Asymmetric Inventory Management and the Direction of Sales Changes

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Abstract

We study manufacturing firms' asymmetric inventory investment in response to sales changes. Focusing on the costs of resource adjustment and stockout which likely differ in sales-increasing and sales-decreasing periods, we predict and find that inventory investment declines less during periods with sales decreases than it rises during periods with sales increases. We validate this claim by showing that managers' expectations of future demand and desire to avoid inventory stockouts are important determinants of this asymmetry. In addition, we find that asymmetric inventory investment provides useful information for predicting future sales growth, and that both managers' and analysts' sales forecasts are positively associated with the asymmetry. Lastly, we document that forecasts of future sales growth that incorporate asymmetric inventory investment are associated with lower absolute forecast errors than benchmark forecasts. Overall, we highlight the importance of inventory information in understanding managers' resource adjustment and utilization decisions that have implications for forecasting future demand. Our findings on asymmetric inventory management provide new insights to fundamental analysis based on inventory signals.

Keywords: *inventory investment; sales decline; demand uncertainty; fundamental analysis; sales forecast; production decision*

JEL Classifications: *M11, M41.*

Data Availability: data used in this study are publicly available through sources identified in the text.

1. Introduction

Inventory investments are strategic decisions that are crucial for successful business operations.[1] In this study, we explore whether managers respond asymmetrically to sales increases versus decreases when determining inventory production, and if so whether this response varies in systematic ways and is informative about future sales. There is prior evidence that managers respond asymmetrically to sales increases versus decreases when adjusting selling, general and administrative (SG&A) expenses. In particular, managers scale up resources more quickly than they scale them down (e.g., Anderson et al. 2003). Although we provide a number of reasons below as to why managers may also respond asymmetrically when determining inventory production, existing research assumes a linear response (Lovell 1961; Bernard and Stober 1989; Dechow et al. 1998; Roychowdhury 2006).

We predict an asymmetric relation between inventory investment and sales changes for three reasons. First, inventory decisions incorporate the cost of adjusting production capacity such as factory space, machinery, and workers. When a firm cuts production volume and dismisses factory employees when sales decline, for instance, it incurs severance pay upon labor termination and search and training costs when employees are re-hired afterwards. To the extent that firms smooth production by keeping unused production capacity minimal, they can avoid such short-run resource adjustment costs (Blanchard 1983; Anderson et al. 2003). Therefore, we expect the incentives for production smoothing to be greater when sales decrease than when sales increase, which in turn limits the extent to which production and inventory investments fall in response to a sales decline. Second, managers' expectations of future demand may also contribute to an asymmetric relation. Managers who envision a favorable future demand condition are likely to

[1] In this paper, we use the terms *inventory investment*, *inventory adjustment*, and *inventory management* interchangeably to reflect managers' changes to inventory stockpiles (Dasgupta et al. 2018).

perceive high congestion costs of scaling up production quickly to catch up to the demand.[2] To avoid congestion costs, managers would not reduce production in sales-decrease periods but maintain a certain capacity utilization level, bringing about asymmetric inventory investment.[3] Third, inventory stockouts represent nontrivial costs to manufacturing firms in competitive product markets. Incentives to avoid stockouts should lead managers to set a lower bound on the level of inventory investment even as sales decrease, which should contribute to an asymmetric behavior of inventory investment (Abel 1985; Rumyantsev and Netessine 2007). Also, costs of inventory stockouts to manufacturing firms should be more salient in an operating environment characterized by high demand uncertainty. In sum, we predict that managers' incentives of production cost minimization, expectations of favorable future demand and considerations of potential stockout costs will contribute to asymmetric inventory investment in response to sales changes.

To better understand how the direction of sales changes affects managers' production and inventory decisions, we turn to the cost asymmetry literature that provides insights on managers' resource adjustment decisions motivated by economic optimization (Anderson et al. 2003). A number of studies in this area argue that managers who are hoping to avoid the costs of resource adjustments retain slack capacity in periods with sales declines, resulting in asymmetric cost behavior. As evidence of asymmetric cost behavior, the studies point to the lower elasticity of operating costs to sales changes in periods with sales decreases relative to periods with sales increases. The literature also suggests that resource adjustment and production decisions are

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[2] Given a certain level of fixed capacity, an unexpectedly high demand causes production congestion and forces the firm to bear economic costs such as diminishing productivity of fixed resources and increasing marginal costs of variable resources (Banker et al. 2014b, Holzhacker et al. 2015).

[3] This is analogous to the underlying motive for sticky costs. For example, Anderson et al. (2003, pp. 48–49) state that "when there is uncertainty about future demand and firms must incur adjustment costs to reduce or restore committed resources, managers may purposely delay reductions to committed resources until they are more certain about the permanence of a decline in demand."

distinct but closely related operating decisions (Hurley and Whybark 1999; Balakrishnan et al. 2004). As demand is realized, managers periodically adjust production levels along with other production parameters such as fixed capacity costs, manufacturing lead-time, and variable production costs. In order to maximize costs in an uncertain demand environment, managers respond to a decline in sales by adjusting both committed capacities and production levels. For example, consistent with the production smoothing explanation, managers facing a sales decline may maintain production levels and accumulate inventories to reduce manufacturing costs per unit and avoid future congestion costs of ramping up production in the short run, instead of divesting committed production capacities in the current period (Banker et al. 2014b). Managers' production decisions in periods with sales decreases thus involve a tradeoff between the expected benefits of building up buffer inventories, as we argue above, and the incremental costs of maintaining production levels even as sales fall. If managers continue to produce inventories despite a decline in sales, their inventory investments are expected to be asymmetric in response to sales increases versus decreases.

Using an asymmetric model of inventory investment, we examine the sensitivity of inventory investment to sales changes when sales increase versus sales decrease. Using a large sample of manufacturing firms from 2002 to 2018, we find that inventory investment falls less during periods with sales decreases than it rises during periods with increasing sales. We conduct additional analyses to explore determinants of asymmetric inventory investment. First, we find that the degree of asymmetric inventory investment increases with the growth in order backlog, a survey-based measure of managerial optimism, realized future sales growth and prior sales increases. This is consistent with managers' positive expectations of future demand being a potential contributor to the asymmetry. Next, we examine the extent to which managers' considerations of inventory stockouts and demand uncertainty influence asymmetric inventory investment. We use an empirical measure of relative stockout costs from Kesavan and Kushwaha (2014), Tobin's Q and volatility of sales growth. We find that asymmetric inventory investment is more pronounced for firms with higher relative stockout costs and higher demand uncertainty. This is consistent with managers' needs for buffer stocks constraining downward inventory adjustment when sales decrease. These results empirically support the idea that managers' expectations of future demand and potential stockout costs underlie asymmetric inventory investment.

