tests on the mean inventory reductions of $\mathrm{ID}_{\mathrm{istq}}$ in Table 3 to examine whether the inventory reductions are significantly different from zero. An alternative use of paired t-tests on the different levels of observations around Q_{start} and Q_{end} did not change our overall results. As the distributions might be skewed or the sample might contain outliers, we also use non-parametric one-sample median tests (Wilcoxon sign-rank test). Additionally, we test the overall direction of the effect using binomial sign tests to analyse whether inventory reductions occur in more than 50% of distressed firms. As stated by Hendricks and Singhal (2005), 'consistency between these two non-parametric tests and the t-statistics would indicate that outliers are not driving the results'.

4.1 *Hypothesis 1: inventory reduction*

The descriptive results for the change in inventories around the identified distress periods are presented in Table 5 for the different performance metrics. The binomial tests reveal that in 66.16–70.20% of the distress events, inventories are reduced until the end of the distress period ($p \leq 0.01$). This result is also reflected in the significant reductions in the median, which range between 6.31 and 9.05 days (Single and MA 4 metrics, $p \leq 0.01$). The corresponding percentage values range between 7.64 and 11.08%, respectively ($p \leq 0.01$). The absolute differences for the mean are also significant at the 1% level, whereas the percentage change metrics of the mean are not significant.

The results presented in Table 5 provide evidence in favour of Hypothesis 1. However, these findings could be the result of an overall industry trend, as found in Chen, Frank, and Owen (2005). We use the $\overline{\mathrm{ID}}_{\mathrm{stq}}$ and $\mathrm{AbI}_{\mathrm{istq}}$ metrics as described in section 3.1 to control for the peer group developments. Tables 6 and 7 present the test results for both peer group controls. In Table 6, we test for significant differences in the changes of $\overline{\mathrm{ID}}_{\mathrm{stq}}$ against the change of Panel A firms' $\mathrm{ID}_{\mathrm{istq}}$. Note that $\overline{\mathrm{ID}}_{\mathrm{stq}}$ is calculated for every quarter observation for each distressed firm such that we are able to calculate the change in $\overline{\mathrm{ID}}_{\mathrm{stq}}$ for periods that are equal to the distress periods of Panel A firms. Table 6 shows the calculated mean and median differences of the inventory reductions for the distressed and industry peers along with the significance levels. The inventory

Table 5. Changes in inventory days of distressed firms.

Metric	Obs.	Mean	Median	% neg.
Single	198	–24.93	–9.05	66.16
		(–5.36)***	(–5.93)***	(0.00)***
Single (%)	198	–3.66	–11.08	66.16
		(–0.63)	(–5.17)***	(0.00)***
MA 2	198	–21.95	–7.64	70.20
		(–5.02)***	(–5.93)***	(0.00)***
MA 2 (%)	198	–5.11	–9.48	70.20
		(–0.88)	(–5.63)***	(0.00)***
MA 4	198	–18.41	–6.31	69.70
		(–4.80)***	(–5.77)***	(0.00)***
MA 4 (%)	198	–5.16	–8.44	69.70
		(–1.21)	(–5.34)***	(0.00)***
Annual	198	–18.75	–8.44	67.68
		(–4.29)***	(–4.74)***	(0.00)***
Annual (%)	198	0.52	–9.43	67.68
		(0.08)	(–3.90)***	(0.00)***

Notes: Results are reported for change metrics as defined in Figure 2. T-statistic for the mean, Wilcoxon sign rank Z-statistic for the median and p-value for the binomial sign test are reported in parentheses. Percentage negative refers to the number of observed negative changes. The level of statistical significance from zero is noted by $*p \leq 0.10$, $**p \leq 0.05$, and $***p \leq 0.01$ for two-tailed tests.

Table 6. Inventory changes of distressed firms and industry peers.

	Distress firms – industry peers		
Metric	Obs.	Δ Mean	Δ Median
Single	198	–21.82	–6.68
		(–4.63)***	(–4.79)***
MA 2	198	–19.48	–6.45
		(–4.43)***	(–5.03)***
MA 4	198	–15.95	–5.5
		(–4.16)***	(–4.77)***
Annual	198	–15.27	–6.14
		(–3.56)***	(–3.63)***

Notes: Results are reported for the differences of mean and median changes between distress firms and industry peers. T-statistic for the mean and Wilcoxon sign rank Z-statistic for the median are reported in parentheses. The level of statistical significance from zero is noted by $*p \leq 0.10$, $**p \leq 0.05$, and $***p \leq 0.01$ for two-tailed tests.

reductions in industry peers ID_{istq} range between –2.46 and –3.48 days for the mean and between –0.81 to –2.37 days for the median. These changes are much smaller than the inventory reductions in distressed firms found in Table 5. For instance, distressed firms reduced their mean inventories, as measured by the metric Single (see Table 6) by –24.93 days whereas mean inventory reductions for the industry control group are only –3.11 days. Thus, the difference of inventory reductions shown in Table 6 between these two groups is –21.82 days, which is highly significant with a t-statistics of –4.63. All other metrics also confirm significant differences in the inventory reductions between distressed firms and the industry control group.

The differences in AbI_{istq} further confirm that distressed firms reduce their inventories more aggressively than their peers. We do not report percentage changes since AbI_{istq} is a unit free metric. Like the results in Table 5, figures in Table 7 also indicate significant inventory reductions for distressed firms ($p \leq 0.01$ for mean and median). Overall, we conclude that we cannot reject Hypothesis 1 and that there is strong empirical evidence that distressed firms reduce their inventories significantly during periods of financial distress.

Table 7. Change in abnormal inventory days of distressed firms.

Metric	Obs.	Mean	Median	% neg.
Single	198	–0.28	–0.11	61.62
		(–4.63)***	(–4.91)***	(0.00)***
MA 2	198	–0.26	–0.10	66.16
		(–4.68)***	(–5.45)***	(0.00)***
MA 4	198	–0.22	–0.10	64.14
		(–4.47)***	(–5.11)***	(0.00)***
Annual	198	–0.21	–0.10	63.13
		(–3.86)***	(–4.15)***	(0.00)***

Notes: Results are reported for change metrics as defined in Figure 2. T-statistic for the mean, Wilcoxon sign rank Z-statistic for the median and p-value for the binomial sign test are reported in parentheses. Percentage negative refers to the number of observed negative changes. The level of statistical significance from zero is noted by $*p \leq 0.10$, $**p \leq 0.05$, and $***p \leq 0.01$ for two-tailed tests.

