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The collapse of Lehman Brothers in 2008 triggered the largest natural experiment to test firm's inventory management capabilities to date. During the ensuing Financial Crisis, firms were suddenly confronted with an unprecedented collapse of demand. This critical situation, often with limited credit availability, put forward an extreme test of firms's inventory responsiveness. Following the demand shock in September 2008, a number of firms managed their inventories responsively, maintaining relative inventory levels fairly constant. Others built up considerable surplus inventory, and others reacted aggressively cutting down stocks. In this paper, we use firm-level empirical data from 1,278 public U.S. manufacturing firms for the period 2005-2011 to understand the drivers behind inventory responsiveness and explore the link between said responsiveness and profitability, market performance, and financial health. On average, firms required six quarters to adapt to the situation. However, the responsiveness varies across sectors. In particular, firms in chemical and electronics sectors required the most time to align inventories to the new realities. In addition, we identify key firm-level factors associated with a responsive adaption of inventory levels to changes in demand. These factors are lower liquidity, lower gross margins, and higher inventory predictability. Firm size, often associated with superior inventory management capabilities, does not have a significant impact. Furthermore, we show that the impact of deviations from the normal inventory levels is not symmetric—inventory reductions appear to be more critical than inventory excesses. Inventory reductions are associated with a decrease in the return on sales, an increase in the probability of bankruptcy, and a decline in short-term stock performance. In the long-term, however, inventory reductions are associated with an increase in a firm's stock performance. Our results confirm the view that managing inventories is indeed critical during crisis periods. Our findings, however, suggest that the short-term view of inventory reduction as an instrument of liquidity needs to be gauged carefully against the tradeoffs between different dimensions of short- and long-term financial performance.

Key words: inventory management; econometrics; panel data; financial crisis; quarterly inventory; inventory hump

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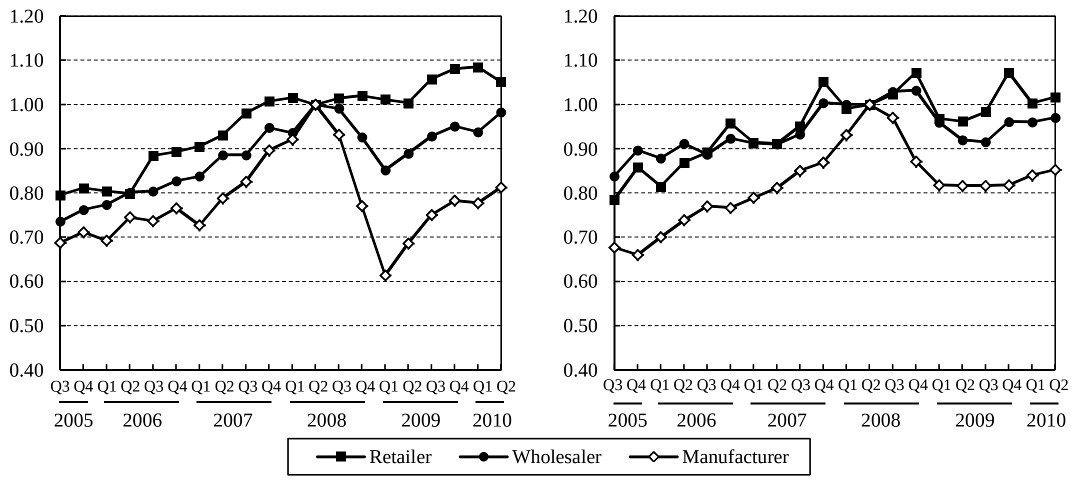


(a) Normalized Aggregate Sales (b) Normalized Aggregate Inventory

Figure 1 **Normalized aggregate sales and inventories in retail, wholesale and manufacturing sectors based on firm level data.**

Note: Values normalized in Q2/2008. Sales in bn US$: 201 (Retailer), 168 (Wholesaler), 2,052 (Manufacturer); Inventory in bn US$: 78 (Retailer), 56 (Wholesaler), 812 (Manufacturer)

1. Introduction

Firms constantly strive to adapt their inventory levels to fluctuating customer demand patterns. Over time, more and more firms have improved their inventory policies and managed to align their inventories to their business objectives. Firms minimized stock-outs while avoiding excessive inventory build-ups (Gaur et al. 2005, Chen et al. 2005, Eroglu and Hofer 2011). Today, firms seem well prepared for managing their supply chains in a stable business environment. However, during the 2008 financial crisis, the unprecedented demand contraction across many industries has challenged firms' inventory management capabilities as never before. While the economy kept drifting downwards in 2008, it reached a significant turning point on September 15 when Lehman Brothers–the fourth largest US investment bank at that time–declared bankruptcy. This, the biggest filing of bankruptcy in U.S. history, precipitated the worst financial panic since the Great Depression. The collapse of Lehman Brothers sent a shock wave through the financial world and triggered an unprecedented drop in the global economy (Duncan 2008). Demand drops in manufacturing industries were particularly severe. Figure 1(a) shows the development of aggregate sales in the retail, wholesale, and manufacturing sectors based on the data analyzed in this paper. Sales show a bullwhip-like behavior: no dip in the retail sector but significant reductions upstream. Aggregate sales in manufacturing dropped by up to 39% within three quarters.

When sales decline, firms need to adjust their inventory levels to these new realities, but they also have incentives to further reduce their inventory investment. Cost-wise, lowering inventory levels

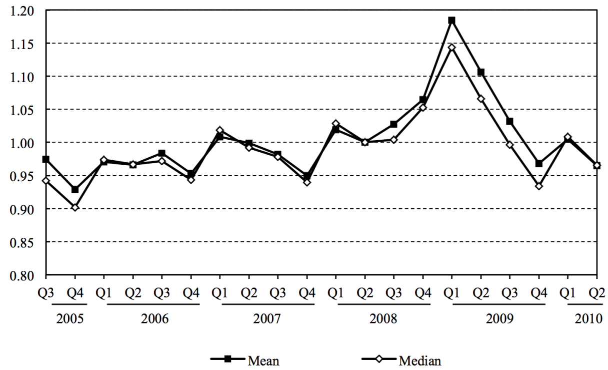


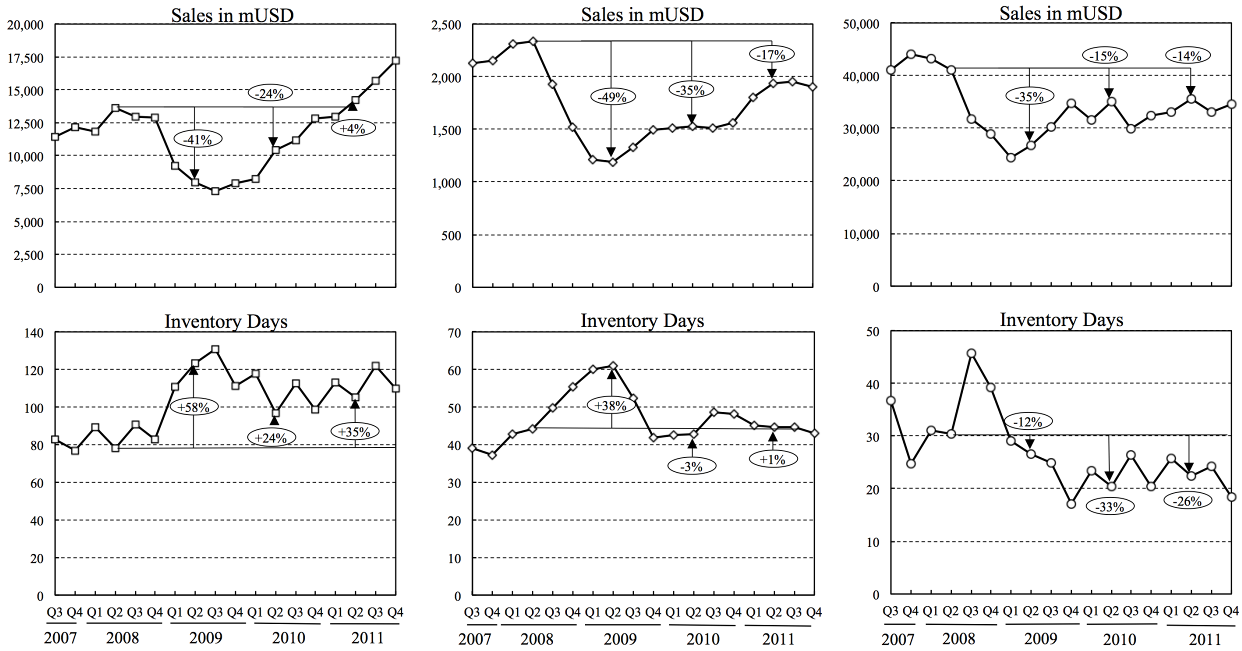
Figure 2 Normalized inventory days for manufacturing.

Note: Values normalized to 1 on Q2 2008.

avoids physical holding, financial holding, and obsolescence cost—particularly important when sales are rapidly shrinking. Credit-wise, lowering inventory levels improves cash flows—thus ensuring liquidity in a situation where credit availability is scarce. In this way, inventories can be used as a substitute for financial instruments (Tribó 2009).

Figure 1(b) shows the evolution of inventories for the retail, wholesale, and manufacturing sectors. The data suggests that the, once the crisis hit, different sectors actively sought to reduce inventories (see also Dooley et al. (2010)). A crisis with rapidly shrinking sales, however, poses a challenge for inventory reductions. It prompts significant actions, which can potentially result in problems if demand recovers faster than expected (Escaith et al. 2010). Furthermore, while anecdotal evidence suggests that the automotive (Dooley et al. 2010) and electronics manufacturing subsectors (Dvorak 2009) put substantial inventory-reducing measures into effect, it is not clear whether systematic reductions took place among all industries—nor the mechanisms behind them. There are a number of levers that firms can pull to decrease different inventory components. For raw materials, firms can freeze material purchases and ask suppliers to take-over inventories. For work-in-process materials, firms can lower production batch sizes and idle production plants. For finished goods inventories, firms can streamline the product portfolio, switch to make-to-order, and sell inventories with significant discounts. The strategy adopted by a given firm–and its impact–will depend upon a number of factors, including its position in the supply chain and the magnitude of its demand collapse.

It's important, therefore, to account for the interaction between demand and inventory changes. Figure 2 shows the mean and median normalized inventory days for the manufacturing sector. This metric expresses the amount of inventory in days of sales (thus accounting for demand fluctuations). Inventory days peaked sharply after the crisis, with a median YoY increase of 11% by Q1 2009. An analysis of aggregate figures yields similar results: median inventory days increased 8% in the



(a) Caterpillar Inc. (b) Dana Holding Corp. (c) Ford Motor Company

Figure 3 **Sales and relative inventories at Caterpillar Inc, Dana Holding Corporation, and Ford Motor Company.**

four quarters immediately following the crisis compared to the four quarters immediately preceding it. (Mean values show steeper increases, which implies that individual values are skewed to the right.) The shock dissipates within 6 quarters. This suggests that, despite suffering the steepest sales decline of all the sectors, manufacturers met the challenge with relative agility.