Next, we provide evidence on the implications of asymmetric inventory investment for forecasting future sales. First, we examine whether asymmetric inventory investment can signal future sales growth. To the extent that asymmetric inventory investment arises from managers' positive expectations of future demand, we predict that it should be incrementally useful in predicting future sales growth. Controlling for current sales growth and lagged changes in inventory relative to sales changes, we find that asymmetric inventory investment is significantly predictive of future sales growth.

Second, we test whether asymmetric inventory investment is reflected in management sales guidance and analyst sales forecasts. If asymmetric inventory investment is predictive of future demand and both managers and analysts impound this information in their forecasts of future demand, we expect the asymmetry to be positively associated with forecasts of future sales by managers and analysts. Using management sales guidance and analyst sales forecasts from the Institutional Brokers' Estimate System (IBES), we find that asymmetric inventory investment is associated with more positive forecasts of future sales by both managers and analysts. With analyst forecasts, we also find that the dispersion in analysts sales forecasts is increasing in the degree of asymmetric inventory investment.

Lastly, we develop a time-series forecasting model of future sales growth based on asymmetric inventory investment and compare the predictive ability of sales growth forecasts based on the model with that of sales growth forecasts based on various benchmark metrics: random-walk time-series models, management sales guidance, and analysts sales forecasts (Fairfield et al. 1996; Banker and Chen 2006; Curtis et al. 2014). Consistent with our results above, we find that sales growth forecasts based on asymmetric inventory investment are associated with lower absolute forecast errors than those based on the benchmark metrics. Collectively, our findings suggest that information about asymmetric inventory investment can be incrementally useful for predicting future sales.

Our paper contributes to several streams of research. First, we shed light on the information that inventory disclosure provides about managers' expectations of business prospects. By analyzing the implications of asymmetric inventory investment for future demand, we provide evidence on the usefulness of inventory disclosure in predicting future sales that can be of interests to academics and investors (Bernard and Noel 1991; Bernard and Stober 1989; Kesavan et al. 2010). Second, our study advances an understanding of managerial decisions in the adjustment and utilization of committed production resources. By conditioning a linear inventory model with the direction of sales changes, we find a nonlinearity in the relation between inventory investment and sales changes and propose its underlying determinants. In doing so, we follow prior accounting studies on cost behavior in incorporating an asymmetric effect of sales changes in the empirical specification and suggest the asymmetric managerial decisions are a result of economic optimization. Lastly, we bridge the operations management literature and the accounting literature by improving an understanding of inventory holding decisions by manufacturing firms. In an extension of the cost behavior literature, we argue that managers not only retain committed resources but also maintain production levels in periods with sales decreases if they have positive expectations of future demand and/or view potential stockout costs as significant. Our results therefore highlight that resource adjustment and utilization decisions are related operating decisions that have implications for forecasting future demand (Hurley and Whybark 1999; Balakrishnan et al. 2004).

The remainder of the paper proceeds as follows. Section 2 discusses the related literature on inventory investment and develops our main hypotheses. Section 3 describes our empirical models and sample. Section 4 presents the empirical findings. Section 5 concludes the paper.

2. Literature review and hypothesis development

Literature on inventory investment

Firms' inventory decisions have been extensively studied in the economics and operations management literature. In the macroeconomics literature, two key papers investigate the motivations behind firms' production and inventory holding decisions at the aggregate level. Blinder (1981) argues that in the presence of variable demand and rising marginal costs, firms smooth production relative to sales, stocking excess inventories when demand falls and liquidating them when demand recovers. In an assessment of the inventory behavior of the American automobile industry, Blanchard (1983) extends the production smoothing model by highlighting the adjustment costs associated with changing the level of output. In recent operations management studies, Rumyantsev and Netessine (2007) use firm-level data in Compustat to test whether classic inventory models from the literature, which are developed mainly at the individual product level, can explain firms' inventory holding decisions. Consistent with the buffering role of inventories, the authors find that firm-level inventories are positively related to demand uncertainty, procurement lead times, and stockout costs. As we do in our study, Kesavan et al. (2010) develop a sales forecasting model based on inventory information and find that analysts do not fully incorporate inventory information in their estimates of future sales.

In the accounting literature, research on fundamental analysis interprets a large increase in inventories relative to sales as a negative signal for future earnings and contemporaneous stock returns (Lev and Thiagarajan 1993; Abarbanell and Bushee 1997, 1998).[4] Other studies suggest that inventory investment signals managers' expectations of future demand. Analyzing the relation between current accruals and firm value, Bernard and Stober (1989) find evidence that inventories provide an incrementally valuable signal for predicting future sales. Examining the informativeness of manufacturing firms' inventory disclosures for predicting future sales and earnings, Bernard and Noel (1991) document that unexpected changes in inventories are a leading indicator of future sales. The authors interpret their results as supporting the hypothesis that managers reveal private information about future demand through inventory investment decisions. In this paper, we add to this literature by documenting managers' asymmetric inventory investment decisions and highlighting the usefulness of asymmetric inventory investment for forecasting future sales.

Asymmetric inventory investment decisions

A number of accounting studies model inventory investment as a linear function of sales level and sales changes. Following Bernard and Stober (1989), Dechow et al. (1998) assume that inventories consist of a sales-based target level and a deviation from the target. Roychowdhury's (2006) model of production costs estimates normal inventory growth as a function of size and current and lagged sales changes. However, the assumption of a linear relation between inventory

[4] Anderson et al. (2007) find that conditioning the interpretation of the SG&A cost signal on the direction of sales change improves their earnings prediction model. In this paper, we find that conditional interpretation of the inventory signal depending on the direction of sales change helps better explain the implications of the inventory signal for future demand.

investment and sales changes does not take into account whether managers incorporate forward-looking information about future demand or consider incentives other than holding and obsolescence costs in their production and inventory decisions when sales increase or decrease.

The cost behavior research in the management accounting literature considers how the direction of changes in activity levels—as measured by sales changes—affects managers' resource commitment decisions. This literature documents empirical findings in support of sticky cost behavior—that is, SG&A costs fall less in response to a sales decrease than they rise for an equivalent sales increase. Anderson et al. (2003) attribute the asymmetry to managers' deliberate resource commitment decisions. As demand changes, managers decide whether to retain committed production resources. Consistent with economic optimization, studies suggest that managers are reluctant to reduce committed resources due to high adjustment costs involved in cutting (acquiring) slack capacity and firing (hiring) labor in the current (future) period as demand declines (rebounds). These decisions depend not only on the direction of current sales changes, but also on the level of adjustment costs, the direction of prior sales changes, expected future demand, and other firm characteristics (e.g., Chen et al. 2012; Dierynck et al. 2012; Banker et al. 2013; Banker and Byzalov 2014; Banker et al. 2014a; Chen et al. 2019).