4.2 *Hypothesis 2: distress length*

As stated in Hypothesis 2, we expect that long distress periods will force firms to seek for alternative turnaround actions that do not necessarily include further inventory reductions. Additionally, the short-term advantages of transforming tied-up inventories into cash at all costs will not translate into long-term benefits, if a firm is not able to resolve distress. To investigate the differences between very short and longer distress periods, we split Panel A observations into two subgroups. Table 8 restates the results of Table 5 with the first group containing 92 firm observations with distress periods lasting from 4 to 5 quarters. The second group consists of 106 distress cases that last for 6–12 quarters. We choose this threshold in order to generate subgroups with comparable sample sizes. Like the test results for the full Panel A, the results of the binomial and sign-rank tests are all significant at the 1% level. At the same time, the t-statistics remain significant for all of the inventory change metrics. However, the two-group t-test on the differences between both sample means is significant only in one case (MA 4, $p \leq 0.1$). In contrast, tests on the differences of the medians yield statistically significant results in most cases. Given that results from both tests differ, it is not clear if we should reject H2 or not. However, we can draw two possible conclusions from these observations. First, a fraction of the firms that are capable of reducing inventories during short distress periods can further reduce inventories during long-lasting distress. Second, additional inventory reductions are not observable at the end of distress periods. Overall, we speculate that short-term actions, presented in Section 2, are more applicable under distress, because they lead to direct cash inflows, whereas the benefits of long-term actions require more time to be effective. The results confirm this notion, as companies that are in financial distress for only a short period can reduce inventories substantially. However, it also seems that firms are able to further reduce inventories in later periods when financial distress lasts for more than 6 quarters. Possibly other, long-term turnaround actions become effective in helping to further reduce inventories.

4.3 *Hypothesis 3: post-distress performance*

Given the reductions in inventory, a key question is whether the effect is sustainable as suggested by practitioners (BCG 2009). In Hypothesis 3, we argue that inventories should not return to their pre-distress levels. Table 9 shows our test results on the sustainability of inventory improvements after a distress period. We compare the levels of inventory days at Q_{+4} (i.e. after) to the equivalent values at Q_{start} (start) and Q_{end} (end). This ensures a gap of one year between the single quarter observations of Q_{end} and Q_{+4}. Unlike in our prior tests of change metrics for hypothesis 2, we conduct paired t-tests for the observed sample mean, whereas the equality of distributions is again tested using Wilcoxon sign rank tests. The number of valid observations decreases from 198 to 181 (single, MA 2, MA 4) or 162 (annual) due to distress cases that fall close to the period cut off.

We find a significant difference between the average ID_{istq} at the beginning of the distress periods Q_{start} and Q_{+4} (all $p \leq 0.01$). The results are very similar to results in Table 5 where we compared the inventory reductions during the distress period. We conclude that after the end of the financial distress period, inventories are still significantly lower than before the distress event. Therefore, inventory reductions seem to be permanent in nature, which we consider as empirical evidence in favour of Hypothesis 3.

When we compare the inventories one year after the end of the distress period with the inventories at the end of the distress period, we do not find any clear-cut trend regarding further inventory reductions. If anything, firms seem to further

Table 8. Change in inventory days for short and long distress periods.

	Distress period 4–5 quarters ($N = 92$)			Distress period 6–12 quarters ($N = 106$)				
Metric	Mean	Median	% neg.	Mean	Median	% neg.	Δ Means	Δ Median
Single	–16.74	–6.01	61.96	–32.03	–14.78	69.81	15.29	8.77
	(–2.77)**	(–3.47)***	(0.03)**	(–4.65)***	(–4.76)***	(0.00)***	(1.65)	(1.69)*
Single (%)	–5.6	–10.19	61.96	–1.97	–14.14	69.81	–3.63	3.95
	(–1.21)	(–3.56)***	(0.03)**	(–0.19)	(–3.77)***	(0.00)***	(–0.31)	(1.54)
MA 2	–14.72	–4.96	67.39	–28.22	–14.07	72.64	13.50	9.11
	(–2.95)***	(–3.48)***	(0.00)***	(–4.1)***	(–4.8)***	(0.00)***	(1.55)	(1.99)**
MA 2 (%)	–8.18	–7.46	67.39	–2.45	–18.32	72.64	–5.73	10.86
	(–3.24)***	(–3.48)***	(0.00)***	(–0.23)	(–4.31)***	(0.00)***	(–0.49)	(2.14)**
MA 4	–11.45	–3.75	67.39	–24.45	–12.13	71.70	13.00	8.38
	(–2.41)**	(–3.19)***	(0.00)***	(–4.21)***	(–4.77)***	(0.00)***	(1.7)*	(2.31)**
MA 4 (%)	–6.39	–4.66	67.39	–4.09	–16.21	71.70	–2.30	11.55
	(–2.9)***	(–3.01)***	(0.00)***	(–0.53)	(–4.14)***	(0.00)***	(–0.27)	(2.6)***
Annual	–13.23	–5.86	65.22	–23.55	–16.41	69.81	10.32	10.55
	(–1.99)**	(–2.71)***	(0.00)***	(–4.09)***	(–3.95)***	(0.00)***	(1.18)	(1.64)
Annual (%)	–4.27	–7.87	65.22	4.67	–15.63	69.81	–8.94	7.76
	(–1.33)	(–2.24)**	(0.00)***	(0.39)	(–3.14)***	(0.00)***	(–0.68)	(1.84)*

Notes: Results are reported for change metrics as defined in Figure 2. T-statistic for the mean, Wilcoxon sign rank Z-statistic for the median and p-value for the binomial sign test are reported in parentheses. Percentage negative refers to the number of observed negative changes. We use two-sample t-tests for the differences in means. Wilcoxon-Mann–Whitney test for differences in medians. The level of statistical significance from zero is noted by $^{*}p \leq 0.10$, $^{**}p \leq 0.05$, and $^{***}p \leq 0.01$ for two-tailed tests.

Table 9. Comparison of inventory days – start vs. after & end vs. after.

		I. (After – Start)		II. (After – End)	
Metric	Obs.	Mean	Median	Mean	Median
Single	181	–22.48	–15.54	0.88	2.01
		(–4.37)***	(–5.12)	(0.25)	(–0.26)
MA 2	181	–23.12	–22.39	–2.14	–2.01
		(–5.21)***	(–5.69)	(–0.77)	(–1.58)
MA 4	181	–22.20	–21.99	–4.66	–3.72
		(–5.21)***	(–5.64)	(–1.9)*	(–2.79)***
Annual	162	–17.11	–13.15	2.91	3.50
		(–3.41)***	(–3.4)	(1.33)	(1.26)

Notes: Results are reported for the **differences** of mean and median changes at the start and after financial distress and the end and after financial distress respectively. T-statistic for the mean and Wilcoxon sign rank Z-statistic for the median are reported in parentheses. The level of statistical significance from zero is noted by $^{*}p \leq 0.10$, $^{**}p \leq 0.05$, and $^{***}p \leq 0.01$ for two-tailed tests.

decrease inventories slightly as indicated for the metric MA 4. Overall, we cannot reject Hypothesis 3 and therefore claim that inventory reductions that occur during financial distress are indeed permanent.

4.4 *Hypothesis 4: defaulting firms*

As argued in Hypothesis 4, we expect that there are differences between the inventory performance of distressed firms, which successfully recover and the firms that file for bankruptcy under a chapter. As there is no equivalent starting point of a distress period in Panel B, we present the change metrics for Q_{-8} in Table 10. We observe that approximately 70% of the sample firms reduce their inventory as distress continues. Unlike the results shown for Panel A in Table 5, we find that the mean values are only significant for MA 4. However, the median values are negative and significant. The presented results are not directly comparable to our previous results on financially distressed firms, as we do not pool distress periods of different lengths. Regarding the $\mathrm{AbI}_{\mathrm{istq}}$ metric, we again show inventory reductions in defaulting firms until their default quarters. The mean change in $\mathrm{AbI}_{\mathrm{istq}}$ is still negative, but only significant for MA 2 and MA 4 differences. Additionally, the inventory

Table 10. Change in inventory days of defaulted firms.