If we inspect these inventory dynamics at the level of individual firms, important differences emerge. Figure 3 shows sales and relative inventory developments at three firms: Caterpillar Inc., Dana Holding Corp., and Ford Motor Company. These firms belong to the automotive manufacturing sector, an industry that has been hit particularly hard by the Financial Crisis. These companies experienced a comparable collapse in sales during the financial crisis but significantly different inventory dynamics. Caterpillar saw quarterly sales drop by 41% within a year from 13.6bn USD to 8.0bn USD (from Q2/2008 to Q2/2009). Over the same period, relative inventory in days of supply increased by a staggering 58%, from 78 days to 124 days. Days of supply at Caterpillar were still at 97 days in Q2/2010, 24 % above pre-crisis levels after two years. In comparison, Dana's revenues fell by 49% from 2.3bn USD to 1.2bn USD (from Q2/2008 to Q2/2009). Similarly to Caterpillar, relative inventory levels at Dana peaked at the start of the crisis. However, the surge is significantly less pronounced with an increase of 38% from 44 days to 61 days. In addition, inventories at Dana settle much faster at the pre-crisis level, settling at around 42 days in Q4/2009. Finally, Ford Motor

Company also experienced a significant sales decline of 35% from 41.1bn USD to 26.8bn USD (from Q2/2008 to Q2/2009). Their inventory days however, *decrease* by 12% over the same time period, from 30 to 27 days. Ford's inventory settles at roughly 20 days (33% decrease) after a year. Note that in all three cases, the inventory behavior stabilizes after 2 years. This suggests that each company reacted to the crisis with a different strategy: maintain high inventory levels (a), react and go back to pre-crisis levels (b), or decrease inventories (c).

These observations motivate our research. Given the importance of inventory management capabilities in crisis situations (Pesch and Hoberg 2015), our objective is to investigate inventory responsiveness in the 2008 financial crisis. Many firms reacted quickly and kept days of supply rather constant, others built up significant surplus-inventories, and yet others lowered their inventories considerably. In the short-term, these decisions affect their financial position (e.g., increasing cash in hand by liquidating inventories) but the medium- and long-term consequences have not yet been explored.

Using empirical methodologies, we leverage quarterly financial data from Standard & Poor's Compustat database to analyze the performance of 1,278 firms in the period between 2005 and 2011. In this paper, we address three research questions with regard to firm's inventory management capabilities in the financial crisis. (i) How did firms react to the significant drop in demand and align their inventory components to the new situation?, (ii) What are the key drivers that enable firms to responsively manage their inventories?, and (iii) What is the financial impact of responsive inventory management?

We find that the steep increase in inventory days was driven mainly by raw material and finished product inventories; WIP inventories stayed essentially constant during the period. Additionally, while the dynamics in the manufacturing industry were qualitatively similar among all sectors, some (e.g., *Food, Beverage, & Tobacco*) were more responsive than others (e.g., *Machinery*). At the firm level, the evidence suggests that the drivers for inventory responsiveness are consistent across the panel. Lower liquidity, lower gross margins, and higher inventory predictability (before the crisis) are associated with higher inventory responsiveness during the crisis. Finally, we find that the financial impact of the inventory response is not symmetrical. In the short term, firms that hold less inventory than expected perform worse along all financial metrics, yet we find no effect associated with holding more inventory than expected. In the long term, however, the data shows that lower inventories are associated with increased market performance, and higher inventories to decreased financial health.

The remainder of the paper is structured as follows. In Section 2, we provide an overview on literature relevant for addressing inventory management in crisis situations. In Section 3, we develop a series of hypotheses based upon existing theory. Then, in Section 4, we introduce the models and methodology used to test our hypotheses, describe the empirical dataset. We follow with Section 5, where we present our results, and finally conclude and summarize our findings in Section 6.

2. Inventory Management in Times of Crisis

Our research builds upon two streams of research. Namely, the empirical operations management literature that analyses firm-level inventory decisions, and macroeconomic and financial literature that investigates the link between economic conditions and inventory investments.

Over the past decade, research in empirical operations management grew considerably on account of a rich stream of literature–supported by secondary data–that studies multiple facets of firm-level inventory investment. Key findings include that inventory levels in many sectors have significantly decreased over the past decades (Chen et al. 2005), that inventory levels can convey important information on a firm's future sales (Kesavan et al. 2010), and that most insights gained from analytical single-product inventory models also hold for aggregate firm-level inventory (Rumyantsev and Netessine 2007b). Additionally, a number of papers identify relationships between inventory investment and the underlying driving factors. For example, production flexibility and number of dealerships in the case of the automotive industry (Cachon and Olivares 2010); the time relative to the fiscal year end in publicly traded firms (Lai 2008); and sales characteristics, gross margins, and capital intensity in the retail industry (Gaur et al. 2005). We refer the reader to Eroglu and Hofer (2011) and Steinker and Hoberg (2013) for comprehensive reviews of this empirical inventory literature, and focus on those studies most immediately relevant to our topic.

The objective of numerous empirical operations management papers is to identify the optimal level of inventory a firm should hold. Research suggests the existence of a 'sweet spot' for firm-level inventory, above or below which performance tends to decrease. Chen et al. (2005) apply a portfolio approach to review the link between firm inventories and stock-returns. They find that firms with the lowest inventories have only ordinary returns while firms with abnormally high inventories show abnormally poor returns. Firms with slightly lower than average inventories exhibit the highest stock returns. Rumyantsev and Netessine (2007a) analyze the impact of responsive inventory management on financial performance. Responsive inventory management refers to a close match between sale and inventory dynamics—a responsive firm will maintain constant relative inventory levels. They find that high deviations from constant inventory days are associated with a lower profitability. Eroglu and Hofer (2011) introduce an inventory leanness measure that takes into account industry-specific inventory management characteristics. Their findings suggest an optimum level of inventory leanness: in about half of the considered industries, inventory leanness increases firm performance up to a certain point beyond which the incremental effect becomes negative. Complementarily, Singhal (2005) analyzes the impact of public inventory-surplus announcements on shareholder value. He finds that those firms that experience excess inventory situations underperform their peers, and that the stock market partially anticipates the negative effects of holding surplus inventory.

The aforementioned studies were conducted in periods of relative stability. However, it seems reasonable to conclude that firms should also minimize deviations from optimal relative inventory levels during crisis periods (see also Kahn and McConnell (2002)). For periods with external demand shocks this would imply that firms should aim to regain appropriate inventory levels shortly after temporary deviations. This reasoning, however, does not factor in credit and financial limitations that can, in such situations, steer inventory investment decisions. To the best of our knowledge, no study explicitly addresses manufacturer's inventory management capabilities in times of crises and the causes, and effects, of the resulting inventory dynamics. Closest to our topic is a recent paper by Kesavan and Kushwaha (2014), who study retail inventory investment during macroeconomic expansions and contractions. They find that the service level of retailers has significant explanatory power on inventory investment. In periods of contraction (expansion), low (high) service level retailers decrease (increase) their inventory investment more than high (low) service level retailers.

Macroeconomic and financial research takes a different perspective on the topic. From the macroeconomic viewpoint, changes in inventory investment are important inasmuch as they play a significant role explaining GDP fluctuations. Blinder and Maccini (1991) emphasize this point and draw attention to the fact that, while it has been known since the 1950s, this relationship was underrepresented for decades in the economics literature. Inventories as an 'adjustment' variable, rather than as a driver of production decisions, had become the mainstream view. This was due, in part, to the widespread use of production smoothing models based on Holt et al. (1960), which assume that production costs are dominant. See Blinder (1986) for an in-depth reflection on the production smoothing model's (in)ability to explain empirical observations. In recent years, however, a large body of macroeconomic as well as financial research literature has been examining the role of inventory investments in the business cycle, analyzing postwar data on recessions (e.g. Sichel (1994), Carpenter et al. (1994), Hendel (1996), Carpenter et al. (1998), Dimelis (2001)). Kahn and McConnell (2002) point out that the effort of firms to keep relative inventory levels in times of crisis constant leads to pro-cyclical absolute inventory movements. The authors estimate that overall inventory disinvestments accounted for 24.5% of the overall slowdown in GDP growth during postwar recessions. As firm disinvest inventories, they amplify reductions in own sales up the supply chain. Guariglia (1999) highlights this 'accelerator effect' as particularly strong for inventories with low adjustment costs. A general argument for reducing inventories in recessions is that constraints on external finance will make firms more reliant on measures of internal finance and hence reduce their inventory investments to meet financial requirements. Companies that are relatively dependent on external finance thereby have to run much larger inventory reductions than less constrained companies (cp. Kashyap et al. (1994), Tribó (2001), Heisz and LaRochelle-Côté (2004), Duchin et al. (2010)). In addition, there are indications that smaller companies have to take more drastic measures when their external finance is constrained (cp. Bagliano and Sembenelli (2004)). For the Financial Crisis, economic research suggests that inventory investment is positively correlated with changes in production and follows the latter with a time-lag of two to three quarters (Abrahamsen and Hartwig 2011).

Due to its immediate effect in the running of operations, the Financial Crisis has also triggered a vast body of practitioner's literature on how to steer firms through the economic downturn. Besides reducing costs, practitioners emphasize the importance of conserving cash by cutting inventories (and aligning other working capital components). During the crisis, consultancies advised firms to prevent inventory growth by canceling raw material shipments and halt production on any orders that have not been confirmed (Booz Allen Hamilton 2008). In the given economic climate, myopic measures are justified as rigorous inventory reductions or implementation of lean manufacturing could take years (BCG 2008). In other words, firms can steer away from high service level commitments in order to navigate the crisis. To support actions, shifts in the incentives system arguably help to quickly focus efforts on inventory reduction by directing additional management attention on materials management (Kedrowski 2010). Overall, firms were advised to react quickly which is possible if all efforts are aligned. For example, a chemical company managed to cut inventory levels by 20 percent in just ten weeks while maintaining high service levels (McKinsey 2009).

Based on the different literature streams explored above, the expected behavior of companies after the start of the crisis is to dynamically align inventories to shrinking demand—and indeed, potentially reduce their inventory coverage. This would allow them to preserve working capital and to avoid inventory holding costs. (The challenge, of course is not losing track of their service levels (Eroglu and Hofer 2011, Rumyantsev and Netessine 2007a).) It's not clear to what extent this occurred, or to what extent inventory responsiveness during the crisis was associated to financial performance. Firms adopted different inventory strategies (see Figure 3), thus we cannot a priory assume a synchronized behavior. Furthermore, it's possible that conditions for specific sectors (i.e., automotive, electronic manufacturing) made the adoption of responsive measures easier, harder, or more critical, than for others.

Our research explores the drivers that allow firms to act responsively during crisis periods; we define a set of measures that quantify the dynamics behind firms' responses and analyze the underlying driving factors—taking into account the difference among subsectors. Further, we investigate if responsive firms benefit financially from their actions. We explore this question by explicitly measuring the short-, medium- and long-term impact of inventory responsiveness on various aspects of a firms' financial performance: profitability, financial health, and market performance. The picture that emerges from our analysis indicates that the consequences of deviating from the 'inventory sweet spot' during the crisis period are not straightforward. On the one hand, inventory dynamics affect the individual dimensions of performance differently. Inventory reductions are negatively associated with profitability and financial health, but positively associated with the long-term market performance. Furthermore, we observe the expected negative association between surplus inventories and long-term financial health, but find that having surplus inventories at the start of the crisis does not appear to affect profitability or market performance.