Because these prior studies largely focus on SG&A costs, they generally provide limited insight on how managers jointly adjust committed resources and production decisions in response to changes in activity levels. In a study more relevant to ours, Balakrishnan et al. (2004) suggest that capacity utilization affects managers' resource adjustment decisions in a way that is asymmetrical to increases and decreases in activity. Using data from the U.S. air cloud wrestling industry, Cannon (2014) finds that managers adjust both capacity and pricing in response to a decline in demand. In this paper, we examine whether firms' inventory investments in response to sales changes depends on the direction of sales changes. In doing so, we consider additional economic aspects of managers' production planning decisions that can be inferred from firms' inventory disclosures. When examining periods with sales declines, prior literature is concerned more about the managers' resource adjustment decisions than their production decisions conditional on resource retention. However, resource adjustment decisions and production decisions are closely related operating decisions that managers jointly determine (Hurley and Whybark 1999). Whether the direction of sales changes affects managers' production decisions remains relatively unexplored, as are the factors motivating such decisions.

We propose three aspects of inventory production decisions that lead us to predict asymmetric inventory investment. First, a large literature on production smoothing suggests that minimizing variation in production relative to sales is a cost-efficient strategy (e.g., Blinder 1981; Blanchard 1983). Abel (1985) suggests that when production costs follow a convex function of production levels, average costs can be lowered by reducing the variation in production relative to sales. Abel (1985) concludes that firms' optimal behavior with regard to inventory investment is consistent with production smoothing. Also, resource adjustments involved in changing production in the short run such as fixed capacity adjustments and employee turnovers are costly and should make production smoothing an effective operating decision. We hypothesize that incentives to optimize intertemporal production costs, in turn, should result in asymmetric inventory investment.[5]

Second, managers' expectations of future demand play a role in short-run resource adjustment and utilization decisions (e.g., Anderson et al. 2003; Chen et al. 2019). In response to

[5] Cost stickiness can also be attributed to managers' capacity utilization decisions. Studies document that firms with a higher capacity utilization, i.e., those that continue to produce even as demand falls in the case of manufacturers, exhibit a greater degree of cost stickiness (Balakrishnan et al. 2004; Banker et al. 2015; Cannon 2014).

a sales decline, managers with positive expectations of future demand can avoid congestion costs of scaling up production in the future by maintaining capacity and production levels (Pindyck 1982; Banker et al. 2014b). Congestion costs in production can arise not only from increasing resources in the short run, but also from a lag in the production process (Abel 1985). Also, because greater demand uncertainty increases congestion costs, we predict that the benefits of maintaining committed capacities and production will be greater when demand is more uncertain.

Lastly, managers' inventory investment decision can be affected by the risk of inventory stockouts in an uncertain demand environment. Inventory stockouts represent potentially nontrivial costs to manufacturing firms in competitive product markets—costs that are typically greater than inventory holding costs (e.g., Corsten and Gruen 2004). Firms therefore maintain buffer stocks to prevent a loss of sales to competitors and to minimize the disruption in the supply chain. A minimum-inventory policy imposes a lower bound on the downward adjustment of inventories, which could contribute to an asymmetry in inventory investment. Based on these considerations, we posit that managers make asymmetric inventory investment decisions in response to sales changes. Accordingly, our main hypothesis is stated in the alternative form:

HYPOTHESIS 1. *The relative magnitude of a decrease in inventory investment for a sales decrease is less than that of an increase in inventory investment for an equivalent sales increase.*

However, our prediction is not without tension. Following the substantial loss of market share to Japanese competitors whose success is often attributed to the just-in-time inventory management, manufacturing firms hold less inventories over time and stock prices of firms with bloated inventories are discounted by the stock market (Lieberman and Demeester 1999; Chen et al. 2005; Ak and Patatoukas 2016). If these factors have a greater impact on firms' inventory investment decisions, inventory investment should behave symmetrically in response to sales changes.

Next, we make two cross-sectional predictions about the settings where managers are more likely to make asymmetric inventory investment in response to sales changes. First, managers with positive expectations of future demand should exhibit a stronger willingness to not only retain unused resources (Anderson et al. 2003; Chen et al. 2019), but also maintain production as they expect a rebound in demand in the near future. This prediction is consistent with managers' expectations driving resource adjustment and utilization decisions. Second, firms facing high stockout costs relative to holding costs will make more asymmetric inventory investments. This is because as sales decline, managers should be more willing to maintain production and accumulate inventories if the costs of inventory stockouts, including lost sales in competitive product markets and disruption in supply chain, are more significant than holding and obsolescence costs. This prediction is consistent with the need for buffer stocks when demand is more uncertain, leading to less downward inventory adjustment when sales decline. Therefore, we make the following hypotheses:

HYPOTHESIS 2a. *Asymmetric inventory investment increases with managers' expectations of an increase in future demand.*

HYPOTHESIS 2b. *Asymmetric inventory investment increases with higher stockout costs.*

The literature on fundamental anaylsis suggests that inventory signals provide valuable information for predicting future sales (Bernard and Noel 1991; Bernard and Stober 1989; Kesavan et al. 2010). Also, Alan et al. (2014) find a positive association between inventory turnover and future stock returns and suggest that changes in inventories convey information about future demand. Similarly, Gaur et al. (2005) and Rumyantsev and Netessine (2007) confirm that efficient inventory management is positively associated with contemporaneous return on assets and stock returns. We extend their work by analyzing the implications of asymmetric inventory investment for predicting future sales growth. To the extent that asymmetric inventory investment arises from managers' positive expectations of future demand, we predict that it should be incrementally useful in predicting future sales growth. Therefore, we make the following hypothesis:

HYPOTHESIS 3. *Asymmetric inventory investment provides useful information for forecasting future sales growth.*