Metric	Obs.	Mean	Median	% neg.
Single	76	–3.46	–4.01	71.05
		(–0.86)	(–2.66)***	(0.00)***
Single (%)	76	0.85	–8.02	71.05
		(0.14)	(–2.75)***	(0.00)***
MA 2	71	–3.98	–3.18	67.61
		(–1.28)	(–2.55)**	(0.00)***
MA 2 (%)	71	–3.20	–8.22	67.61
		(–0.83)	(–2.61)***	(0.00)***
MA 4	67	–5.29	–6.43	65.67
		(–2.75)***	(–2.90)***	(0.01)**
MA 4 (%)	67	–5.66	–10.09	65.67
		(–2.36)**	(–2.70)***	(0.01)**
Abnormal inventory				
Single	76	–0.13	–0.06	63.16
		(–1.58)	(–2.02)**	(0.03)**
MA 2	71	–0.12	–0.07	60.56
		(–2.10)**	(–2.26)**	(0.10)*
MA 4	67	–0.13	–0.12	62.69
		(–3.01)***	(–2.94)***	(0.05)*

Notes: Results are reported for change metrics as defined in Figure 3. T-statistic for the mean, Wilcoxon sign rank Z-statistic for the median and p-value for the binomial sign test are reported in parentheses. Percentage negative refers to the number of observed negative changes. The level of statistical significance from zero is noted by $^*p \leq 0.10$, $^{**}p \leq 0.05$, and $^{***}p \leq 0.01$ for two-tailed tests.

reductions shown here are generally lower compared to the previous results presented in Table 7. Overall, we conclude that defaulting firms seem to react similar to distressed companies, because defaulting firms also reduce their inventories. However, the defaulting firms' decrease in inventories – in particular mean inventory decrease – is much smaller than the inventory reductions in distressed firms that do not default. Either, defaulting firms lack the ability or potential to reduce their inventory or, the inventory reduction takes place much earlier and is not observable during our defined period. The performance differences between firms with successful turnarounds and defaulting firms may also result from differences in additional turnaround activities that they carry out. Overall, we find empirical support in favour of Hypothesis 4.

4.5 *Hypothesis 5: pre-distress inventory performance*

Hypothesis 5 claims that the varying inventory actions across firms depend on pre-distress inventory performance. We expect higher inventory reduction potential for firms with poor pre-distress inventory performance, i.e. those with high inventory levels ($\mathrm{ID}_{\mathrm{istq}}$). To measure the firms' pre-distress performance, we assign each sample firm to an industry peer group quartile based on its inventory days at the beginning of a distress period (Q_{start}). We create two dummy variables to indicate high or low inventory levels relative to those of a firm's industry peer group at the beginning of its distress period. To ensure clear differentiations between the two groups, we assign firms in the first quartile to the group of lean performers, Low-ID, and we assign firms in the fourth quartile to the High-ID group. These dummies are used as explanatory variables for the change in inventory days until the end of a distress period. Note that in line with standard notation, we always denote regression coefficients as β_i. However, the regression coefficients differ by regression Equation (7) to (9). The regression model to test hypothesis 5 is specified as follows:

$$\begin{aligned} &\triangle\, \mathrm{ID}_{\mathrm{istq}} = \beta_0 + \beta_1\, \mathrm{ID}^{\mathrm{High}}_{\mathrm{is,\,start}} + \beta_2\, \mathrm{ID}^{\mathrm{Low}}_{\mathrm{is,\,start}} \\ &i = \text{firm index}, \qquad s = \text{3-digit NAICS industry index}, \\ &\mathrm{tq} = \text{time series quarter}, \qquad \mathrm{start} = \text{distress quarter } Q_{\mathrm{start}} \end{aligned} \tag{7}$$

Table 11 presents the regression output of firms' changes in inventory days depending on the pre-distress inventory performance. The coefficient of the High-ID dummy ($\mathrm{ID}^{\mathrm{High}}_{\mathrm{is,\,start}}$) is always negative and significant at the 1% level, which

Table 11. Regression of change in inventory days on pre-distress inventory performance dummies.

	(1) Single	(2) MA 2	(3) MA 4	(4) Annual
Dummy High-ID	–33.60***	–40.48***	–35.04***	–29.23***
	(–3.21)	(–4.21)	(–4.15)	(–2.96)
Dummy Low-ID	8.56	9.72	8.15	7.12
	(0.67)	(0.83)	(0.79)	(0.59)
Constant	–16.81***	–12.07**	–9.815**	–11.64**
	(–2.77)	(–2.16)	(–2.00)	(–2.03)
N	198	198	198	198

Notes: T-statistics in parentheses. The level of statistical significance from zero is noted by $^{*}p \leq 0.10$, $^{**}p \leq 0.05$, and $^{***}p \leq 0.01$ for two-tailed tests. Dependent variables (1)–(4) are all absolute change metrics.

Table 12. Regression of change in inventory days on initial firm size.

	(1) Single	(2) MA 2	(3) MA 4	(4) Annual
Dummy Large-Size	17.56	14.33	12.52	14.20
	(1.56)	(1.37)	(1.36)	(1.34)
Dummy Low-Size	–12.91	–23.62**	–19.81**	–12.78
	(–1.09)	(–2.15)	(–2.05)	(–1.15)
Constant	–26.45***	–20.41***	–17.24***	–19.48***
	(–4.23)	(–3.51)	(–3.38)	(–3.31)
N	198	198	198	198

Notes: T-statistics in parentheses. The level of statistical significance from zero is noted by $^{*}p \leq 0.10$, $^{**}p \leq 0.05$, and $^{***}p \leq 0.01$ for two-tailed tests. Dependent variables (1)–(4) are all absolute change metrics.

indicates that firms with initially high $\mathrm{ID}_{\mathrm{istq}}$ exhibit substantial reductions in $\mathrm{ID}_{\mathrm{istq}}$ under distress. The findings are consistent with our hypothesis, because poor inventory performance prior to distress bears a higher optimisation potential. In contrast, lean inventories at the beginning of a distress period are not significantly associated with reduction efforts. The constant term in the regression represents the intermediate groups (i.e. neither high nor low pre-distress inventories). The constant term is negative and significant, indicating that also firms with 'normal' inventory levels reduce their inventories during periods of financial distress. Overall, the results indicate that firms reduce their inventory more when they had higher pre-distress inventory levels. Thus, we cannot reject Hypothesis 5.