3. Hypotheses Development

Based on operations and supply chain management literature, we can identify a number of potential factors associated with inventory dynamics in the crisis period. In section 3.1, we develop four hypotheses on the relationship between firms' inventory responsiveness in the crisis and gross margins, liquidity, inventory predictability, and firm size. In section 3.2, we develop two hypotheses on the relationship between observed inventory dynamics and financial performance.

3.1. Inventory Dynamics

Prior research on inventories provides evidence that gross margins (i.e. overall product margin) are an important determinant for inventory investments (Kesavan et al. 2010, Rumyantsev and Netessine 2007a). Firms with low gross margins are often seen to execute much tighter control on their inventories compared to peers with higher gross margins. In line with stochastic inventory theory and the critical ratio in the newsvendor model (Cachon and Terwiesch 2009), firms are expected to avoid excess inventories with high holding or obsolescence costs if gross margins are low. In situations with rapidly shrinking customer demand, firms with lower gross margins should be carefully watching developments and manage inventories timely and proactively. Firms with higher gross margins typically have higher inventories to avoid stock-outs and to provide higher service levels (Kesavan and Kushwaha 2014). While these firms should also reduce inventories if demand contracts, they are expected to react more slowly. Firms with higher gross margins are used to higher inventory levels (Gaur et al. 2005) and have an interest to avoid stock-out situations if demand recovers earlier than expected. Therefore, we posit a relationship between a firm's gross margin and the inventory surplus in the crisis period in the following hypothesis:

HYPOTHESIS 1. *Gross margins are negatively associated with a firm's inventory management responsiveness in the crisis.*

The finance literature generally distinguishes two sources for financing operations and future growth: external financing, such as credits or equity obtained from the outside; and internal financing, such as current assets or retained earnings obtained from within (Brealey 2012). A key characteristic of the financial crisis was the reduced access to loans for many firms, which acted as a negative shock to the supply of external finance (Ivashina and Scharfstein 2010). In particular, firms with low liquidity where affected most by the limited availability of credits. While corporate investment declined significantly, the decline was greatest for firms with financial constraints such as low cash reserves or high net short-term debt (Duchin et al. 2010).

Inventories are often seen as an important component of a firm's working capital that can be reduced for self-financing of the firm (Hofmann et al. 2011). Converting inventory into cash seems to be particularly important if no external financing is available. Carpenter et al. (1998) find evidence that firms' inventory investment decreases when they face cash flow constraints. Pesch and Hoberg (2015) analyze the inventory behavior of firms in financial distress. They outline that firms with lower liquidity reduce inventories to avoid bankruptcy. Udenio et al. (2014) observe this behavior for a chemical company that is affected by the economic crisis.

Based on these arguments, we posit a relationship between a firm's liquidity and the inventory surplus in the crisis period in the following hypothesis:

HYPOTHESIS 2. *Liquidity is negatively associated with a firm's inventory management responsiveness in the crisis.*

Recent research has highlighted the financial consequences of temporary supply-demand mismatches: inventory shortages result in poor customer service and have negative implications for current and future sales (Hendricks and Singhal 2005) while excess inventories are costly and bear the risk of obsolescence (Hendricks and Singhal 2009). However, aggregate firm inventories are typically fluctuating throughout the year due to a number of factors (Steinker and Hoberg 2013). Some of these fluctuations can be traced back to seasonality or growth (e.g. anticipation inventory, demand patterns, or reporting periods) and can be considered as predictable inventory fluctuations. Other inventory fluctuations stem from positive or negative sales surprises, long production lead times, or poor supply chain setups and occur unpredictability. Thomas and Zhang (2002) document the negative abnormal returns for this abnormal inventory growth. Firm's with good inventory management policies and processes should be capable to compensate for these unpredictable fluctuations. Based on the findings by Singhal (2005), Eroglu and Hofer (2011), and Rumyantsev and Netessine (2007a) firms should manage inventory according to the relevant 'sweet spots' thus minimizing deviations from the optimal levels. Temporary, unpredictable deviations from these preferred levels (i.e., abnormal inventory growth and abnormal inventory decline) can be taken as an indicator for a firm's limited inventory management capabilities in normal economic conditions. As a result, we expected that firms that are not able to manage inventories before the crisis are particularly affected in the crisis. To measure a firm's inventory predictability we calculate the residuals of the best available forecast in the pre-crisis period. Accordingly, we expect a positive relationship between inventory predictability and a firm's inventory management performance in the crisis as we posit in the following hypothesis:

HYPOTHESIS 3. *Higher inventory predictability before the crisis is positively associated with a firm's inventory responsiveness in the crisis.*

Firm size has often been positively associated with inventory performance. Rumyantsev and Netessine (2007a) and Gaur and Kesavan (2007) have empirically confirmed the existence of economies of scale in inventory management and provide evidence of lower inventory levels of larger firms. While economies of scale and pooling of inventories are natural benefits of larger firms, these firms also have potentially superior inventory management practices. Larger firms firms generally have more financial resources to fund expensive investments in inventory and logistic systems, information technology, and flexible production and warehousing systems (Gaur et al. 2005). These investments will enable a tighter control. Larger firms are also more likely to benefit from formal processes such as lean management implementations that enable reductions in relative levels and more responsive inventory management (Demeter and Matyusz 2011, Lieberman et al. 1999).

However, we also see multiple mitigating factors for the firm size effect in crisis situations. First, larger firms generally have more financial resources and depend to a lesser extent on freeing up cash from inventories in a crisis situation. Second, larger firms can take advantage of lower raw material prices and build up anticipation stocks to reduce unit costs and against price increases. Third, larger firms are often required to takeover inventories from suppliers and customers with limited financial resources to provide support for their supply chain partners in a crisis. Considering all mitigating factors, we still follow the general line of the literature and expect a positive relationship between firm size and inventory management's responsiveness in the crisis we posit in the following hypothesis:

HYPOTHESIS 4. *Firm size is positively associated with a firm's inventory management responsiveness in the crisis.*

3.2. Financial Performance

Inventory management is widely considered to have a significant impact on firm and supply chain performance (Shapiro and Wagner 2009, Capkun et al. 2009). According to classic inventory theory, firms should manage inventories in line with demand to avoid costly supply mismatches. Rumyantsev and Netessine (2007a) emphasize that stock-outs typically lead to explicit (e.g. express shipments, overtime work, compensations for customers) or implicit costs (e.g. lost of goodwill, loss of future business). On the other hand, overstocks also trigger explicit (e.g. cost of capital, physical holding cost, obsolescence) or implicit costs (e.g. markdowns, price protection). Thus, all deviations from the optimal inventory levels are penalized and should be reflected in the financial performance of a company. Empirical operations literature provides wide evidence for this line of argumentation. Chen et al. (2005) find that abnormaly low or high inventories have a significant performance impact for manufacturing firms, while Kesavan and Mani (2013) highlight the consequences of abnormal inventory growth (i.e., the deviation of actual inventory growth from expected inventory growth) for retailers. Eroglu and Hofer (2011) find that a 'relative-inventory sweet spot' exists and that it is based on the specific industry a company is operating in.

The empirical operations management literature commonly applies different dimensions for measuring the financial performance of a firm. We broadly distinguish three performance categories: profitability, financial health, and market performance. Profitability relates to the income generated based on the revenues and expenses in a period. Common profitability metrics such as return-on-sales or return-on-assets are widely applied in operations literature (e.g. Kovach et al. (2015)). They provide a direct perspective on the firm's current financial performance. Financial health relates to a firm's ability to meet its financial obligations based on its assets and liabilities. The financial health is typically measured based on multiple dimensions to provide a holistic perspective. Current operations literature frequently applies financial health when analyzing inventory impacts (e.g. Swamidass (2007), Pesch and Hoberg (2015)). Market performance, expressed by share prices and market capitalization, relates to investor's expectations on a firm's future trajectory based on available public and private information. Market performance have been found to be affected by firms that signal inventory efficiency (Chen et al. 2005, Kesavan and Mani 2013).

Based on the previous discussion, we develop two hypotheses that link inventory dynamics with the financial performance. To analyze the financial performance we consider all three performance dimensions (profitability, financial health, and market performance). We expect any inventory surplus in the crisis to negatively affect the financial performance of a firm in the crisis. Any inventory increases from the preferred level will trigger explicit and implicit overage costs that should be reflected in the financial performance. Due to the focus on credit availability and liquidity during the crisis, we expect this effect to be particularly severe during this period. Likewise, we expect any inventory deficit in the crisis period to negatively affect the financial performance due to shortage costs. Shortages became apparent in several industries following the partial recovery of demand. Thus, we expect the effect of inventory deficit on financial performance to be significant in the medium to long term. Note that in generating these hypotheses we assume a pre-crisis inventory that represents the firm's preferred inventory level without slack inventory. The preferred inventory is based on the firm's strategic supply chain setup (e.g. production footprint, distribution network, IT system). The supply chain setup has has been established with mid- to long-term investments and can typically not be altered rapidly after the start of the crisis. Thus, any inventory deficit should also impact the financial performance. All in all, we hypothesize that:

HYPOTHESIS 5. *Inventory surplus in the crisis period is negatively associated with the financial performance (expressed by profitability, financial health and market performance).*

HYPOTHESIS 6. *Inventory deficit in the crisis period is negatively associated with the financial performance (expressed by profitability, financial health and market performance).*

4. Methodology

4.1. Normalizing and Forecasting Sales and Inventories

While the timing and magnitude of financial effects will, most likely, differ over different firms and industries, it's essential to define a common 'crisis timeline' for the analysis to yield reasonable results. Accordingly, we distinguish between a pre-crisis period (Q3/2005 to Q2/2008) and a crisis period (Q3/2008 to Q2/2011). The pre-crisis period enables us to use the 'normal' firm behavior (before the outbreak of the crisis) as a control. We select Q2/2008 as a cutoff date for the pre-crisis periods, as Q3/2008 relates to the first quarter with a reduction in aggregate sales. In addition, the collapse of Lehmann Brothers on September 15, 2008–widely seen as the trigger for the financial crisis–falls into this quarter. The twelve pre-crisis quarters ensure a sufficiently long inintial time series that does not skew the actual pre-crisis firm performance based on earlier trends. Throughout the paper we use the subscript p to denote the time period of a variable or observation. We adopt the convention that a negative p refers to a pre-crisis period and positive periods p refer to in-crisis periods. $p = -1$ is the last pre-crisis period, and $p = 1$ the subsequent period, defined as the start of the crisis. (We omit the use of $p = 0$ due to its ambiguity.) A key performance measure we apply in this study is the relative firm inventory, also referred to as inventory days. We define the inventory days in period p (ID_p) as the ending inventory in the period (INV_p) normalized by the cost of goods sold during said period ($COGS_p$) and scaled by the average number of days per period. In the case of quarterly observations this results in:

$$ID_p = 365/4 * INV_p/COGS_p \tag{1}$$

The inventory day metric is a common measure in operations management and is often referred to as a key performance indicator for inventory and supply chain planners, as inventory levels need to reflect sales. Some fluctuations in absolute firm-level inventories are driven by valuation changes due to variation in commodity prices (e.g. steel, oil) in the Financial Crisis. However, by normalizing inventory with COGS into inventory days most of these valuation changes should be accounted for.