3. Empirical models and sample selection

Empirical models

The baseline empirical model we use in this paper is a variant of the inventory and production models used in Roychowdhury (2006) and Gunny (2010).[6] Specifically, we model inventory investment ($\Delta INVENT_{it}$) as a function of sales level ($SALES_{it}$) and sales changes ($\Delta SALES_{it}$). In addition, we include control variables including market value of equity ($SIZE_{it}$), Tobin's Q (Q_{it}), asset intensity ($ASSETINT_{it}$), labor intensity ($EMPINT_{it}$), return on net operating assets ($RNOA_{it}$), and operating leverage ($OPLEV_{it}$) that can be correlated with resource adjustment costs and expectations about the future demand (Nissim and Penman 2001; Banker et al. 2014a). To examine whether inventory investment in response to sales changes depends on the direction of sales changes, we interact $\Delta SALES_{it}$ with an indicator variable for a sales decline (DEC_{it}) and estimate the following OLS model:[7]

$$\begin{aligned}\Delta INVENT_{it} = {} & \beta_1(1/A_{it-1}) + \beta_2 SALES_{it} + \beta_3 \Delta SALES_{it-1} + \beta_4 DEC_{it-1} + \beta_5 DEC_{it-1}{*}\Delta SALES_{it-1} \\ & + \boldsymbol{\beta_6 \Delta SALES_{it}} + \beta_7 DEC_{it} + \boldsymbol{\beta_8 DEC_{it}{*}\Delta SALES_{it}} \\ & + \beta_9 SIZE_{it} + \beta_{10} Q_{it} + \beta_{11} ASSETINT_{it} + \beta_{12} EMPINT_{it} + \beta_{13} RNOA_{it} + \beta_{14} OPLEV_{it} \\ & + Industry\ Fixed\ Effects + Year\ Fixed\ Effects + \varepsilon_{it} \qquad (1)\end{aligned}$$

where
$\Delta INVENT$ = change in total inventories divided by lagged total assets,

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[6] Our results are robust to using alternative specifications such as Lovell's (1961) target adjustment inventory model as utilized in Guariglia and Mateut (2006) and Caglayan et al. (2012) (untabulated).
[7] In untabulated results, we further include interaction terms between control variables with current sales changes in both directions. Our inferences do not change with these additional variables.

$1/A$ = inverse of total assets,
$SALES$ = sales divided by lagged total assets,
$\Delta SALES$ = change in sales divided by lagged total assets,
DEC = 1 if sales decline for the year, and 0 otherwise,
$SIZE$ = the natural logarithm of the market value of equity,
Q = Tobin's Q,
$ASSETINT$ = asset intensity,
$EMPINT$ = employee intensity,
$RNOA$ = return on net operating assets from Nissim and Penman (2001),
$OPLEV$ = operating leverage from Nissim and Penman (2001).

Following prior studies on inventory, we adjust all last-in, first-out (LIFO) inventories to first-in, first-out inventories by adding back the LIFO reserve to mitigate the effect of inventory accounting on our results (Feng et al. 2015). In line with prior studies, we expect β_6 to be positive as managers increase (decrease) inventory levels when sales increase (decrease). In line with Hypothesis 1, we expect β_8 to be negative. That is, when sales decline, inventories do not decrease as much as they increase for an equivalent amount of sales increase. Thus, variations in β_8 reflect the degree of asymmetric inventory investment. The sum of the coefficients, $\beta_6 + \beta_8$, measures the rate of inventory investment for a decline in sales. We also include lagged sales changes ($\Delta SALES_{it-1}$) and its interaction with an indicator for sales decline (DEC_{it-1}) to allow for a delayed response of inventory to sales changes given production lead time (Rumyantsev and Netessine 2007). In model (1), we include 3-digit SIC industry fixed effects and year fixed effects to account for industry-specific and cyclical changes in inventories. In model (1) and those that follow, we estimate regression equations using the ordinary least squares and adjust standard errors for clustering at the firm and year levels (Petersen 2009).

In assessing the asymmetric behavior of inventory investment in response to sales changes, we explore two cross-sectional variations: managers' expectations of future demand and stockout costs. These tests allow us to identify the forces that lead to asymmetric inventory investment.

Following prior literature (e.g., Banker et al. 2014a), we include interaction terms with both positive and negative sales changes in estimating the following OLS model:

$$\begin{aligned}\Delta INVENT_{it} = {} & \beta_1(1/A_{it-1}) + \beta_2 SALES_{it} + \beta_3\Delta SALES_{it-1} + \beta_4 DEC_{it-1} + \beta_5 DEC_{it-1}{*}\Delta SALES_{it-1} \\ & + \boldsymbol{\beta_6\Delta SALES_{it}} + \beta_7 DEC_{it} + \boldsymbol{\beta_8 DEC_{it}{*}\Delta SALES_{it}} \\ & + \beta_9 PART_{it} + \beta_{10} PART_{it}{*}\Delta SALES_{it}{*} + \boldsymbol{\beta_{11} PART_{it}{*}DEC_{it}{*}\Delta SALES_{it}} \\ & + \beta_{12} SIZE_{it} + \beta_{13} Q_{it} + \beta_{14} ASSETINT_{it} + \beta_{15} EMPINT_{it} + \beta_{16} RNOA_{it} + \beta_{17} OPLEV_{it} \\ & + \textit{Industry Fixed Effects} + \textit{Year Fixed Effects} + \varepsilon_{it} \qquad (2)\end{aligned}$$

where *PART* denotes the two partitioning variables—managers' expectations of future demand and stockout costs. Detailed definitions of cross-sectional determinants of inventory investment are provided in the Appendix.

For tests on the implications of asymmetric inventory investment for future sales growth, we estimate the following OLS model, which relates future sales growth ($\Delta SALES_{it+1}$) to an inventory signal ($INVSIG_{it}$) conditional on the direction of sales changes:

$$\begin{aligned}\Delta SALES_{it+1} = {} & \boldsymbol{\beta_1 INVSIG_{it}} + \beta_2 DEC_{it} + \boldsymbol{\beta_3 DEC_{it}{*}INVSIG_{it}} \\ & + \beta_4 INVSIG_{it-1} + \beta_5 DEC_{it-1} + \beta_6 DEC_{it-1}{*}INVSIG_{it-1} + \beta_7 INVSIG_{it-2} + \beta_8 DEC_{it-2} \\ & + \beta_9 DEC_{it-2}{*}INVSIG_{it-2} + \textit{Control Variables} + \textit{Industry Fixed Effects} \\ & + \textit{Year Fixed Effects} + \varepsilon_{it} \qquad (3)\end{aligned}$$

where $INVSIG_{it}$ is defined as the ratio of total inventories to lagged total inventories minus the ratio of sales to lagged sales and measures a disproportionate change in inventories relative to sales changes, following Lev and Thiagarajan (1993).[8] The dependent variable in model (3) is year t + 1 sales changes scaled by lagged total assets. Control variables include current sales changes ($\Delta SALES_{it}$), Tobin's Q (Q_{it}), firm age ($LNAGE_{it}$), firm size ($SIZE_{it}$), book leverage (LEV_{it}), cash holdings ($CASH_{it}$), and return on assets (ROA_{it}). By interacting $INVSIG_{it}$ with an indicator for a sales decline (DEC_{it}), we estimate the magnitude of the association between future sales growth and asymmetric inventory investment in periods with sales decline. Further, we include lagged

[8] In examining the implications of SG&A cost stickiness for earnings prediction, Anderson et al. (2007) follow the same methodology to capture the magnitude of cost stickiness.

values of *INVSIG* and their interactions with an indicator for a sales decline to control for the information content of lagged values of the inventory signal. We predict β_3 to be positive, which is consistent with asymmetric inventory investment being incrementally useful for predicting future sales growth.