4.6 *Hypothesis 6: firm size*

As previously described, Hypothesis 6 is concerned with the effect of firm size as an additional driving factor of inventory behaviour in financial distress. To test for differences between small and large firms, we use a similar regression model as for Hypothesis 5. We control for firm size by taking the logarithm of sales, $\log(\mathrm{sales}_{\mathrm{istq}})$, in the first distress quarter (Q_0). As before, the Large-Size $\mathrm{Size}^{\mathrm{Large}}_{\mathrm{is,\,start}}$ dummy equals one if the firm falls into the fourth quartile at the beginning of the distress period, whereas the Low-Size dummy $\mathrm{Size}^{\mathrm{Low}}_{\mathrm{is,\,start}}$ equals one for small firms in the first quartile. The regression model is given as follows:

$$\begin{aligned} &\triangle\, \mathrm{ID}_{\mathrm{istq}} = \beta_0 + \beta_1\, \mathrm{Size}^{\mathrm{Large}}_{\mathrm{is,\,start}} + \beta_2\, \mathrm{Size}^{\mathrm{Low}}_{\mathrm{is,\,start}}, \\ &\quad i = \text{firm index}, \qquad s = \text{3-digit NAICS industry index}, \\ &\quad \mathrm{tq} = \text{time series quarter}, \qquad \mathrm{start} = \text{distress quarter}\, Q_{\mathrm{start}}. \end{aligned} \tag{8}$$

The regression output in Table 12 indicates differences in the magnitude of inventory reductions between small and large firms. The coefficients of the Large-Size dummy are not significant and have a positive sign, but the overall effect remains negative (sum of Large-Size coefficient and constant < 0). The results indicate that large firms do not differ from medium-sized firms with respect to inventory reductions during financial distress. However, we observe a significant and negative coefficient for the Small-Size dummy for the MA 2 and MA 4 change metrics. We consider this additional negative effect for small firms as empirical evidence in favour of Hypothesis 6. As argued before, small firms need to rely more on inventory reductions during periods of distress, because they have less access to alternative (external) capital funds in comparison with large firms. We also claim that small firms generally have more focused product lines and use less efficient inventory management techniques. During periods of distress, inventory optimisation methods and the resulting inventory reductions might therefore be more valuable for smaller companies. In contrast, large firms tend to have diversified product lines and several subsidiaries, which increase the complexity of any inventory adjustment effort. Thus, inventory optimisations (i.e. fast inventory reductions) might be more difficult to achieve for larger firms.

4.7 *Hypothesis 7: turnaround strategy*

To test hypothesis 7, we will again use a regression model with dummy variables that indicate whether a firm pursues a particular turnaround strategy. Extreme increases in a firm's market share, as defined in Section 3.1, indicate that a firm pursues a growth strategy to alleviate financial distress, while decreasing market share is indicative of a product or market refocus. Likewise, drastic increases in sales and assets are associated with a revenue expansion turnaround strategy, while strong asset reductions are a signal of downsizing efforts. Cost-cutting strategies should be reflected by strongly declining SGA or SGATS ratios. For the aforementioned variables, we define 'growth-dummies' that equal 1 if the annual change metric exceeds the 90% decile and 'decrease-dummies' that equals 1 if the change for the respective variable is lower than the 10% decile. For instance, the variable SGA^{dec} equals 1 if the change of selling and general administrative expenses (SGA) is in the lowest category (i.e. lower than 10% decile). A decrease in SGA (i.e. value in lowest SGA change category) indicates that a firm is likely to pursue a cost-cutting strategy as a means to resolve financial distress.

The regression model is as follows:

$$\begin{aligned}\triangle\, \text{ID}_{\text{istq}} = {} & \beta_0 + \beta_1\, \text{MktShare}^{\text{inc}} + \beta_2\, \text{Sales}^{\text{inc}} + \beta_3\, \text{Assets}^{\text{inc}} + \beta_4\, \text{Assets}^{\text{dec}} \\ & + \beta_5\, \text{MktShare}^{\text{dec}} + \beta_6\, \text{SGA}^{\text{dec}} + \beta_7\, \text{SGATS}^{\text{dec}} \\ & i = \text{firm index},\ s = \text{3-digit NAICS industry index},\ \text{tq} = \text{time series quarter}, \\ & \text{inc} = \text{increase dummy},\ \text{dec} = \text{decrease dummy}\end{aligned} \tag{9}$$

Table 13 presents the results for our regression model for two different dependent variables. In the first case, the annual difference in ID_{istq} is the dependent variable; in the second case, the percentage annual difference is used. Both models report significant and negative coefficients for the $\text{SGATS}_{\text{dec}}$ dummy. This finding implies an association between substantial cuts in overhead costs and reductions in inventory. Similarly, the negative coefficient of $\text{Assets}_{\text{dec}}$ implies an analogous association with asset reductions strategies, i.e. downsizing activities. These findings confirm the hypothesized signs in Table 1 and are consistent with the early findings of Hambrick and Schecter (1983). As expected, for revenue expansion turnaround strategies ($\text{Assets}^{\text{inc}}$) we find an increase in inventories rather than inventory reductions. Surprisingly, we also find a positive coefficient on the market-share decrease variable which is contrary to our expectation. However, the results of the regression are generally in line with our expectations and provide empirical evidence for our Hypothesis 7. The magnitude of inventory reduction under financial distress seems to depend, at least partly, on the turnaround strategy chosen by the company. In particular, cost-cutting and downsizing (i.e. asset reduction) strategies are associated with inventory reductions during the financial distress period.

Overall, we conclude that our main hypothesis, that firms will reduce inventory days under financial distress, cannot be rejected. Our findings are robust when we compare inventory adjustments with the inventory behaviour of the industry peer groups. We understand our results as strong empirical evidence that distressed firms generate cash from their balance sheets by reducing inventories, which is in line with findings of prior studies (e.g. Hambrick and Schecter 1983). Our results also provide insights into the magnitude of inventory reductions during economic downturns and periods of financial distress (Carpenter et al. 1994; Guariglia 1999). We find that a large fraction of inventory reductions occurs even during relatively short periods of financial distress, indicating that firms rely on short-term asset reductions as suggested by Ofek (1993). We also highlight that the decrease in inventory days persists at least one year after a distress period, which suggests that inventory reductions may not only help firms to resolve financial distress, but that the inventory reductions might be beneficial in the long-run (BCG 2009). Consistent with those of other studies, our results stress the dependency of inventory on firm characteristics, such as pre-distress performance and firm size (Hendricks and Singhal 2005; Rumyantsev and Netessine 2007). In particular, lean inventory at the beginning of a distress period prohibits further reductions in inventories during financial distress, while firms with initial high inventory levels can benefit from reducing their inventories sharply during financial distress. Although our results are quite robust and highly significant, we will conduct some additional robustness tests in the next section to validate our findings.

Table 13. Regression of annual changes in inventory days on turnaround strategy dummies.