While the relative inventory in days of supply provides the basis for analyzing inventory dynamics in a single-firm setting, comparing the performance of multiple companies in the crisis requires an additional normalization to account for differences in relative inventories. Therefore, we introduce the ID_p^N (normalized inventory days) metric that standardizes firm inventory days in the crisis based on the pre-crisis inventory levels. It is calculated as follows:

$$ID_p^N = INV_p/INV_{p=-1} \tag{2}$$

Based on the ID_p^N metric we can now compare the reaction of firms with different relative inventories. Likewise, we define $SALE_p^N$ as the normalized sales metric used to compare sales developments across firms.

Firm inventories and sales are dynamic figures that often follow a natural trend and seasonality. Over time, sales tend to increase due to new product launches or new market introduction whereas relative inventories tend to decrease due to better inventory management policies or lean management initiatives. Further, sales often peak in the fourth financial quarter due to sales incentives and inventories are reduced for stock keeping and cash flow optimization. To quantify the effect of the credit crisis on sales and inventories, we need to control for these natural dynamics. Thus, we use the pre-crisis period to estimate a forecasting model for inventories and sales for each firm and use an out of sample forecast to project what 'normal' sales and inventory dynamics would have been in the absence of a crisis. (See the Appendix for an overview of the methodology and results of the estimation procedure.) Using this methodology, we estimate the projected inventory days for each crisis period ($\widehat{ID}_p$), as well as the projected normalized inventory days ($\widehat{ID}_p^N$), projected sales($\widehat{SALE}_p$), and projected normalized sales ($\widehat{SALE}_p^N$). These projections serve as the basis for the dynamic performance metrics through the computation of the projection error (Δ), defined as the difference between observed and projected data (e.g., $\Delta ID_p = \widehat{ID_p} - ID_p$).

4.2. Variables

4.2.1. Dynamic Performance Metrics Based on the inventory and sales projections, we obtain absolute and relative error terms for a firm's crisis performance in each quarter that account for the 'normal' dynamics. We now aggregate these error terms into a performance metric to quantify the firm's inventory management responsiveness. Hoberg et al. (2007) provide an overview on metrics from systems engineering that are applicable to compare the responsiveness of inventory systems. Typically, a Heaviside step change in the input is applied to test the responsiveness. Similar to the proposed ITAE metric, we introduce the integral positive error (IPE) metric which penalizes positive deviations from the target state. In contrast to the ITAE metric that penalizes long-lasting deviations from a target state, however, the IPE penalizes only positive deviations from the target state, and weighs all positive deviations equally. The IPE metric for normalized inventory, measuring the cumulative inventory day surplus up to period P, is defined as follows

$$\left|ID^N\right|_+^P = \sum_{p=1}^{P} \max\left(0, ID_p^N - \widehat{ID}_p^N\right). \tag{3}$$

Likewise, we use the integral negative error (INE) to define a sales deficit metric $\left|SALE^N\right|_-^P$,

$$\left|SALE^N\right|_-^P = \sum_{p=1}^{P} \max\left(0, \widehat{SALE}_p^N - SALE_p^N\right). \tag{4}$$

For completeness, we also define the complementary measures of sales surplus $\left|SALE^N\right|_+^P$ and inventory deficit $\left|ID^N\right|_-^P$. These metrics capture the cumulative dynamic performance of a firm.

IPE measures inventory (and sales) surplus cumulatively from the onset of the crisis up to time P while INE measures cumulative inventory (and sales) deficits. Figure 4 shows a stylized sketch of the intuition behind these metrics. Setting $P = \{4, 8, 12\}$ we quantify the short-, medium-, and long-term inventory of a given firm during the crisis. For example, we distinguish firms with an initial inventory surge (high $\left|ID^N\right|_+^4$), as well as track the developments through time, such as how fast inventories stabilize at normal levels, or whether they continue changing (whether $\left|ID^N\right|_+^P$ and $\left|ID^N\right|_-^P$ stabilize after 8 or 12 periods).

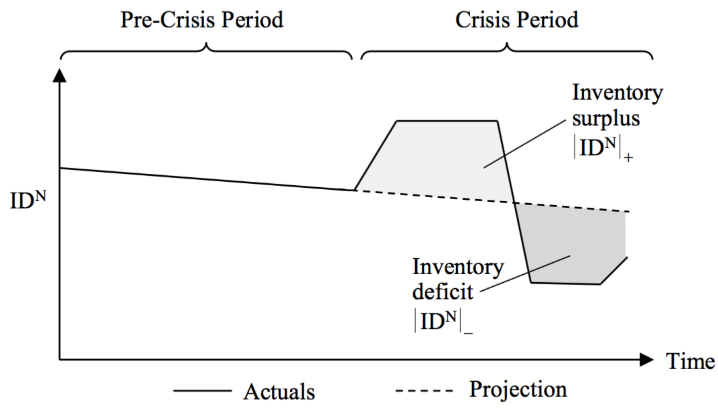


Figure 4 **Dynamic metrics.**

4.2.2. Dynamic Financial Metrics We follow a similar approach to measure the financial and market performance of firms. We introduce three metrics used to measure different aspects of a firm's health, and we aggregate them at different points in time to characterize the short-, medium-, and long-term performances.

Profitability We measure the profitability with the Return On Sales metric (ROS). This metric measures the operating profit margin by quantifying profit to sales ratio (Kovach et al. 2015). A higher ROS indicates that the firm generates more overall profit per each monetary unit sold. Formally, ROS is calculated for each firm and time period p through:

$$ROS_p = \frac{Net\ Income_p}{(Sales_p + Sales_{p-1})/2}. \tag{5}$$

We calculate the mean ROS during the 12 quarters before the crisis to establish a baseline of profitability per company:

$$ROS_{pre} = \frac{1}{12} \sum_{p=-12}^{-1} ROS_p, \tag{6}$$

and the mean for P periods after the start of the crisis to establish snapshots of the dynamic profitability of each firm:

$$ROS_{crisis}^{P} = \frac{1}{P} \sum_{p=1}^{P} ROS_p. \tag{7}$$

As we do in §4.2.1, we use $P = \{4, 8, 12\}$ for short-, medium-, and long-term performances respectively.

Financial health We use Altman's Z score as a proxy for the financial performance of a firm. This metric was developed in 1968 by Professor Edward Altman, as way to quantify a firm's probability of bankruptcy—the lower the score, the higher the bankruptcy probability (Altman 1968). We adopt Randall et al.'s (2006) formula for its calculation:

$$\begin{aligned} Altman\ Z_p = & 6.56(working\ capital_p / total\ assets_p)+ \\ & + 3.26(retained\ earnings_p / total\ assets_p)+ \\ & + 6.72(earnings\ before\ income\ taxes_p / total\ assets_p)+ \\ & + 1.05(mkt\ value\ of\ equity_p / book\ value\ of\ debt_p). \end{aligned} \tag{8}$$

As we did for operational efficiency, we calculate the pre-crisis mean as a baseline for each firm and period:

$$AZ_{pre} = \frac{1}{12} \sum_{p=-12}^{-1} Altman\ Z_p, \tag{9}$$

and the mean for P periods to establish snapshots of the bankruptcy risk through time:

$$AZ^P_{crisis} = \frac{1}{p} \sum_{p=1}^{P} Altman\ Z_p. \tag{10}$$

Market performance Finally, we introduce Tobin's Q ratio as a measure of the market performance and expectations of a firm. Introduced by Brainard and Tobin (1968), the Q ratio is used to quantify a firm's performance through the expectations of the market; it measures a firm's 'intangible assets' by calculating the ratio of the total market value of a firm to its total assets.

$$Tobin's\ Q_p = \frac{Market\ \ Value_p + Preferred\ \ Stock_p + Debt_p}{Total\ \ Assets_p}. \tag{11}$$

A high Q ratio indicates a firm that is valued by the market at a higher price than it's indicated purely by value of its assets. Conversely, a low Q ratio indicates a firm that is valued lower than the sum of its assets, which indicates a negative sentiment from the markets. Similarly to the other performance measures, we calculate a baseline:

$$TQ_{pre} = \frac{1}{12} \sum_{p=-12}^{-1} Tobin's\ Q_p, \tag{12}$$

and aggregate snapshots at arbitrary points P:

$$TQ^P_{crisis} = \frac{1}{P} \sum_{p=1}^{P} Tobin's\ Q_p. \tag{13}$$

4.2.3. Other Variables In addition to variables associated with the dynamic performance and the financial performance we apply a number of explanatory variables to test the different hypothesis. In line with Rumyantsev and Netessine (2007b) we calculate the gross margin of firm i as the percentage difference between net sales and the cost of goods sold $(Sales_i - COGS_i)/Sales_i$. The crisis likely affects a firm's gross margin, e.g. due to more competition with higher discounts. The pre-crisis inventory predictability is the second important independent variable. We calculate the pre-crisis inventory predictability as the sum of forecast errors of the best inventory projection in the pre-crisis period. (See Appendix for details on the projection methodology.) As a proxy for the liquidity we use the current ratio which is a widely accepted financial metric to measure a firm's ability to meet creditor's short term demands. For firm i it is calculated as $(CurrentAssets_i/CurrentLiabilities_i$. For firm size, standard literature commonly applies either income statement or balance sheet items. We used total asset variable from the balance sheet since it summarizes all current and fixed assets. Finally, we use the pre-crisis inventory level measured in inventory days as a control. Table 1 provides a summary of all the variables used in this study.

Table 1 Description of variables.