For tests on whether managers and analysts incorporate asymmetric inventory investment in their forecasts of future sales, we follow Koo and Lee (2018) and estimate the following OLS model relating management sales guidance and analyst sales forecasts to the inventory signal conditional on the direction of sales changes:

$$FORECAST_{it+1} = \boldsymbol{\beta_1 INVSIG_{it}} + \beta_2 DEC_{it} + \boldsymbol{\beta_3 DEC_{it}*INVSIG_{it}} \\ + Control\ Variables + Industry\ Fixed\ Effects + Year\ Fixed\ Effects + \varepsilon_{it} \quad (4)$$

where *FORECAST* denotes management's and analysts' sales forecast attributes which we measure by the following seven variables. The variable *MFHIGHER* (*AFHIGHER*) is management sales guidance (analyst consensus sales forecast) for the year t + 1 minus sales in year t, scaled by the market value of equity at the beginning of the fiscal year.[9] The variable *MFERROR* (*AFERROR*) is the difference between management sales guidance (analyst consensus sales forecast) for year t + 1 and sales in actual year t + 1. The variable *MFACCURACY* (*AFACCURACY*) is the negative of the absolute difference between management sales guidance (analyst consensus sales forecast) for year t + 1 and actual sales in year t + 1. The variable *AFDISPERSION* is the standard deviation of individual analyst sales forecasts for year t + 1 scaled by the consensus sales forecast. Following Koo and Lee (2018), control variables in this model include the standard deviation of quarterly sales ($STDREV_{it}$), the standard deviation of monthly stock returns during the fiscal year ($STDRET_{it}$), market value of equity ($SIZE_{it}$), return on assets (ROA_{it}), abnormal stock returns ($BHAR_{it}$), Tobin's

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9 Specifically, we convert forecast variables to a per-share basis and scale them by the stock price at the beginning of the fiscal year.

Q (Q_{it}), research and development intensity ($RDINT_{it}$), advertising expense intensity ($ADINT_{it}$), the correlation between quarterly stock returns and seasonal sales changes ($RRCORR_{it}$), a loss indicator for the following year ($LOSS_{it+1}$), analyst following ($ANALYSTS_{it}$), and forecast horizon from the date of forecasts to the date of fiscal year-end ($MFHORIZON_{it+1}$ for management sales guidance and $AFHORIZON_{it+1}$ for analyst forecasts). For tests using analyst forecasts as the dependent variable, we also control for the presence of management guidance ($GUIDANCE_{it}$), lagged forecast dispersion ($AFDISPERSION_{it}$), and lagged values of each dependent variable.

Sample selection

Our sample is from the annual Compustat file covering the period from 2002 to 2018. Following prior literature on inventory investment, we focus on manufacturing firms in Compustat North America with SIC codes between 2000 and 3999. Additionally, in line with prior literature, we exclude firm-year observations with total inventory greater than or equal to total assets and those with a zero/negative book value of equity or total assets. Finally, to prevent outliers from affecting our inferences, we winsorize all continuous variables at 1% and 99% of their respective distributions. These procedures result in a baseline sample of 27,632 firm-year observations for the period from 2002 to 2018, with varying sample sizes for subsequent analyses.

For tests using management sales guidance and analyst sales forecasts, we use IBES Guidance and IBES Detailed History files, which include management sales guidance and analyst sales forecasts issued between 2002 and 2018. Analyses for management guidance are conducted at the guidance level and analyses using analyst forecasts are conducted at the consensus level. We discard observations with a stock price of less than $1 per share and annual sales of less than $10 million. In these analyses, the sample sizes are 14,532 guidance-firm-year observations for management sales guidance and 12,951 firm-year observations for analyst sales forecasts.

4. Empirical results

Descriptive statistics

Table 1 presents descriptive statistics for the key variables. The mean (median) sales change is 0.084 (0.053) and the mean (median) inventory investment is 0.013 (0.006). In an untabulated plot, we find that annual inventory investment is highly procyclical, rising consistently in economic expansions and declining significantly in economic contractions as defined by the National Bureau of Economic Research (Kashyap et al. 1994). Similar to cost behavior studies, about 34% of the sample firm-year observations experience a decline in sales (Anderson et al. 2003; Banker et al. 2014a). Overall, the distributions of the key variables are similar to those found in prior studies (Caglayan et al. 2012; Guariglia and Mateut 2006).

[Insert Table 1 here]

Inventory investment and sales changes: Baseline results

In Table 2, we present the regression results from estimating the baseline specification in model (1).[10] In column (1), we estimate the baseline model without an indicator for a sales decline and its interaction with sales changes, and find that the coefficients on $\Delta SALES_{it-1}$ and $\Delta SALES_{it}$ are positive and statistically significant, consistent with lagged and current sales changes being positively associated with inventory investment. In terms of economic interpretation, a one standard deviation increase in sales change is associated with an increase of 0.0233 in inventory investment, which represents about 42% of the standard deviation of inventory investment.[11] In column (2), we include the interaction term in the model and find that the coefficient on the interaction term $DEC_{it}*\Delta SALES_{it}$ is significantly negative (p-value < 0.01). The coefficient

[10] In untabulated analyses, we find similar results when we estimate model (1) by industry subgroups within the broader manufacturing industry and when we use subcomponents of inventories (raw materials, work-in-process and finished goods) as the dependent variable in model (1).
[11] 0.0233 = 0.087*0.268; 42% = 0.0233/0.056.

translates into a 38% lower sensitivity of inventory investment to sales changes and is consistent with our prediction that manufacturing firms asymmetrically adjust their inventory decisions to sales increases and decreases.[12] This result provides support for our main hypothesis that inventory investment falls less with a sales decrease than it increases with an equivalent amount of sales increase.[13]

[Insert Table 2 here]

Cross-sectional tests of asymmetric inventory management

Expectations of future demand

We posit that one of the main drivers of asymmetric inventory investment is managers' expectations of future demand. Changes in current demand require managers to decide whether to adjust available capacity, alter production levels, and stockpile inventories. As managers evaluate the relative benefits and costs of these operating decisions, expectations of future demand should play a significant role. If managers forecast a rebound in demand in the near future, the benefits of stockpiling inventories in the current period and avoiding a possible stockout could outweigh the costs of maintaining capacity and holding inventories. Thus, we predict that the degree of asymmetric investment increases with managers' expectations of future demand.