Turnaround strategy	Metric	(1) Absolute	(2) Percentage
Revenue increase			
	$MktShare_{inc}$	–2.02	54.62
		(–0.09)	(1.38)
	$Sales_{inc}$	–29.93	31.03
		(–1.35)	(0.80)
	$Assets_{inc}$	28.92**	–32.39
		(2.00)	(–1.29)
Asset reduction			
	$Assets_{dec}$	–40.99***	–33.01
		(–3.03)	(–1.41)
Product/Market refocus			
	$MktShare_{dec}$	39.62**	16.19
		(2.57)	(0.60)
Cost cutting			
	SGA_{dec}	–11.52	4.80
		(–0.71)	(0.17)
	$SGATS_{dec}$	–87.04***	–73.93***
		(–6.23)	(–3.05)
Model parameters			
	Constant	–8.93**	3.68
		(–2.01)	(0.48)
	N	198	198

Notes: T-statistics in parentheses. The level of statistical significance from zero is noted by $*p \leq 0.10$, $**p \leq 0.05$, and $***p \leq 0.01$ for two-tailed tests. Dependent variable: (1) absolute difference of annual ID change, and (2) percentage difference of annual ID change.

5. Robustness checks

Our analysis up to this point uses the original Altman Z-Score to identify firms that suffer from financial distress. Over the last decades, the Z-Score has been used likewise by practitioners and academics as an indicator of financial distress and to predict bankruptcy (e.g. Swamidass 2007; Ellinger et al. 2011). It has been shown that the original Altman Z-Score is still a reasonable indicator for predicting financial distress (Altman, Giancarlo, and Franco 1994; June and Reza 2012).

However, inventory is included in the calculation of the original Altman Z-Score which is a potential concern. More specifically, four of the five Z-Score ratio variables contain either total assets or working capital, which themselves contain inventory as one component. For instance, total assets and working capital, which together form the ratio variable X_1, both contain inventories.

To rule out a 'mechanical relationship' between inventories and the Altman Z-Score, we conduct two types of robustness checks. First, in a sensitivity analysis we show that the original Altman Z-Score is relatively invariant to changes in inventories alone. As a result, inventory reductions during the distress period will only marginally affect the Z-Score. Second, we estimate a sample specific and a modified inventory-free Z-Score. The sample specific re-estimated Z-Score takes into account the characteristics of our sample that might differ from the original sample which Altman used more than 40 years ago. The modified inventory-free Z-Score is derived by removing inventories from all variables. Using both, the original but re-estimated Z-Score and its modified, inventory-free variant, we repeat our core analysis and find that our initial results hold for the alternative Z-Scores.

5.1 *Sensitivity analysis of Altman Z-Score*

In this section, we discuss the sensitivity of the original Altman Z-Score to changes in inventories. As a first step, we calculate the mean Altman Z-Score over all companies and all periods in the sample. We then reduce the inventories of all firms stepwise by –5% to –75%, leaving all other variables unchanged. As a result, four of the five Z-Score ratio variables that contain either total assets or working capital change affecting thereby the value of the Z-Score. As shown in Table 14, even strong reductions in inventories by as much as –75% will c.p. change the Altman Z-Score by less than 5%. Although we find strong and significant inventory reductions for financially distressed companies, these inventory reductions are generally nowhere

Table 14. Sensitivity of Altman Z-Score to changes in inventories.

	Inventory mn USD		Altman Z-Score	
% Change	Mean	Median	Mean	% Change
Act	253.34	24.51	4.48	–
–5%	240.67	23.28	4.47	–0.22%
–10%	228.01	22.06	4.46	–0.45%
–15%	215.34	20.83	4.45	–0.69%
–20%	202.67	19.61	4.44	–0.93%
–25%	190.00	18.38	4.43	–1.18%
–50%	126.67	12.26	4.37	–2.59%
–75%	63.33	6.13	4.29	–4.34%

close to –75%. Therefore, we can safely conclude that endogeneity between the Z-Score and inventories is not a practically relevant problem for our analysis. Companies will neither become distressed solely because of extraordinary high or low inventories, nor will they leave the distress zone by reducing inventories alone. However, the strong and highly significant inventory reductions that we document for the majority of firms during financial distress indicate that inventory adjustments are one of several turnaround actions that distressed firms adopt to alleviate financial distress and free up cash that was formerly tied-up in form of unproductive inventories.

5.2 *Defining alternative Z-Scores*

In this section, we derive the alternative sample-specific and inventory-free Z-Scores in line with the original methodology used by Altman (1968). We re-estimate the Z-Score for companies that span our sample period from 1995–2007 by matching firms in the UCLA-LoPucki Bankruptcy Research Database to manufacturing firms within the North-America Compustat database. More specifically, we use a sample of 61 default firms and apply propensity score matching to identify 199 suitable non-default control firms. Using this sample of 260 default and non-default firms, we then conduct a discriminant analysis to re-estimate the Z-Score and to derive the inventory-free Z-Score. For each of the two Z-Score variants, we use two alternative classification rules to identify financially distressed companies. More specifically, we classify firms solely based on the discriminant value making no further assumptions about the true distress probability in the population sample. However, corporate bankruptcy and financial distress are relatively rare events given the large number of companies in the Compustat universe. Therefore, we will also carry out financial distress classifications using Bayesian priors that reflect the ex-ante probability of firms being in financial distress in the population sample. Thus, in total we re-run our analysis with four different alternatives to classify financially distressed firms (i.e. Original and modified Z-Score each with and without Bayesian priors).

We prepare the data in line with the procedures in Section 3. Altman (1968) used annual data to estimate the coefficients for the original Z-Score. As we are using quarterly data, we calculate the ratio variables $X_1, \ldots, X_5$ using quarterly variables, but subsequently compute the one-quarter trailing moving average of these five variables over one year to align our calculations with Altman's original approach. Using moving average values also eliminates any seasonality from the data. For instance, we define the first ratio variable as $X_1^Q = \text{Working Capital}_{itq}/\text{Total Assets}_{\text{itq}}$, where the superscript Q in X_j^Q denotes that the ratio variables are calculated using quarterly data. For the inventory free variants of the variables (i.e. $\text{Xmod}_1^Q \ldots \text{Xmod}_5^Q$), we subtract inventories from the variables – e.g. $\text{Xmod}_1^Q = (\text{Working Capital}_{\text{itq}} - \text{Inventory}_{\text{itq}})/(\text{Total Assets}_{\text{itq}} - \text{Inventory}_{\text{itq}})$. The moving average variables of X_j^{MA}, $j = 1, \ldots, 5$, which we use for the discriminant analysis, are then calculated as the one-quarter trailing moving average over the last four quarters:

$$X_j^{\text{MA}} = \frac{1}{4} \sum_{\text{tq}-4}^{\text{tq}-1} X_j^Q, \quad j = 1, \ldots, 5 \tag{10}$$

$$\text{Xmod}_j^{\text{MA}} = \frac{1}{4} \sum_{\text{tq}-4}^{\text{tq}-1} \text{Xmod}_j^Q, \quad j = 1, \ldots, 5 \tag{11}$$

As mentioned before, there are 61 usable defaulting companies that meet all of the above criteria and that can be matched uniquely to the firm-identifier (GVKEY), calendar year and calendar quarter in the Compustat data. The Compustat data in contrast contains 2959 non-defaulting companies, which corresponds to a default rate of approximately 2% of the companies. However, a discriminant analysis on a sample with only 61 default cases vs. 2959 non-default cases is likely not to yield meaningful and reliable results. Therefore, we need to reduce our sample size and find one or more reasonable control firms for each of the defaulting firms. Given that the variables $X_1, \ldots, X_5$ have explanatory power for discriminating between defaulting and non-defaulting firms, we expect that healthy firms will have quite distinct values on these variables compared to defaulting companies. However, before conducting the discriminant analysis, we want to rule out the possibility that any differences in the variables $X_1, \ldots X_5$ of defaulting vs. non-default firms are merely the result of any underlying confounding factors (e.g. different firm-sizes). Finding appropriate sample matches can be done by matching subsequently on different variables (e.g. industry first, then firm-size etc.) or by matching on all of these variables simultaneously using propensity score matching, which was popularized by Rosenbaum and Rubin (1983). Propensity score matching facilitates the matching, because it reduces the matching dimension to a single metric.