Category	Variable	Variable type	Metric	References
Dynamic performance	Crisis inventory surplus	Dependent^a, independent^b	$\|ID^N\|_+$	Hoberg et al. (2007), Nise (2010), Dejonckheere et al. (2004)
	Crisis inventory deficit	Independent^b	$\|ID^N\|_-$	
	Crisis sales surplus	Independent^b	$\|SALE^N\|_+$	
	Crisis sales deficit	Control^a, independent^b	$\|SALE^N\|_-$	
Financial performance	Profitability	Dependent^b	ROS	Kovach et al. (2015)
	Financial health	Dependent^b	Altman's Z	Altman (1968)
	Market performance	Dependent^b	Tobin's Q	Lang et al. (1989)
Others	Gross margin	Independent^a	*GrossMargin*	Rumyantsev and Netessine (2007), Eroglu and Hofer (2011)
	Pre-crisis inventory predictability	Independent^a	*InvPredictability*	
	Liquidity	Independent^a	*CurrentRatio*	
	Inventory level	Independent^a	*ID*	
	Firm size	Independent^a	*TotalAssets*	

Note: (a) Analysis of inventory dynamics (b) Analysis of financial performance

4.3. Data and Descriptive Statistics

We use quarterly financial data for U.S. publicly listed firms from the manufacturing sector (NAICS 31-33). All data is obtained from Standard & Poor's Compustat North America database accessed via Wharton Research Data Services (WRDS). To study the inventory performance in the financial crisis we select firm data for six consecutive years from Q3/2005 to Q2/2011. We clean the raw data in several ways. We require firms to be reported for the entire period to rule out any survivor bias. Firm observations with negative values for total assets, cost of goods sold, inventory, and any remaining duplicates are excluded from our analysis. Additionally, we exclude firms with less than one million US$ in reported sales to avoid any distortions by small firms. To avoid distortion in

Table 2 **Descriptive statistics (Values in mn US$)**

	Mean	Median	Std. Dev.
Sales	1068.20	111.72	3127.86
COGS	902.11	65.69	4380.48
Inventory	537.59	60.74	1902.68
Total Assets	5584.12	454.47	21711.01
Tobins q	1.51	1.08	1.88
Altman's Z	3.08	2.33	9.67
ROS	0.04	0.07	0.26
Firms	1278		
Firm-quarters	33228		

computations of seasonality or double coverage of performance figures, we remove companies that change their fiscal end month during the observation time frame, thereby assuring that the quarterly data for all companies is always exactly three months apart. Most firms report results in December, March, June, and September. Some companies, however, issue their reports one (106 firms) or two (74 firms) months later. For the sake of simplicity, we merge the quarterly reports of every three months to periods, assuming that the few later reports have been issued simultaneously with the majority. In line with standard financial economics literature we winzorize relative metrics at the 1% level to control for outliers and erroneous data (Gompers et al. 2005).

Table 2 summarizes the resulting dataset. Note that the income statement items sales and cost-of-goods-sold relate to quarterly values whereas the balance sheet items inventory and total assets relate to the actual values on the report date. Average values are typically above median values, highlighting the positive skewness of the data for most variables. Our final sample contains 1,278 manufacturing firms with 33,228 firm-quarter observations.

Table 3 shows the evolution of inventory days and normalized inventory days split among raw material, work in process, and finished goods components. It also shows the average values of the pre-crisis and short-, medium- and long-term crisis periods. In all cases the differences between pre- and post-crisis averages are significant at the $p = 0.05$ level (Two-sample Wilcoxon Mann-Whitney rank-sum test). Raw material and Finished Goods component inventories increased significantly with the start of the crisis and it took manufacturers close to 6 quarters to go back to pre-crisis levels. WIP inventories, on the other hand, were managed responsively—manufacturing firms pulled operational levers to keep WIP inventories under control. This helped mitigate the effect of the increase in raw material and finished goods components, which required a longer time to be reverted. At this level, we see no evidence of widespread inventory take-overs of suppliers, which would skew the sample further in the direction of finished goods rather than raw material inventories.

Table 3 Development of inventory components in manufacturing firms 2005-2011

			Raw Material			WIP			Finished Goods			Total		
Year	**Quarter**	**Period**	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**
2005	3	-12	36.7	27.7	33.7	23.7	14.3	28.8	44.8	33.4	40.2	105.2	86.1	69.1
	4	-11	34.9	25.3	32.0	22.3	13.0	27.8	42.7	33.2	37.2	99.4	83.7	64.8
2006	1	-10	36.2	28.3	31.5	23.8	14.6	28.8	45.2	34.2	40.2	104.9	89.1	66.0
	2	-9	35.6	28.6	30.1	23.3	13.6	27.6	46.1	34.0	42.1	104.6	87.2	66.3
	3	-8	36.4	28.8	31.0	23.5	14.0	27.6	46.7	35.0	41.5	106.1	89.0	66.9
	4	-7	36.2	27.9	31.8	22.8	12.7	28.5	44.5	34.3	39.0	103.3	86.1	66.2
2007	1	-6	37.6	29.5	33.0	23.8	14.0	28.6	47.4	36.1	40.8	108.6	92.6	67.6
	2	-5	37.1	28.6	32.6	23.8	13.3	29.1	47.5	35.3	43.0	108.0	89.3	69.4
	3	-4	36.7	28.4	31.8	23.5	14.0	28.6	47.0	33.4	42.1	107.0	87.6	68.6
	4	-3	36.0	27.5	31.5	22.5	12.4	28.2	45.2	34.0	40.1	102.8	87.1	65.9
2008	1	-2	38.1	29.4	32.4	24.3	14.0	30.1	49.6	37.7	43.4	111.7	92.9	71.0
	2	-1	38.1	28.7	34.4	23.3	13.5	28.3	48.0	35.8	42.3	109.3	90.7	69.7
	3	1	38.5	28.8	34.2	23.9	13.8	29.5	48.5	37.1	42.5	110.8	91.4	71.7
	4	2	40.3	29.5	36.0	23.8	13.5	29.6	51.8	39.4	44.4	115.0	95.7	72.5
2009	1	3	44.6	33.7	38.7	26.2	14.7	32.5	57.3	44.6	48.8	127.5	105.5	79.7
	2	4	41.9	31.7	36.9	24.9	13.7	31.1	53.3	40.2	46.6	119.3	96.0	77.4
	3	5	38.9	28.9	34.2	23.4	13.2	28.8	49.6	36.4	43.2	111.7	91.6	72.4
	4	6	36.8	28.3	32.1	22.9	11.7	29.1	45.6	34.4	39.8	104.9	85.0	68.8
2010	1	7	37.3	30.2	30.9	24.0	13.3	29.4	47.2	35.3	40.3	108.4	91.9	67.8
	2	8	35.9	28.5	30.3	22.4	12.7	28.0	45.6	34.1	40.6	103.7	87.3	65.8
	3	9	36.4	29.5	29.7	23.0	12.7	28.7	46.6	35.3	41.1	106.2	90.2	66.0
	4	10	35.9	29.0	29.6	22.2	11.5	28.8	45.0	35.3	38.6	102.8	90.3	63.7
2011	1	11	38.3	31.4	30.4	23.8	13.0	30.2	48.6	37.6	41.2	110.6	98.6	66.6
	2	12	38.0	30.4	31.2	23.5	12.4	30.2	47.9	37.1	41.3	109.5	93.9	66.9
Pre-Crisis ($-12 \leq p \leq -1$)			36.6	28.2	32.2	23.4	13.6	28.5	46.2	34.7	41.0	105.9	88.5	67.6
Crisis short-term ($1 \leq p \leq 4$)			41.3	30.9	36.5	24.7	13.9	30.7	52.7	40.3	45.6	118.1	97.1	75.3
Crisis med-term ($1 \leq p \leq 8$)			39.3	30.0	34.2	23.9	13.3	29.8	49.9	37.7	43.3	112.7	93.0	72.0
Crisis long-term ($1 \leq p \leq 12$)			38.6	30.0	32.9	23.7	13.0	29.7	48.9	37.2	42.4	110.9	93.1	69.9
ΔCrisis med-term/Pre-Crisis			7.2%	6.2%	6.3%	2.4%	-2.3%	4.5%	7.9%	8.6%	5.6%	6.4%	5.2%	6.5%

Note. Only for manufacturing firms with inventory breakdown available for all quarters (734 firms, 20552 firm-quarters).

At the aggregate level, we see no evidence of synchronized reductions in inventory days. If we look at the dynamic performance metrics, however, a richer picture comes into view. Table 4 summarizes the dynamic performance metrics by subsector. Table 4(a) shows the inventory dynamics and Table 4(b), the sales dynamics. There is significant heterogeneity in the response of the different subsectors. Some subsectors (e.g., *Food, Beverage, & Tobacco*) are more responsive than others (e.g., *Machinery*). Interestingly, the subsectors with higher than average sales decrease ($\left|SALE^N\right|_-$) also exhibit a higher than average inventory peak ($\left|ID^N\right|_+$), and lower than average inventory recovery ($\left|ID^N\right|_-$). This implies that the magnitude of the demand collapse limits the responsiveness of a firm. A possible explanation for this effect is related to the evolution of the different inventory components. As we have seen, WIP inventories are the most responsive, thus, as demand keeps falling, firms are unable to responsively adapt their raw material and finished goods inventories. Note, however, that there is also significant heterogeneity among firms of a particular subsector. This is indicated by the simultaneous positive indicators of inventory surplus and deficit, and signals that firms indeed responded in different ways (as illustrated in §1).

Heterogeneity is also present in the financial performance. Table 5 summarizes the financial metrics per subsector. On the one hand, the pre-crisis financial metrics appear to be good indicators of relative performance during the crisis (i.e., sectors like *Chemicals & Plastics*, which generally had above average pre-crisis indicators also had above average crisis indicators). On the other hand, the dynamic performance varied greatly among the sectors. Some (e.g., *Food, Beverage, & Tobacco*) went through the crisis with relative stability, while others (e..g, *Computer, Electronics, & Equipment*) suffered higher volatility.

Table 6 shows the correlation among all the variables in our sample dataset. As can be expected, pre- and post-crisis metrics exhibit a relatively high degree of correlation in certain cases. Other variables are log-transformed in the regressions, which helps mitigate any other correlation effects.

Table 4 Descriptive statistics of dynamic performance.

Industry	Firms	$\lvert ID^N\rvert_+^4$ Mean (Med., SD)	$\lvert ID^N\rvert_+^8$ Mean (Med., SD)	$\lvert ID^N\rvert_+^{12}$ Mean (Med., SD)	$\lvert ID^N\rvert_-^4$ Mean (Med., SD)	$\lvert ID^N\rvert_-^8$ Mean (Med., SD)	$\lvert ID^N\rvert_-^{12}$ Mean (Med., SD)
Food, Beverage, & Tobacco	89	0.39 (0.09, 0.72)	0.75 (0.22, 1.57)	1.32 (0.42, 3.34)	0.50 (0.20, 1.42)	1.23 (0.54, 2.88)	2.05 (1.09, 4.39)
Textiles, Apparel, & Leather	49	0.31 (0.19, 0.42)	0.53 (0.27, 0.74)	1.04 (0.51, 1.23)	0.31 (0.12, 0.54)	0.88 (0.50, 1.38)	1.34 (0.67, 2.33)
Paper & Publishing	46	0.58 (0.35, 0.64)	1.09 (0.65, 1.36)	1.91 (0.92, 2.43)	0.14 (0.04, 0.21)	0.40 (0.14, 0.44)	0.68 (0.15, 0.77)
Chemicals & Plastics	202	0.84 (0.37, 1.70)	1.88 (0.60, 4.13)	3.47 (0.83, 10.79)	0.33 (0.14, 0.56)	0.92 (0.49, 1.47)	1.66 (0.74, 2.66)
Metal	91	1.00 (0.58, 1.26)	1.82 (0.99, 2.66)	2.71 (1.08, 4.58)	0.21 (0.10, 0.29)	0.61 (0.40, 0.71)	1.12 (0.68, 1.33)
Machinery	124	0.87 (0.63, 0.87)	1.48 (1.07, 1.46)	2.08 (1.25, 2.24)	0.24 (0.05, 0.43)	0.67 (0.22, 1.00)	1.29 (0.53, 1.76)
Computer, Electr., & Equip.	442	0.96 (0.51, 1.42)	1.85 (0.92, 3.12)	3.06 (1.30, 5.78)	0.32 (0.08, 0.65)	0.92 (0.36, 1.57)	1.63 (0.54, 2.76)
Transportation Equipment	81	1.04 (0.68, 1.21)	1.72 (1.09, 1.96)	2.54 (1.53, 3.00)	0.14 (0.00, 0.29)	0.52 (0.12, 0.89)	1.03 (0.27, 1.64)
Other	154	0.72 (0.43, 0.87)	1.36 (0.73, 1.91)	2.18 (1.08, 3.35)	0.39 (0.13, 0.77)	1.02 (0.39, 1.80)	1.82 (0.65, 3.11)
Total	1278	0.83 (0.43, 1.28)	1.60 (0.70, 2.81)	2.63 (1.06, 5.98)	0.31 (0.10, 0.68)	0.86 (0.38, 1.57)	1.54 (0.64, 2.68)