To proxy for managers' expectations of future demand, we first use the decile rank of change in order backlog (ΔOB_{it}) as a positive leading indicator of future sales (Lev and Thiagarajan 1993; Anderson et al. 2003; Banker et al. 2014a). Next, we utilize an empirical measure of managerial outlook on future profitability from the quarterly surveys of chief financial officers (CFOs) of

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[12] 38% = 0.037/0.098.

[13] We find consistent results when we measure inventory investment using different inventory components and when we estimate the model using a more refined industry classification (untabulated). We interpret the results on inventory components as supporting an additional explanation for asymmetric inventory investment in periods with sales declines: managers continue to purchase regular amounts of raw materials to maintain relationships with suppliers.

public and private firms in the U.S. Specifically, we use the annual mean response of CFOs in rating their optimism about their firms' future financial prospects (Question 2b) from Duke CFO Global Business Outlook (*OUTLOOK*).[14] Finally, if managers incorporate internal forecasts of future demand in their current inventory decisions and have a reasonably accurate foresight of future demand for the near term, managers who anticipate a rebound in demand after a sales decline are likely to engage in production smoothing and accumulate inventories. Therefore, we use the decile rank of realized future sales growth in year $t + 1$ ($\Delta SALES_{it+1}$) as an additional proxy for managerial expectations of future demand.[15]

[Insert Table 3 here]

In column (1) of Table 3, Panel A, we find a significantly negative coefficient on $\Delta OB_{it}*DEC_{it}*\Delta SALES_{it}$ (p-value < 0.05), which is consistent with a greater level of asymmetric inventory investment in the presence of a positive leading indicator of future sales. In column (2), the coefficient on $OUTLOOK_{it}*DEC_{it}*\Delta SALES_{it}$ is also negative and significant (p-value < 0.10), indicating that managers' positive outlooks on future demand is associated with a greater degree of asymmetric inventory investment. In column (3), we also find a significantly negative coefficient on $\Delta SALES_{it+1}*DEC_{it}*\Delta SALES_{it}$ (p-value < 0.01), suggesting that managers whose firms subsequently realize a higher growth in sales make asymmetric inventory investment to a greater extent. In sum, these results suggest that managers' expectations of future demand play a significant role in asymmetric inventory investment.

Prior research on cost behavior suggests that the direction of prior sales changes is an important determinant of managers' resource adjustment decisions (Anderson et al. 2003; Banker et al. 2014a). Managers become more optimistic (pessimistic) about future sales following a prior

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[14] Duke CFO Global Business Outlook for the 2004 - 2018 period is available at https://www.cfosurvey.org.
[15] We find similar results using the average sales growth over the three years $t + 1 \sim t + 3$ (untabulated).

sales increase (decrease). In Table 3, Panel B, we adopt a multi-period model of inventory investment to examine whether managers incorporate the direction of prior sales changes in their resource adjustment and utilization decisions. Following Banker et al. (2014a), our multi-period model incorporates the directions of prior sales changes as an additional signal on the permanence of a change in demand. The terms INC_{it-1} and INC_{it-2} (DEC_{it-1} and DEC_{it-2}) are indicators of a prior sales increase (decrease) in year $t-1$ and year $t-2$, respectively.[16] Columns (1) and (2) present the results for the two- and three-period models, respectively. In the two-period model in column (1), we find a greater degree of asymmetric inventory investment in periods with sales decline following prior sales increases than in periods with two consecutive sales declines (two-tailed p-value of the difference = 0.07). In the three-period model in column (2), we continue to find a greater degree of asymmetric inventory investment in periods with current sales declines following sales increases than in periods with three consecutive sales declines (two-tailed p-value of the difference = 0.06). Consistent with our main prediction, these results suggest that the direction of prior sales changes influences managers' expectations of future demand and affects managers' short-term resource adjustment and utilization decisions, resulting in asymmetric inventory investment.

[Insert Table 4 here]

[16] Specifically, we estimate the following multi-period models using OLS following Banker et al. (2014a):

(1) Two-period interactive model: $\Delta INVENT_{it} = \beta_1(1/A_{it-1}) + \beta_2 SALES_{it} + \beta_3 \Delta SALES_{it-1} + \beta_4 DEC_{it-1} + \beta_5 DEC_{it-1} * \Delta SALES_{it-1} + \beta_6 INC_{it-1} * \Delta SALES_{it} + \beta_7 INC_{it-1} * DEC_{it} * \Delta SALES_{it} + \beta_8 DEC_{it-1} * \Delta SALES_{it} + \beta_9 DEC_{it-1} * DEC_{it} * \Delta SALES_{it} + \beta_{10} SIZE_{it} + \beta_{11} Q_{it} + \beta_{12} ASSETINT_{it} + \beta_{13} EMPINT_{it} + \beta_{14} RNOA_{it} + \beta_{15} OPLEV_{it} + \textit{Industry Fixed Effects} + \textit{Year Fixed Effects} + \varepsilon_{it}$

(2) Three-period interactive model: $\Delta INVENT_{it} = \beta_1(1/A_{it-1}) + \beta_2 SALES_{it} + \beta_3 \Delta SALES_{it-1} + \beta_4 DEC_{it-1} + \beta_5 DEC_{it-1} * \Delta SALES_{it-1} + \beta_6 INC_{it-2} * INC_{it-1} * \Delta SALES_{it} + \beta_7 INC_{it-2} * INC_{it-1} * DEC_{it} * \Delta SALES_{it} + \beta_8 DEC_{it-2} * INC_{it-1} * \Delta SALES_{it} + \beta_9 DEC_{it-2} * INC_{it-1} * DEC_{it} * \Delta SALES_{it} + \beta_{10} INC_{it-2} * DEC_{it-1} * \Delta SALES_{it} + \beta_{11} INC_{it-2} * DEC_{it-1} * DEC_{it} * \Delta SALES_{it} + \beta_{12} DEC_{it-2} * DEC_{it-1} * \Delta SALES_{it} + \beta_{13} DEC_{it-2} * DEC_{it-1} * DEC_{it} * \Delta SALES_{it} + \beta_{14} SIZE_{it} + \beta_{15} Q_{it} + \beta_{16} ASSETINT_{it} + \beta_{17} EMPINT_{it} + \beta_{18} RNOA_{it} + \beta_{19} OPLEV_{it} + \textit{Industry Fixed Effects} + \textit{Year Fixed Effects} + \varepsilon_{it}$