The first step entails calculating the propensity score by estimating a logit or probit model on binary variable (often called the treatment variable) which in our case is the variable $Default$. $Default$ equals 1 for the default quarter of the defaulting firms and is 0 in all other cases. We omit the time and firm subscripts for simplicity and estimate the following probit model to compute the propensity score:

$$\begin{aligned}\text{Default} = \alpha + \beta_1 \text{ Total Assets} + \beta_2 \text{ Time} + \beta_3 \text{ NAICS}_{32} \\ + \beta_4 \text{NAICS}_{33} + \beta_5 \text{ Recession}_{2001} + \beta_6 \text{ Recession}_{2007}\end{aligned} \tag{12}$$

The variable Total Assets in a given quarter is included as a control for firm size. The variable $Time$ denotes the time quarters and runs 1 for the first quarter of 1995 until 52 for the fourth quarter of 2007. Including a time variable allows us to control for changing default probabilities over time and to ensure that the time quarter is included in the propensity score computation, which should help to find matched control firms that are relatively close in time to the default event. To account for industry effects, we also include two dummy variables for the 2-digit NAICS industries 32 and 33. Finally, default probabilities might be higher during recessions. We therefore also include two dummy variables for the recessions in 2001 (Q1–Q4 2001) and the financial crisis starting in 2007 (Q4-2007). It is important to note, that our objective is not to derive a complete set of confounding factors for the propensity score matching, but rather to match the default companies to control firms on some key variables such that we are able to reduce our estimation sample in a reasonable way for the subsequent discriminant analysis. We omit the regression output table, because it is not of direct interest. However, all variables except the recession dummy for 2007 were statistically significant.

The next step in our matching analysis entails predicting the propensity scores for all companies. The propensity scores are used by the matching algorithm to select match-control pairs. There are several matching algorithms that can be used (e.g. nearest neighbour matching vs. kernel matching) and we apply the k-nearest neighbour matching procedure to find matches for the 61 default companies. Nearest neighbours are those companies whose propensity scores are most similar to the defaulting firm under consideration. We assign up to four different control firms for each of the 61 default companies. With this approach, we obtain a final sample of 260 companies (61 default firms and 199 control firms). With 61 default companies, our sample is nearly twice as large as the one used by Altman (1968). We use the sample of 260 firms to run the linear discriminant analysis for the sample specific Z-Score:

$$Default = \beta_0 + \beta_1\, X_1^{\text{MA}} + \beta_2\, X_2^{\text{MA}} + \beta_3\, X_3^{\text{MA}} + \beta_4\, X_4^{\text{MA}} + \beta_5\, X_5^{\text{MA}} \tag{13}$$

Likewise, we run the following linear discriminant analysis for the inventory free Z-Score:

$$\begin{aligned}Default = \beta_0^{\text{mod}} + \beta_1^{\text{mod}}\, \text{Xmod}_1^{\text{MA}} + \beta_2^{\text{mod}}\, \text{Xmod}_2^{\text{MA}} + \beta_3^{\text{mod}}\, \text{Xmod}_3^{\text{MA}} \\ + \beta_4^{\text{mod}}\, \text{Xmod}_4^{\text{MA}} + \beta_5^{\text{mod}}\, \text{Xmod}_5^{\text{MA}}\end{aligned} \tag{14}$$

Table 15 shows the canonical and the standardised coefficients from the linear discriminant analysis for both Z-Scores.

As expected, these values are quite different from the canonical coefficients obtained by (Altman, 1968) since our critical discriminant value is normalised to 0 (not 1.81), which also affects the scale of the coefficients. The canonical discriminant coefficients can be used to calculate the discriminant score. The standardised coefficients are informative about the discriminatory power of the individual variables. It is important to note that the estimation of the canonical and standardised coefficients occurs independently of any priors, and prior probabilities are solely used for classifying firms in the subsequent step. Also note that the sign on the standardised coefficient is not important and that only the absolute magnitude of the standardised coefficient is relevant. Most notably, the first three variables are the most important variables in both analyses, the original, but re-estimated Z-Score and the modified, inventory-free Z-Score. The first three variables do not change across the original and inventory-free variants of the discriminant analysis. However, variable X_5 becomes more important for the inventory free version of the Z-Score.

Table 15. Canonical and standardized coefficients from linear discriminant analysis.

Variable	Sample-specific Z-Score		Variable	Inventory-free Z-Score	
	Canonical	Standardised		Canonical	Standardized
X_1^{MA}	3.18	0.73	Xmod_1^{MA}	2.40	0.75
X_2^{MA}	0.49	0.21	Xmod_2^{MA}	0.38	0.20
X_3^{MA}	22.11	0.52	Xmod_3^{MA}	18.11	0.52
X_4^{MA}	0.00	–0.01	Xmod_4^{MA}	0.00	0.01
X_5^{MA}	0.18	0.03	Xmod_5^{MA}	0.97	0.20
Constant	–0.99	N.A.	Constant	–0.73	N.A.

	Actual	Without Priors Classification: Non-Default	Without Priors Classification: Default	With Priors Classification: Non-Default	With Priors Classification: Default
Re-estimated Z-Score	*Non-Default*	185 (93%)	14 (7%) **Type II**	194 (97.5%)	5 (2.5%) **Type II**
	Default	10 (16.4%) **Type I**	51 (83.6%)	25 (41%) **Type I**	36 (59%)
Inventory Free Z-Score	*Non-Default*	183 (92%)	16 (8%) **Type II**	193 (97%)	6 (3%) **Type II**
	Default	11 (18%) **Type I**	50 (82%)	28 (46%) **Type I**	33 (54%)

Priors:		Priors:	
Non-Default	**Default**	**Non-Default**	**Default**
0.5	**0.5**	**0.765**	**0.235**

Figure 4. Classification tables using different Z-Score classification approaches.

When no Bayesian updating and prior probabilities are used for the classification, then the canonical discriminant coefficients can be used to calculate the discriminant scores which in turn are used for classification. As the critical threshold is 0, observations with below zero discriminant scores will be classified as defaulting firms and, observations with positive discriminant scores as non-defaulting firms. Using priors in the classification is slightly more difficult and involves conditional probabilities. Due to space constraints, we omit the mathematical details at this point, but refer the interested reader to Rencher and Christensen (2012) for further details.

Figure 4 shows the leave-one-out classifications from the four different Z-Score approaches.