(a) Dynamic inventory performance

Industry	Firms	$\lvert SALE^N\rvert_+^4$ Mean (Med., SD)	$\lvert SALE^N\rvert_+^8$ Mean (Med., SD)	$\lvert SALE^N\rvert_+^{12}$ Mean (Med., SD)	$\lvert SALE^N\rvert_-^4$ Mean (Med., SD)	$\lvert SALE^N\rvert_-^8$ Mean (Med., SD)	$\lvert SALE^N\rvert_-^{12}$ Mean (Med., SD)
Food, Beverage, & Tobacco	89	0.43 (0.12, 1.05)	0.98 (0.22, 2.39)	1.87 (0.46 , 4.48)	0.33 (0.16, 0.46)	0.77 (0.49, 0.98)	1.22 (0.62, 1.64)
Textiles, Apparel, & Leather	49	0.20 (0.01, 0.45)	0.59 (0.04, 1.17)	1.16 (0.15, 2.21)	0.45 (0.42, 0.39)	1.04 (0.94, 0.91)	1.56 (1.19, 1.48)
Paper & Publishing	46	0.21 (0.02, 0.48)	0.49 (0.02, 1.21)	1.05 (0.06, 2.47)	0.57 (0.49, 0.47)	1.20 (1.03, 0.98)	1.79 (1.58, 1.51)
Chemicals & Plastics	202	0.34 (0.06, 0.61)	0.78 (0.13, 1.44)	1.48 (0.28, 2.67)	0.53 (0.36, 0.62)	1.14 (0.88, 1.34)	1.74 (1.17, 2.13)
Metal	91	0.15 (0 .00, 0.28)	0.26 (0.02, 0.68)	0.55 (0.05, 1.39)	0.96 (0.91, 0.6)	2.23 (2.03, 1.30)	3.25 (3.26 , 2.09)
Machinery	124	0.27 (0.02, 0.82)	0.66 (0.04, 2.01)	1.41 (0.12, 3.79)	1.01 (0.76, 1.15)	2.22 (1.89, 1.98)	3.09 (2.52 , 2.79)
Computer, Electr., & Equip.	442	0.24 (0.03, 0.51)	0.60 (0.1, 1.17)	1.29 (0.26, 2.42)	0.81 (0.59 , 0.88)	1.72 (1.21, 1.86)	2.57 (1.71, 2.98)
Transportation Equipment	81	0.09 (0 .00, 0.3)	0.25 (0 .00, 0.65)	0.67 (0.04, 1.47)	0.80 (0.74, 0.65)	1.63 (1.74, 1.18)	2.22 (2.09, 1.66)
Other	154	0.16 (0.01, 0.33)	0.40 (0.02, 0.98)	0.83 (0.05, 2.08)	0.65 (0.53, 0.71)	1.45 (1.04 , 1.52)	2.23 (1.62, 2.33)
Total	1278	0.24 (0.02, 0.58)	0.58 (0.06, 1.38)	1.21 (0.16, 2.69)	0.72 (0.54, 0.80)	1.56 (1.18, 1.63)	2.31 (1.71, 2.52)

(b) Dynamic sales performance

4.4. Model Specification

4.4.1. Inventory Dynamics In line with previous research (Gaur et al. 2005, Rumyantsev and Netessine 2007a) we apply a multiplicative regression model to test the proposed inventory dynamics hypotheses (H1-H4). We propose the following specification to model the integral positive error of normalized inventory days for firm i, $\lvert ID^N\rvert_+^P$:

$$log(\lvert ID_i^N\rvert_+^P) = log(GrossMargin_{pre,i}) + log(CurrentRatio_{pre,i}) + log(InvPredictability_i) +$$

Table 5 Descriptive statistics of financial performance

Industry	TQ_{pre} Mean (Med., SD)	TQ^{4}_{crisis} Mean (Med., SD)	TQ^{8}_{crisis} Mean (Med., SD)	TQ^{12}_{crisis} Mean (Med., SD)	ROS_{pre} Mean (Med., SD)	ROS^{4}_{crisis} Mean (Med., SD)
Food, Beverage, & Tobacco	1.645 (1.278, 1.332)	1.231 (0.949, 0.765)	1.306 (1.089, 0.802)	1.370 (1.132, 0.827)	0.084 (0.080, 0.092)	0.073 (0.072, 0.112)
Textiles, Apparel, & Leather	1.338 (1.113, 1.050)	0.696 (0.556, 0.494)	0.805 (0.679, 0.537)	0.877 (0.800, 0.559)	0.076 (0.084, 0.074)	0.039 (0.056, 0.091)
Paper & Publishing	1.012 (0.890, 0.521)	0.732 (0.676, 0.390)	0.779 (0.744, 0.394)	0.809 (0.775, 0.403)	0.079 (0.080, 0.058)	0.055 (0.051, 0.076)
Chemicals & Plastics	2.041 (1.388, 2.084)	1.341(0.890, 1.410)	1.419 (0.970, 1.504)	1.515 (1.058, 1.504)	-0.047 (0.075, 0.483)	0.007 (0.065, 0.392)
Metal	1.390 (1.110, 1.303)	0.811 (0.686, 0.674)	0.870 (0.671, 0.748)	0.946 (0.791, 0.898)	0.101 (0.096, 0.095)	0.035 (0.041, 0.133)
Machinery	1.470 (1.201, 1.267)	0.852 (0.736, 0.761)	0.978 (0.827, 0.829)	1.083 (0.932, 0.857)	0.056 (0.090, 0.255)	-0.020 (0.054, 0.309)
Computer, Electr., & Equip.	1.759 (1.205, 1.925)	0.972 (0.663, 1.325)	1.135 (0.772, 1.643)	1.238 (0.862, 1.838)	-0.026 (0.052, 0.346)	-0.072 (0.014, 0.403)
Transportation Equipment	1.130 (0.853, 1.291)	0.724 (0.595, 0.952)	0.809 (0.660, 1.065)	0.907 (0.747, 1.215)	0.069 (0.076, 0.115)	0.012 (0.028, 0.187)
Other	1.630 (1.315, 1.192)	0.969 (0.79, 0.776)	1.057 (0.848, 0.905)	1.123 (0.890, 0.936)	0.050 (0.079, 0.165)	0.015 (0.047, 0.175)
Total	1.643 (1.184, 1.664)	0.990 (0.730, 1.111)	1.102 (0.824, 1.291)	1.191 (0.890, 1.399)	0.018 (0.076, 0.305)	-0.012 (0.041, 0.317)

Industry	ROS^{8}_{crisis} Mean (Med., SD)	ROS^{12}_{crisis} Mean (Med., SD)	AZ_{pre} Mean (Med., SD)	AZ^{4}_{crisis} Mean (Med., SD)	AZ^{8}_{crisis} Mean (Med., SD)	AZ^{12}_{crisis} Mean (Med., SD)
Food, Beverage, & Tobacco	0.077 (0.075, 0.114)	0.078 (0.082, 0.116)	2.145 (1.459, 2.513)	2.134 (1.472, 2.303)	2.332 (1.586, 2.606)	2.366 (1.649, 2.799)
Textiles, Apparel, & Leather	0.053 (0.062, 0.089)	0.052 (0.056, 0.088)	2.922 (1.951, 3.392)	2.568 (1.697, 2.763)	2.972 (2.266, 3.120)	3.127 (2.370, 3.351)
Paper & Publishing	0.064 (0.057, 0.065)	0.072 (0.064, 0.058)	1.028 (0.752, 1.010)	0.973 (0.857, 0.963)	1.050 (0.907, 1.030)	1.109 (0.941, 1.072)
Chemicals & Plastics	0.015 (0.075, 0.389)	0.020 (0.080, 0.385)	3.398 (1.382, 9.017)	2.037 (1.339, 4.846)	2.092 (1.621, 5.478)	2.140 (1.745, 6.472)
Metal	0.049 (0.045, 0.098)	0.060 (0.054, 0.084)	1.984 (1.459, 3.018)	2.019 (1.476, 3.182)	2.185 (1.541, 3.167)	2.404 (1.689, 3.372)
Machinery	0.022 (0.060, 0.210)	0.045 (0.075, 0.176)	2.240 (1.754, 3.847)	1.582 (1.629, 5.051)	1.873 (1.898, 5.010)	2.067 (2.194, 4.820)
Computer, Electr., & Equip.	-0.043 (0.027, 0.379)	-0.020 (0.033, 0.318)	2.964 (2.031, 7.088)	1.403 (1.588, 9.224)	1.516 (1.864, 10.453)	1.632 (2.097, 11.466)
Transportation Equipment	0.033 (0.038, 0.151)	0.043 (0.052, 0.134)	1.473 (1.142, 2.931)	1.152 (1.142, 4.242)	1.185 (1.221, 4.807)	1.255 (1.381, 5.237)
Other	0.025 (0.057, 0.171)	0.029 (0.053, 0.186)	2.091 (1.659, 3.481)	1.467 (1.416, 4.739)	1.580 (1.546, 5.100)	1.721 (1.634, 4.773)
Total	0.008 (0.049, 0.294)	0.021 (0.057, 0.264)	2.565 (1.648, 5.969)	1.636 (1.476, 6.404)	1.772 (1.632, 7.165)	1.886 (1.773, 7.799)

Table 6 Correlation table of sample composition

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	ROS_{pre}	1.00														
2	ROS^{12}_{crisis}	0.67	1.00													
3	TQ_{pre}	-0.35	-0.24	1.00												
4	TQ^{12}_{crisis}	-0.37	-0.38	0.68	1.00											
5	AZ_{pre}	0.07	0.08	0.35	-0.04	1.00										
6	AZ^{12}_{crisis}	0.46	0.46	-0.12	-0.40	0.52	1.00									
7	$\lvert SALE^N \rvert^4_+$	-0.20	-0.03	0.09	0.08	0.04	0.00	1.00								
8	$\lvert SALE^N \rvert^4_-$	0.01	-0.24	-0.10	-0.13	-0.03	-0.05	-0.30	1.00							
9	$\lvert ID^N \rvert^4_+$	-0.14	-0.13	0.05	0.05	-0.09	-0.07	-0.03	0.25	1.00						
10	$\lvert ID^N \rvert^4_-$	-0.18	-0.21	0.19	0.20	0.07	-0.19	0.36	-0.12	-0.21	1.00					
11	$GrossMargin$	0.21	0.39	0.18	0.11	0.12	0.07	0.00	-0.14	0.03	-0.07	1.00				
12	$CurrentRatio$	-0.03	-0.10	0.05	-0.05	0.41	0.29	0.00	0.09	0.02	0.03	0.11	1.00			
13	$InventoryDays$	0.00	-0.03	0.05	0.03	0.10	0.04	0.06	0.06	-0.10	0.05	0.38	0.24	1.00		
14	$TotalAssets$	0.10	0.09	-0.07	-0.05	-0.06	-0.02	-0.07	-0.05	0.00	-0.03	-0.03	-0.14	-0.10	1.00	
15	$InvPredictabililty$	-0.22	-0.21	0.17	0.18	0.03	-0.11	0.18	0.00	0.04	0.28	0.18	0.14	0.51	-0.08	1.00