Stockout costs

Next, we examine an additional factor that could lead to asymmetric resource adjustment and capacity utilization decisions by managers, stockout costs. In Hypothesis 2b, we predict that firms whose stockout costs in competitive product markets are greater than inventory holding costs are more likely to use asymmetric inventory investment as an operational strategy. To test this, we adopt an empirical measure of stockout costs relative to inventory holding costs from Kesavan and Kushwaha (2014). We estimate the ratio of gross margin to the weighted cost of capital and create an indicator variable (*SCIC*) equal to 1 for observations with the ratio above the industry–year median, and 0 otherwise. The measure is expected to reflect managers' incentives to avoid stockouts and thus the need to maintain buffer stocks. In Table 4, column (1), we find that asymmetric inventory investment is significantly more pronounced for firms with higher relative stockout costs (p-value < 0.10). We also test whether demand uncertainty increases managers' incentives to hold buffer inventories when sales decline. We hypothesize that higher demand uncertainty should make managers more concerned about potential stockout costs, giving them an incentive to smooth production and accumulate inventories. This follows from prior studies suggesting that inventories are used to mitigate the effect of demand uncertainty on operations and that the association between sales volatility and inventories is significantly positive (Lovell 1961; Bo 2001; Caglayan et al. 2012). We use two proxies of demand uncertainty: Tobin's Q (*Q*) and volatility of sales growth (*SGVOL*). In Table 4, columns (2) and (3) show that asymmetric inventory investment significantly increases with *Q* (p-value < 0.05) and *SGVOL* (p-value < 0.10). These results are in line with our previous result on stockout costs and suggest that incentives to avoid stockouts and build buffer stocks also lead to asymmetric inventory investment.

Asymmetric inventory management and future sales growth

Association between inventory signals and future sales growth

Our evidence reported above suggests that firms' asymmetric inventory investments are positively associated with managers' expectations of future demand. If the managers' use of asymmetric inventory investment is an efficient decision based on the tradeoffs between the marginal benefits of inventories and the marginal costs of production in excess of current demand, asymmetric inventory investment should predict higher future sales growth. Specifically, we expect changes in inventory in periods with sales declines to be incrementally useful in predicting future sales growth after controlling for current sales growth and other determinants (Bernard and Noel 1991; Bernard and Stober 1989).

[Insert Table 5 here]

In Table 5, column (1), we find a significantly positive coefficient on $INVSIG_{it}$ (p-value < 0.01), consistent with Bernard and Noel (1991) and Bernard and Stober (1989). In addition, a positive and significant coefficient on the interaction term $DEC_{it}*INVSIG_{it}$ (p-value < 0.05) suggests that asymmetric inventory investment in periods with sales declines provides information that is incrementally useful in predicting future sales growth. In columns (2) and (3), we include lagged values of *INVSIG* up to year $t-2$ and allow for multiple years' asymmetric inventory investment to provide information about future sales growth. While we find that $INVSIG_{it-1}$ and $DEC_{it-1}*INVSIG_{it-1}$ provide useful information about future sales growth, the magnitudes and significance of the coefficients on $INVSIG_{it}$ and $DEC_{it}*INVSIG_{it}$ remain similar to those reported in column (1). Overall, these results suggest that managers' asymmetric inventory investment provides an incrementally useful signal for predicting future sales growth. This extends prior studies on the predictive ability of inventory disclosure. Next, we test whether managers and analysts incorporate the information content of asymmetric inventory investment in their forecasts of future sales.

[Insert Table 6 here]

Association between inventory signal and management sales guidance

First, we examine whether management sales guidance incorporates managers' expectations of future demand as reflected in their inventory decisions. We focus on management guidance of annual sales for year $t + 1$. The unit of analysis for this test is at the individual guidance level, following Koo and Lee (2018).

In Table 6, we find that $INVSIG_{it}$ has a significant incrementally positive relation with management sales guidance relative to current sales, $MFHIGHER_{it+1}$, in periods with sales declines (p-value < 0.05). This result is consistent with our prediction that managers who accumulate larger amounts of inventories in periods with sales declines issue higher sales guidance for the following year. Untabulated results by inventory components suggest that managers are providing higher sales guidance as they accumulate more finished goods inventories in periods with sales declines. We also find that $INVSIG_{it}$ has statistically insignificant association with either $MFERROR_{it+1}$ or $MFACCURACY_{it+1}$, consistent with $INVSIG_{it}$ being unrelated to the over-/under-estimation of future sales. Our results are unaffected when we use the first sales guidance issued during the year. These results suggest that management sales guidance incorporates the information content of asymmetric inventory management, consistent with our earlier results suggesting that asymmetric inventory investment is predictive of future sales growth.

[Insert Table 7 here]

Association between inventory signals and analyst sales forecasts

Next, we examine whether and to what extent analysts incorporate the information content of asymmetric inventory investment in their forecasts of future sales. In addition to $AFHIGHER_{it+1}$, $AFERROR_{it+1}$, and $AFACCURACY_{it+1}$, we also examine the association between $INVSIG_{it}$ and the dispersion in individual analyst forecasts, $AFDISPERSION_{it+1}$. In these tests, we control for lagged values of the dependent variables as well as the forecast dispersion.

In Table 7, we find that the coefficient on $DEC_{it}*INVSIG_{it}$ is significantly positive in the $AFHIGHER_{it+1}$ model (p-value < 0.10), consistent with analysts issuing more positive sales forecasts when the degree of asymmetric inventory investment is higher. This result is consistent with the previous results showing that asymmetric inventory investment provides information that is useful for predicting future sales growth. In the next column, we find that $INVSIG_{it}$ in periods with sales declines has a negative, but statistically insignificant relation with $AFERROR_{it+1}$. This could mean that when analysts predict future sales, they underreact to the information in inventory signals in periods with sales declines. Collectively, these results suggest that analysts' sales forecasts may partially incorporate the implications of asymmetric inventory management for future sales. In terms of the accuracy of analyst sales forecasts, we find a negative but statistically insignificant relation between $INVSIG_{it}$ and $AFACCURACY_{it+1}$ in periods with sales declines. Lastly, we find that $INVSIG_{it}$ is significantly positively associated with $AFDISPERSION_{it+1}$ in periods with sales declines (p-value < 0.01). This result is consistent with analysts facing heightened uncertainty in predicting future sales when managers build inventories in periods with sales declines.[17] Overall, our results suggest that while analysts reflect the information content of

[17] Untabulated results by inventory components suggest that the positive relation between analyst forecast dispersion and asymmetric inventory investment is primarily driven by the work-in-process and finished goods inventories.

asymmetric inventory investment in their sales forecasts to some extent, their individual forecasts exhibit a greater degree of disagreement with respect to asymmetric inventory investment.[18]

[Insert Table 8 here]

Sales forecasting models based on asymmetric inventory management

Our results to this point suggest that the information content of asymmetric inventory investment can be useful for forecasting future sales growth. Thus, we test whether forecasts of future sales growth based on a time-series model incorporating asymmetric inventory investment provide more accurate predictions of changes in future demand than forecasts based on other metrics. We follow the related prior literature and estimate forecasts of sales growth in year $t + 1$ using the past seven years of time-series data (Banker and Chen 2006; Fairfield et al. 1996; Curtis et al. 2014). We find that our results are robust to using either four or five years of data in the forecast estimation. Specifically, we estimate forecasts of future sales growth using the following time-series models that incorporate past time series of sales changes (*RW* Model), the direction of past sales changes (*BC* Model), and asymmetric inventory investment (*ASYINV* Model).