In the upper part of Figure 4, we report the results for the original but re-estimated Z-Score both with and without priors. We set the priors proportional to the group sizes. As 61 out of 260 companies are default firms, the ex-ante probability for a default case is 23.5% in our sample. When no prior probabilities are specified, priors of 0.5 are implicitly assumed in a two-group case. As can be seen in Figure 4, when we use the full Z-Score without priors, we are able to classify 93% of non-default and almost 84% of the default firms correctly. When we use priors, we are able to classify more than 97% of non-default firms correctly and reduce the *type II error* thereby from 7 to 2.5%. A low *type II error* ensures that we do not wrongly classify healthy firms as distress firms. However, using priors increases the *type I error* and we 'miss' to classify

Table 16. Change in inventory days for different distress indicators.

	No priors						Priors (non-distress = 97% & distress = 3%)					
	Z-Score$^{\text{SampleSpecific}}$ (N=219)			Z-Score$^{\text{Inventory free}}$ (N=211)			Z-Score$^{\text{SampleSpecific}}$ (N=76)			Z-Score$^{\text{Inventory free}}$ (N=76)		
Variable	Mean	Median	% Neg.	Mean	Median	% Neg.	Mean	Median	% Neg.	Mean	Median	% Neg.
Single	–28.84	–12.14	69%	–38.1	–16.99	72%	–35.57	–10.49	61%	–47.91	–32.5	76%
	(–5.33)***	(–6.13)***	(0.00)***	(–6.63)***	(–6.79)***	(0.00)***	(–3.09)***	(–2.56)**	(0.08)*	(–3.54)***	(–4.44)***	(0.00)***
Single (%)	–7.35	–18.84	69%	–9.13	–21.61	72%	–1.98	–11.47	61%	–15.18	–29.9	76%
	(–1.69)*	(–5.48)***	(0.00)***	(–1.97)*	(–5.83)***	(0.00)***	(–0.25)	(–1.53)	(0.08)*	(–1.96)*	(–3.92)***	(0.00)***
MA 2	–19.05	–8.27	68%	–30.64	–15.02	72%	–27.74	–4.15	55%	–45.76	–30.99	76%
	(–4.29)***	(–5.25)***	(0.00)***	(–6.6)***	(–7.17)***	(0.00)***	(–3.05)***	(–2.33)**	(0.42)	(–4.51)***	(–4.64)***	(0.00)***
MA 2 (%)	–4.77	–13.06	68%	–10.22	–15.6	72%	0.09	–6.44	55%	–20.05	–29.46	76%
	(–1.29)	(–4.61)***	(0.00)***	(–2.73)***	(–6.25)***	(0.00)***	(0.01)	(–1.65)*	(0.42)	(–3.97)***	(–4.28)***	(0.00)***
MA 4	–21.85	–8.43	70%	–27.39	–15.21	77%	–26.66	–11.08	64%	–41.69	–29.28	82%
	(–5.51)***	(–6.36)***	(0.00)***	(–7.53)***	(–8.24)***	(0.00)***	(–3.16)***	(–2.74)***	(0.02)**	(–5.16)***	(–5.37)***	(0.00)***
MA 4 (%)	–9.21	–12.5	70%	–12.41	–15.22	77%	–4.82	–11.44	64%	–21.4	–26.39	82%
	(–3.36)***	(–6.1)***	(0.00)***	(–4.84)***	(–7.41)***	(0.00)***	(–0.76)	(–2.07)**	(0.02)**	(–5.06)***	(–5.04)***	(0.00)***
Annual	–20.89	–12.51	68%	–22.34	–12.82	70%	–32.97	–16.57	64%	–43.4	–37.47	76%
	(–5.10)***	(–5.9)***	(0.00)***	(–6.09)***	(–6.61)***	(0.00)***	(–2.98)***	(–2.99)***	(0.02)**	(–4.13)***	(–5.05)***	(0.00)***
Annual (%)	–4.83	–16.32	68%	–5.79	–14.07	70%	–0.85	–17.57	64%	–16.28	–28.86	76%
	(–1.00)	(–5.56)***	(0.00)***	(–1.23)	(–5.87)***	(0.00)***	(–0.1)	(–2.14)**	(0.02)**	(–2.37)**	(–4.13)***	(0.00)***

Notes: Results are reported for change metrics as defined in Figure 2. T-statistic for the mean, Wilcoxon sign rank Z-statistic for the median and p-value for the binomial sign test are reported in parentheses. Percentage negative refers to the number of observed negative changes. The level of statistical significance from zero is noted by $^{*}p \leq 0.10$, $^{**}p \leq 0.05$, and $^{***}p \leq 0.01$ for two-tailed tests.

Table 17. Industry peer comparison of inventory days for different distress indicators.

	No priors				Priors (non-distress = 97% & Distress = 3%)			
	Z-Score$^{\text{SampleSpecific}}$		Z-Score$^{\text{Inventory free}}$		Z-Score$^{\text{SampleSpecific}}$		Z-Score$^{\text{Inventory free}}$	
Variable	Mean ($N = 219$)	Median	Mean ($N = 211$)	Median	Mean ($N = 76$)	Median	Mean ($N = 76$)	Median
Single	–24.31	–8.18	–32.88	–11.49	–30.13	–11.49	–43.8	–30.43
	(–4.5)***	(–4.89)***	(–5.83)***	(–5.83)***	(–2.69)***	(–5.83)***	(–3.32)***	(–4.13)***
MA 1	–15.34	–5.47	–26.57	–12.09	–22.73	–12.09	–41.65	–28.32
	(–3.46)***	(–3.99)***	(–5.79)***	(–6.19)***	(–2.58)***	(–6.19)***	(–4.2)***	(–4.34)***
MA 2	–18.58	–6.8	–23.76	–12.73	–22.15	–12.73	–37.95	–26.51
	(–4.79)***	(–5.46)***	(–6.62)***	(–7.23)***	(–2.71)***	(–7.23)***	(–4.84)***	(–5.06)***
Annual	–17.71	–10.6	–18.2	–9.61	–28.9	–9.61	–39.73	–35.82
	(–4.43)***	(–5.23)***	(–5.06)***	(–5.68)***	(–2.7)***	(–5.68)***	(–3.88)***	(–4.77)***

Notes: Results are reported for change metrics as defined in Figure 2. T-statistic for the mean, Wilcoxon sign rank Z-statistic for the median and p-value for the binomial sign test are reported in parentheses. Percentage negative refers to the number of observed negative changes. The level of statistical significance from zero is noted by $*p \leq 0.10$, $**p \leq 0.05$, and $***p \leq 0.01$ for two-tailed tests.

quite a few default firms. A percentage of 59% or 54% (inventory free Z-Score) of correctly classified default firms might seem poor at first glance. However, it is important to note that only 23.5% of the firms are default firms. A random assignment of default vs. non-default firms would therefore yield a hit-rate of 23.5% of correctly identified default firms. Thus, our model performs more than twice as accurate as a random assignment.