All Correlations above |0.072| are significant at the 0.01 level

$$log(TotalAssets_{pre,i}) + log(ID_{pre,i}) + log(\lvert SALE^N_i \rvert^P_+) + IndustrySector_i + \epsilon_i, \quad (14)$$

where $i = 1, ..., 1278$ is a firm index, $P = \{4, 8, 12\}$, the aggregation period for the dynamic measures, and *pre* indicates the use of a pre-crisis value for the measure. We use the last period before the crisis in our analysis; the use of different pre-crisis periods, as well as a grand pre-crisis average does not increase the model fit nor change the direction or significance of the effects. Note that we include an industry sector indicator variable to control for any deviations corresponding to industry-wide factors. Likewise, we used the same model to estimate the integral positive error of absolute inventory days $|ID|_{+}^{P}$ and the results were consistent. To check the robustness of our results we performed alternative analysis with different model specifications. A linear model (without logged variables) performs similarly in terms of the direction of the effects. However, since the linear specification results in a worse goodness-of-fit we report exclusively the results of the multiplicative regression. We also tested interactions among several of the variables and using an industry indicator based on 3- and 6-digit NAICS codes. With this too, we see no improvement in the fit of the model nor change in the direction of the main effects.

4.4.2. Financial Performance We use three different models to estimate the impact of inventory and sales dynamics on the financial performance of the firms in the sample. Each model centers on one dimension of financial performance as quantified in Section 4.2.2: Profitability, Market Performance, and Financial Health. The econometric specification of the models is as follows:

$$FPM_{crisis,i}^{P} = FPM_{pre,i} + \left|SALE_i{}^N\right|_{+}^{4} + \left|ID_i{}^N\right|_{+}^{4} + \left|SALE_i{}^N\right|_{-}^{4} + \left|ID_i{}^N\right|_{-}^{4}) + IndustrySector_i + \epsilon_i, \qquad (15)$$

where FPM refers to one of the financial performance metrics ($FPM = \{ROS, TQ, AZ\}$), $i = 1, ..., 1278$ is a firm index, and $P = \{4, 8, 12\}$, the aggregation period.

For robustness, we repeated the analysis using additional periods in the independent variables. The results and model fit do not change significantly. Thus, we report the regressions with the performance metrics calculated during the first four periods. The use of a multiplicative regression model, using logged variables, for the entire sample is not possible due to a number of dependent variables that take negative values during the period. Partial estimation with the positive sub-sample reveals consistent results.

5. Results

5.1. Inventory Dynamics

Table 7 provides the results for the estimation of the dynamic inventory models specified by Equation (14). We used the *regress* command in Stata 13 to run the regression models. Note that we ran the model for normalized inventory and for the absolute inventory as independent variables. The results are consistent for both inventory metrics. In addition, we also varied the numbers of crisis periods from 4, 8 to 12. Across all regression models, we find support for hypothesis 1, 2 and 3 while we have to reject hypothesis 4. Note that signs in the table reflect the relationship to the inventory surplus metric which is a reverse measure for the inventory responsiveness as stated in the hypothesis. For hypothesis 1, the estimates indicate a negative association between firm's gross margins and a firm's inventory management responsiveness in the crisis, i.e., firms with higher gross margins show a higher crisis inventory surplus. The relationship is highly significant ($p < 0.005$) for all model specifications. This is line with our expectations in hypothesis 1 since firms with lower

Table 7 Inventory dynamics regression analysis

Coefficient	Normalized Inventory $log(\lvert ID^N\rvert_+^4)$	$log(\lvert ID^N\rvert_+^8)$	$log(\lvert ID^N\rvert_+^{12})$	Absolute Inventory $log(\lvert ID\rvert_+^4)$	$log(\lvert ID\rvert_+^8)$	$log(\lvert ID\rvert_+^{12})$
$LOG(GrossMargin)$	0.082***	0.128***	0.171***	0.256***	0.289***	0.338**
	(0.022)	(0.031)	(0.038)	(0.089)	(0.096)	(0.100)
$LOG(CurrentRatio)$	0.039	0.066*	0.085*	0.204*	0.291***	0.281***
	(0.020)	(0.028)	(0.034)	(0.081)	(0.088)	(0.091)
$LOG(InvPredictability)$	0.193***	0.303***	0.372***	0.486***	0.618***	0.734***
	(0.017)	(0.024)	(0.029)	(0.068)	(0.075)	(0.077)
$LOG(TotalAssets)$	0.004	0.006	0.010	0.032	0.040	0.044
	(0.006)	(0.008)	(0.010)	(0.023)	(0.025)	(0.025)
$LOG(ID)$	-0.326***	-0.522***	-0.683***	0.045	-0.168	-0.351***
	(0.024)	(0.034)	(0.042)	(0.098)	(0.107)	(0.111)
$LOG(\lvert SALE^N\rvert_-^4)$	0.407***			1.467***		
	(0.032)			(0.129)		
$LOG(\lvert SALE^N\rvert_-^8)$		0.270***			0.863***	
		(0.031)			(0.097)	
$LOG(\lvert SALE^N\rvert_-^{12})$			0.218***			0.654***
			(0.031)			(0.082)
Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	0.382***	0.656***	-1.657***	0.991***	-1.084*	-0.516
	(0.103)	(0.147)	(0.417)	(0.180)	(0.457)	0.475
R^2 (adj)	0.249	0.228	0.223	0.219	0.187	0.173
N	1,249	1,249	1,249	1,249	1,249	1,249

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.005$

gross margins are required to adjust inventories more rapidly to shrinking demand, e.g. to avoid costly write-offs and holding costs. For the liquidity measured by the current ratio, we find support for hypothesis 2 in five of the six regression models. Liquidity is negatively associated with a firm's inventory management responsiveness in the crisis, i.e., firms with a higher current ratio show a higher crisis inventory surplus. This seems to be particularly true in the mid to long term (p=8 and p=12) as firms with low liquidity more actively manage inventories to free up cash. Estimates for the inventory predictability are positively related to a firm's inventory management responsiveness in the crisis, i.e. firms with higher unexplained pre-crisis inventory variation have more inventory surplus in the crisis period. The relationship is highly significant ($p < 0.005$) in all six models. This is line with our expectations in hypothesis 3 and highlights that fluctuations in the pre-crisis inventory levels are an indicator for less focus on for inventory leanness in the crisis. Results for the firm size do not indicate a negative relationship to the crisis inventory surplus contrary to hypothesis 4. In fact, the coefficients in all models are not significant. Accordingly, we reject the hypothesis. As discussed before, other effects like large firms taking over inventory for small partners or large firms have easier access to external finance are possible explanations for the missing support for hypothesis 4. Note that the signs of the controls are as expected. A higher sales reduction in crisis periods increases the crisis inventory surplus as shrinking sales have a dual effect on a firm's efforts to align inventory: First, absolute inventories must be further reduced to keep relative inventories constant. Second, the reduced sales triggers a reduced outflow of products which makes it more difficult to reduce inventories. A second control of interest is the average pre-crisis inventory level. Results indicate a mixed but generally positive relationship between prior inventory levels and the crisis inventory responsiveness. The industry controls are partially significant. (E.g., *Metal* and *Machinery* industries show a lower inventory responsiveness.)

5.2. Financial Performance

Table 8 Financial performance regression analysis

Coefficient	Profitability			Market performance			Financial health		
	ROS^4_{crisis}	ROS^8_{crisis}	ROS^{12}_{crisis}	TQ^4_{crisis}	TQ^8_{crisis}	TQ^{12}_{crisis}	AZ^4_{crisis}	AZ^8_{crisis}	AZ^{12}_{crisis}
$\|SALE^N\|^4_+$	0.056***	0.048***	0.036***	0.075	0.016	-0.081	0.412	0.478	0.825*
	(0.012)	(0.011)	(0.010)	(0.043)	(0.052)	(0.055)	(0.266)	(0.307)	(0.347)
$\|ID^N\|^4_+$	-0.009	-0.004	-0.002	0.035	0.041	0.063*	-0.187	-0.295*	-0.401**
	(0.005)	(0.005)	(0.004)	(0.019)	(0.023)	(0.024)	(0.116)	(0.135)	(0.152)
$\|SALE^N\|^4_-$	-0.117***	-0.089***	-0.079***	-0.149***	-0.123***	-0.119***	-0.295	-0.332	-0.296
	(0.009)	(0.008)	(0.007)	(0.031)	(0.037)	(0.040)	(0.189)	(0.219)	(0.248)
$\|ID^N\|^4_-$	-0.093***	-0.069***	-0.060***	-0.133***	0.009	0.196***	-2.043***	-2.365***	-3.140***
	(0.011)	(0.010)	(0.009)	(0.038)	(0.045)	(0.048)	(0.228)	(0.263)	(0.298)
ROS_{pre}	0.604***	0.618***	0.572***						
	(0.022)	(0.020)	(0.018)						
TQ_{pre}				0.450***	0.513***	0.550***			
				(0.014)	(0.017)	(0.018)			
AlZ_{pre}							0.678***	0.716***	0.701***
							(0.023)	(0.027)	(0.030)
Industry controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	0.087***	0.070***	0.071***	0.561***	0.475***	0.550***	1.700***	2.004***	2.340***
	(0.025)	(0.023)	(0.020)	(0.091)	(0.108)	(0.018)	(0.543)	(0.628)	(0.711)
R^2 (adj)	0.488	0.509	0.526	0.483	0.462	0.471	0.421	0.382	0.331
N	1,278	1,278	1,278	1,278	1,278	1,278	1,278	1,278	1,278

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.005$

Table 8 shows the results for the estimation of the financial inventory models specified by Equation (15). Here, as well, we used the *regress* command in Stata 13. In terms of financial performance, the influence of inventory and sales dynamics is complex. In the short term ($P = 4$), we find support for hypothesis 6 ($p < 0.005$) and reject hypothesis 5 across all measures of financial performance. In the medium and long term ($P = 8, 12$), we find support for hypothesis 6 in the profitability and financial health dimensions ($p < 0.005$), reject it in the market performance dimension, and find support for hypothesis 5 in the financial health dimension ($p < 0.05$).