A trade-off between *type I* and *type II errors* is typical for many statistical tests, and it is not clear beforehand which error type we should reduce. On the one hand, one might prefer a low *type I error* and argue that we should identify as many distress firms as possible. However, this might lead to a 'distorted' sample, because we might also wrongly include many healthy firms into the distress sample. On the other hand, one might prefer a low *type II error* and argue that it is better to have a clear-cut sample of financially distressed firms – albeit we might miss to classify many 'borderline' financially distressed firms. We will not make a definite statement on this point, but rather report results for both cases – with and without priors. Consistent results from both approaches will be strong empirical support for the robustness of our results.

5.3 *Empirical results with alternative Z-Scores*

In this section, we provide the results from our robustness tests and the alternative metrics of financial distress. In Tables 16 and 17 we show the counterparts of Tables 5 and 6 from Section 4. They show the test results for financial distress classifications made with the sample-specific Z-Score and the inventory-free variant. Further, we conduct classifications with and without Bayesian priors. As financial distress and corporate default are rare events, we assume a 'true' distress probability of 3% in the population sample. An assumed financial distress rate of 3% is relatively conservative and ensures that we minimise the error type II when classifying firms as financially distressed (see Section 5.2). As expected, we obtain a much smaller distress sample of only 76 firms when we classify firms using priors and use an ex-ante distress-probability of 3%. As can be seen from Tables 16 and 17, our results are robust to the four different specifications of financial distress. Two main observations can be made from tables.

First, when the inventory-free Z-Score is used to classify firms, results seem to be generally stronger and inventory reductions seem to be more pronounced. A possible explanation for this finding might be that we have eliminated the potentially confounding relationship between the Z-Score and inventories. Second, when prior probabilities are used for classifications, our sample size reduces to 76 distress cases, but mean and median inventory reductions appear to be larger in magnitude. The probability that firms, which are not financially distressed are wrongly classified as distressed firms, is much smaller when priors are used for the classification (i.e. smaller *type II error*). Thus, the distress sample that we derive using priors should be 'cleaner' in the sense that only truly distressed companies are considered.

Since the results are generally stronger for the classification with priors, we understand the results as further empirical evidence for our core hypothesis: Firms reduce inventories during financial distress. Overall, we conclude that our results are very robust to alternative specifications of the Z-Score and different classifications. The results shown here are qualitatively identical to the main results in Section 4 and give further support to our findings.

6. Conclusion

Financial distress, as a threat to firm survival, forces firms to undertake appropriate turnaround activities. From among the various actions that firms can take to resolve their distress, researchers and practitioners suggest restructuring of inventories to free-up cash from tied-up capital. In this study, we analyse 198 firm distress events and find strong empirical evidence for significant reductions of inventories during financial distress. Approximately 70% of financially distressed firms reduce their inventories with average reductions between 18.41 and 24.93 inventory days (median –6.31 to –9.05 days) until the end of each firm-specific distress period. Although inventories affect the Z-Score, they only contribute a small effect to successful turnarounds, i.e. strong inventory reductions do not lead firms out of distress. However, exploiting internal cash resources supports the success of an entire turnaround.

We show that the magnitude of inventory reductions under financial distress depends on many factors such as firm size and turnaround strategy. Our results are extremely robust to different classifications of financial distress and the core insight, that firms reduce inventories during financial distress, holds under different distress classification schemes.

Naturally, our study has also some limitations. The default sample results, as listed in Panel B, are not directly comparable to the results listed in Panel A because there are no starting points for the distress periods that can be matched to our definition of Panel A. As noted in the results section, defaulting firms seem to behave in the same way as distressed firms, but may not be able to overcome their distress within our chosen maximum period of 12 quarters due to more severe distress or lack of firm management ability. The results presented in Panel B indicate that, prior to bankruptcy, defaulting firms do not reduce inventory by the same amount as distressed firms. More research on the different behaviour of defaulting vs. non-defaulting firms will help to reveal the importance of short-term asset restructuring efforts in situations of financial distress.

A further limitation is the scope of our analysis. We study short-term inventory actions, but our model does not account for any changes within the supply chain. More specifically, prior research has pointed out the important role of supplier and customer behaviour in resolving distress. Hertzel et al. (2008) already provide evidence of negative wealth effects that may occur within the supply chain if a network partner experiences distress or if that partner defaults. Further, Hendricks and Singhal (2005) have shown that supply chain disruptions at key suppliers or customers have negative financial consequences for the company. Thus, changes in the inventories of key suppliers or their development of accounts receivables might generate a general effect on the supply chain. Recent studies show that shifting costs along the supply chain will not lead to long-term improvements for all network partners (Hofmann and Kotzab 2010; Lambert and Pohlen 2001). Future research on how supply chain partners can help to mitigate financial distress will certainly be a fruitful research path.

Our analysis indicates that most inventory reductions seem to occur within a relatively short period of time after the onset of financial distress. For example, firms rely on selling obsolete or slow-moving inventory. These actions are relatively easy to implement and entail low adjustment costs (Carpenter et al. 1994). Furthermore, we show that inventory reductions are persistent; we find no reversion of inventory days to pre-distress levels after distress.

We identify important factors that differentiate distressed firms from one another and influence their inventory decisions. Lean inventory at the beginning of a distress period lowers a firm's ability to reduce its inventory days any further to raise cash because the remaining inventory is essential to ongoing business operations. In contrast, having an initially high level of inventory days allows for substantial reductions and optimisation benefits during distress periods. Firm efforts or ability to reduce inventory days also depend on firm size, but the effect is less significant than expected. However, on average, small firms implement more aggressive reductions in their inventory days than do large firms due to their less complex operations and more focused business lines. At the same time, we expect small firms to have fewer alternative capital resources during times of scarce liquidity.

Finally, we find that inventory reduction is positively correlated with extreme asset reductions and cost cutting strategies in turnaround situations, but we generally argue that short-term inventory reductions are valuable strategic options in times of severe financial distress.

Our findings imply three practical recommendations for firms that experience financial distress. First, if distressed firms have lean inventories, firm management and turnaround managers should spend less time on inventory reduction efforts because the expected benefits will be rather low. A simple comparison of the firm with the industry average and firm size should be sufficient to determine a firm's current status. Second, firms that are in financial distress should adjust their sales forecasts early to account for declining demand and to prevent the unnecessary build-up of inventory. As previously noted, improvements in forecasting methods will provide sustainable efficiency gains that will even adapt to future growth prospects. Third, firms are advised to achieve high flexibility in their operations to generate a buffer that will protect them during the short periods of financial distress that may occur for various reasons.

In summary, inventory adjustments are promising turnaround options because they provide cash inflows and likely increase the efficiency of a distressed firm's supply chain. Distressed firms are advised to evaluate their inventory performance so that they can exploit these benefits, which may increase their odds of a business turnaround.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix 1

Table A1. Distribution of financial distress and default in panels.

Distribution of Fiscal years in panels in %												
Year	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Panel A - First distress year	4.55	5.56	18.69	10.61	18.18	13.64	14.14	2.02	6.06	6.57		
Panel B - Default year		2.34	3.91	6.25	14.06	16.41	17.97	15.6	9.38	7.03	5.47	1.56