In our hypothesis development, we implicitly theorized that the financial impact of inventory dynamics would be consistent across the different financial metrics and across time aggregation periods. These results, however, show that inventory dynamics affect different financial metrics in subtly different ways. In particular, inventory surplus does not affect the financial performance in the short- to medium-terms. This is in contrast with research performed during stable conditions (e.g., Eroglu and Hofer 2011) that suggests that inventory has a symmetric effect, with performance decreasing at both sides of an optimum level. In the longer term, however, the financial health of the company is negatively affected by the initial inventory surplus. A possible explanation for this observation is that in the face of a financial shock such as the 2008 crisis, the relative influence of inventory surpluses decreased while other factors, such as credit availability became more important. In terms of market performance, there is anecdotal evidence that suggests that firms that applied considerable inventory reductions failed to deliver when demand started to recover (approximately after Q2 2009, see Figure 1) and therefore faced significant losses of market share. This can explain why the market rewarded, in the long term, those companies with surplus inventory. Those firms with inventory on-hand benefited from competitors' stock-outs.

Industry controls are non-significant for every specification of the profitability regression, and partially significant only in the short term for market performance and financial health (*Computer, Electronics, & Electrical Equipment* industries show lower than average performance). The other control, pre-crisis performance, is a highly significant predictor of crisis performance.

Finally, it's interesting to note that the relationship between sales and financial performance is also far from straightforward. The strong relationship between profitability and sales is as expected (i.e., sales deficits are associated with lower profitability and sales surplus with higher profitability). Sales dynamics, however, have essentially no effect on financial health, and an asymmetric effect on market performance. The market reacts negatively to worse-than-expected sales, but it does not react positively to better-than-expected sales.

In summary, our results show that, during a crisis, there is a significant difference in the way in which inventory dynamics affect various aspects of financial performance in different time scales. Profitability and financial health show largely consistent results, while market performance appears to be led by different criteria. Our results also differ from insights obtained from the analysis of non-crisis data. Most remarkable is the fact that the effect of inventory dynamics is not symmetric. Inventory deficits appear to have a stronger negative impact. This suggests that during stable times performance is sensitive to optimal inventory levels, but following the onset of a crisis other concerns take precedence such that instead of an 'inventory sweet spot' the concern is to have 'enough' inventory to avoid stock-outs.

6. Conclusions

In this paper we analyzed the way in which manufacturing firms used their inventories to respond to the shock of the 2008 financial crisis, the drivers associated with high inventory responsiveness, and the financial implications of said responsiveness.

Our results show that median inventory days during the first year of the crisis were 8% larger than the year before; firms required on average six quarters to align their inventories with the new demand realities. Manufacturers aligned their WIP materials essentially instantly, but required additional time to bring raw material and finished goods inventories in line with the demand.

In line with our hypothesis, we found that inventory responsiveness is associated with lower gross margins and lower liquidity. This implies that with the advent of the crisis, firms whose financial position is sensitive to their inventory investment undertook responsive actions. The data shows that higher pre-crisis inventory predictability is also associated with inventory responsiveness—thus, firms that exert a tight control in stable periods are also able to react responsively. Firm size, on the other hand does not have an effect on responsiveness. This suggests that economies of scale in inventory management are not effective in crisis situations.

With regards to the financial impact of the inventory responsiveness, we confirmed several past findings based upon stable conditions, but also found several key differences. Most notably, our results suggest that the symmetric effect of deviating from the inventory 'sweet spot', where too high–as well as too low–inventories are associated with negative financial performance (Eroglu and Hofer 2011, Rumyantsev and Netessine 2007b), does not hold in the presence of a crisis of this magnitude. We show that reducing inventories below this sweet spot is indeed associated with lower performance, but find no evidence of the opposite effect. We see that profitability is not affected by inventory surplus, while financial health is affected in the medium- to long-term. Furthermore, our results reveal a very complex relationship between inventory responsiveness and market sentiment: surplus inventories, as well as reductions, are associated with increased performance in the long-term. It's possible that this result is related to the market share dynamics observed in the aftermath of the crisis—firms with surplus inventories benefited when demand started to recover and competitors experienced stock outs.

Our results have several implications for managers. On the one hand, we show that managers used inventories to navigate the crisis. However, we also show that changes in inventory levels must be taken seriously, and the long-term consequences must be evaluated. In particular, our results indicate that different aspects of financial performance are affected differently by the responsiveness of a firm. This begs the question of who is the principal stakeholder—put differently, what is the priority when the crisis hits? Our results suggest that firms should be responsive but not reduce inventories below the normal 'sweet spot'. However, in the short term, aggressive inventory reductions increase the liquidity of the firm. Thus, despite their negative effect on the financial performance, firms may consider this tradeoff. (Anecdotal evidence does imply that when the crisis hit, inventory decisions responded to a large extent to credit considerations.) Therefore, for managers an important question is "how much is responsive enough?"

Our research has a number of limitations. While our research allows us to gain valuable insights into inventory management dynamics in the financial crisis, the methodology is certainly limited in different aspects. First of all, we apply secondary firm-level data from S&P Compustat's database which allows us to analyze the inventory practices of more than 1200 firms in the given period. However, the data is available on a quarterly basis only and we are not able to gain more detailed insights into weekly or monthly dynamics. In particular, early in the crisis events were very dynamic and any additional breakdown in time would allow additional analysis. Further, Compustat contains financial metrics but does not explicitly reveal any information on management decisions and practices that would be valuable add-ons. Second, our methodology requires any firm to report financial numbers for the entire period, and we disregard any firms with incomplete observations. Therefore, we cannot rule out a survivor bias since firms that have filed bankruptcy or have been acquired are not considered in our data set. Finally, we have to acknowledge that each firm was potentially affected by the crisis at a different point in time. In line with the economics literature we have defined Q3/2008 as the start of the crisis period. However, certain industries might have been hit earlier or later by the crisis. We have opted for an approach with a common time line to reduce the complexity of the analysis rather than defining individual crisis periods. However, our analysis considers longer time windows for calculating the performance metrics and to study the aggregate dynamics (i.e., two years before start of crisis, three years into crisis). Thus, any deviations from the Q3/2008 will be smoothed out.

Our findings suggest several directions for future research. First, our analysis on the financial impact on inventories opens up the discussion on the appropriate levels of inventory in crisis situations. Eroglu and Hofer (2011) have investigated the optimal inventory levels over a long time period and identified different relationships by industry. It would be interesting to better understand the optimal inventory response in times of (economic) crisis. To do so, a methodology can be developed that identifies response patterns in separate industries and then analyses the financial impact of these patterns. Another interesting research question that could not be addressed in this paper is the role of supply chain partners taking over inventory. Even though we were unable to see it in the aggregate data, there is anecdotal evidence that firms in the financial crisis shifted inventories to suppliers or customers to reduce working capital requirements. By doing so financially healthy firms could support their less stable partners. However, the same could also happen due to power. Leveraging supplier-customer information it would be interesting to investigate the extent to which inventories were shifted and to quantify the magnitude. An additional research idea relates to the origin of our problem: despite the significant loss in economic welfare, the financial crisis also represents a large natural experiment for testing firm's inventory management capabilities. There are other shocks in the recent past that can be leveraged for investigating inventory management capabilities of affected firms, (i.e. the Thailand floods or the Japanese tsunami). However, since the events are less global in nature any analysis would like need to rely on different data sources.

Appendix

We forecast sales and inventory days of each firm through the crisis to use as a baseline with which to define abnormal inventory days and sales. Each firm might have a different preferred way to build-up and reduce inventories throughout the year, as well as different sales patterns. Thus, rather than using a fixed a-priori defined forecasting methodology, we test alternative forecasting approaches for each firm to fit the inventory days (and sales) during the pre-crisis period. Following this, we use the best-fit forecast per firm to produce an out of sample forecast for each crisis period ($\widehat{ID}_p; \widehat{SALE}_p$). We apply four standard forecasting approaches with/without linear trend and with/without seasonality: simple moving average forecast (no trend, no seasonality) (Silver et al. 1998); Holt-Winters double exponential smoothing (trend, no seasonality) (Silver et al. 1998); percentage moving average seasonal estimation method (no trend, seasonality) (Nahmias and Olsen 2015); and Holt-Winters triple exponential smoothing (trend, seasonality) (Nahmias and Olsen 2015) Based on the forecast errors of these approaches we identify the approach with the best fit for each firm. As an example, Table 9 shows the percentage of firms where we use each forecasting method for inventory days per subsector. We see that the majority of firms have a show significant trend and seasonality in the data.

Table 9 Forecasting methdologies applied for crisis period inventory projection.

	Inventory Projection (Trend / Seasonality)			
Industry	No/No	Yes/No	No/Yes	Yes/Yes
Food, Beverage & Tobacco	1.1%	12.4%	22.5%	64.0%
Textiles, Apparel & Leather	0.0%	8.2%	26.5%	65.3%
Paper & Publishing	0.0%	21.7%	23.9%	54.3%
Chemicals & Plastics	2.5%	18.3%	27.7%	51.5%
Metal	4.4%	16.5%	18.7%	60.4%
Machinery	0.8%	18.5%	27.4%	53.2%
Computer, Electronics & Electrical Equipment	4.1%	27.4%	20.4%	48.2%
Transportation Equipment	3.8%	20.0%	26.3%	50.0%
Other	0.0%	16.2%	26.6%	57.1%
Total	1.8%	17.7%	24.4%	56.0%

Table 10 shows the inventory-day projection errors in the data. For the crisis-period, the inventory-day projection error is an indicator for abnormal firm inventories that controls for trends and seasonality present in the data.

Table 10 **Deviation of Firm-Level Inventory Levels from Projection**

			ΔID		ΔID^N	
Year	**Quarter**	**Period**	**Mean**	**Median**	**Mean**	**Median**
2005	3	-12	1.65	0.88	0.97%	1.74%
	4	-11	0.95	0.39	-4.59%	0.50%
2006	1	-10	-0.80	-0.24	-1.21%	-0.51%
	2	-9	-0.22	0.24	0.67%	0.33%
	3	-8	0.51	0.21	1.12%	0.59%
	4	-7	1.93	0.50	-2.70%	0.61%
2007	1	-6	1.75	0.34	0.46%	0.69%
	2	-5	1.91	0.14	0.93%	0.36%
	3	-4	-0.91	-0.08	-0.63%	0.06%
	4	-3	0.15	-0.14	-0.63%	-0.48%
2008	1	-2	1.61	0.41	-1.01%	0.66%
	2	-1	0.91	0.07	-1.97%	0.00%
	3	1	2.11	0.00	6.28%	0.64%
	4	2	8.23	3.75	15.36%	5.58%
2009	1	3	13.26	5.04	21.18%	8.55%
	2	4	9.61	3.53	21.52%	5.63%
	3	5	1.43	0.23	11.88%	1.33%
	4	6	-1.81	-0.76	13.17%	-1.17%
2010	1	7	-2.40	-1.53	13.00%	-2.04%
	2	8	-2.25	-2.07	17.45%	-3.51%
Pre-Crisis ($-12 \leq p \leq -1$)			0.79	0.18	-0.71%	0.29%
Crisis ($1 \leq p \leq 8$)			3.53	1.22	14.98%	2.20%

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