Random Walk *(RW)* Model:

$$\Delta SALES_{it+1} = \Delta SALES_{it}$$

Banker and Chen (2006) *(BC)* Model:

$$\Delta SALES_{it+1} = \Delta SALES_{it} + DEC_{it} + DEC_{it}{*}\Delta SALES_{it}$$

Asymmetric Inventory *(ASYINV)* Model:

$$\Delta SALES_{it+1} = \Delta SALES_{it} + DEC_{it} + DEC_{it}{*}\Delta SALES_{it} + \Delta INVENT_{it} + DEC_{it}{*}\Delta INVENT_{it}$$

where $\Delta SALES_{it}$ denotes sales change scaled by lagged total assets, $\Delta INVENT_{it}$ denotes change in inventory scaled by lagged total assets, and DEC_{it} is an indicator of a sales decline. We

[18] Prior studies suggest that analysts' forecasts tend to be more accurate for firms with management guidance (Hutton et al. 2012). When we split our sample based on the presence of management guidance, we find that, in the firms that do not provide management guidance, the relation between the dispersion in analyst sales forecasts and the inventory signal (*INVSIG*) in periods with sales declines is significantly more pronounced. Other attributes of analysts' forecasts do not appear to be affected.

also compare the accuracy of these forecasts with those based on analysts' consensus sales forecasts (*AF*) and management sales guidance (*MF*). We compare the accuracy of these forecasts in terms of the absolute forecast errors (AFE), defined as the absolute value of the difference between realized future sales growth and the sales forecasts. The results are reported in Table 8. In Panel A, we find that the *RW* model is associated with median (mean) AFE of 0.08 (0.128). When we incorporate the direction of sales changes following Banker and Chen (2006), we find that the *BC* model is associated with a median (mean) AFE of 0.054 (0.098), which is lower than that of the *RW* model. Incorporating both asymmetric sales changes and asymmetric inventory investment, the *ASYINV* model is associated with a median (mean) AFE of 0.024 (0.064), which is lower than that of either the *RW* or the *BC* models. Furthermore, AFE of the *ASYINV* model is lower than that of *AF* or *MF*. These results suggest the usefulness of incorporating asymmetric inventory adjustments in sales forecasts. In Panel B, we formally test pairwise differences in AFE between these models, and find that the sales forecasts from the *ASYINV* model, *AF*, and *MF* generally outperform the forecasts from the *RW* and *BC* models (p-value < 0.01). Furthermore, we find that the sales forecasts from the *ASYINV* model result in a lower AFE, compared to *AF* and *MF* (p-value < 0.01). Overall, the results in Table 8 suggest that incorporating asymmetric inventory investment in time-series models provides incrementally useful information for forecasting future sales growth.

[Insert Table 9 here]

Additional tests

Financial constraints

Studies in financial economics suggest that inventory investment is significantly affected by firms' financial constraints (Carpenter et al. 1994; Dasgupta et al. 2018; Kashyap et al. 1994). The classic inventory literature (e.g., Graves et al. 2004) treats inventory decisions as independent of financing decisions, consistent with the Modigliani and Miller (1958) world in which a firm's operational and financing decisions can be made independently with a perfect capital market. Accordingly, inventories will be funded via a production–sales process and thus do not require external financing. A recent paper by Yang and Birge (2018) suggests that trade credit is the only external source of financing that retailers use to finance inventories. In contrast, other studies consider inventory management in the presence of budgetary constraints (e.g., Hadley and Whitin 1963; Sherbrooke 1968). Some of the recent studies in this area suggest that a firm's optimal inventory and financing decisions are simultaneously determined (e.g., Archibald et al. 2002; Buzacott and Zhang 2004; Xu and Birge 2006). To the extent that inventory investment in general requires external financing and a decline in demand increases the cost of external financing, we predict that asymmetric inventory investment should be negatively related to financing constraints.

In Table 9, we examine whether financial constraints affect firms' abilities to engage in asymmetric inventory investment. We use five general measures of firms' abilities to fund working capital in the form of inventory: the Kaplan–Zingales Index (*KZINDEX*), Altman's Z-score (*ZINDEX*; multiplied by −1 so that a higher value indicates financial distress), book leverage (*LEV*), cash holdings (*CASH*), and return on assets (*ROA*). In columns (1) to (3), we find that the degree of asymmetric inventory investment is a significantly decreasing function of *KZINDEX*, *ZINDEX*, and *LEV*, consistent with financial constraints limiting firms' abilities to maintain production levels and inventory. In columns (4) and (5), on the other hand, the results suggest that firms with more ample internal liquidity and higher profitability exhibit a higher degree of asymmetric inventory investment.

These results are generally consistent with prior literature documenting the negative impact of financial constraints on firms' inventory investments and suggest that financial constraints affect the degree of asymmetric inventory investment. In addition, our evidence is in line with that of Dasgupta et al. (2018) who suggest that to avoid costly adjustments in fixed capital, financially unconstrained firms are willing to hold more inventory in response to adverse shocks to demand.

Additional cross-sectional tests

A caveat in using sales change as a proxy for change in activity level is that sales are a product of sales volume and sales price, both of which are generally unobservable to empiricists. As the management literature argues, managers can lower selling prices to maintain customer relationships and sales volume when overall demand declines (Ardalan 1994). If firms respond to a decline in demand by strategically lowering sales prices to maintain sales volume, we expect asymmetric inventory investment to be more pronounced. For example, Cannon (2014) shows that managers respond to declining demand by adjusting selling prices downward so that sales volume matches their existing capacity, rather than by leaving capacity idle. Given the lack of data on sales prices in our study, we use change in gross margin as a proxy for adjustments in sales prices. In untabulated tests, we find that the degree of asymmetric inventory investment is not associated with changes in gross margin, providing no support for the idea that managers strategically lower sales prices to preserve sales volume when demand declines.

In addition, we examine whether asymmetric inventory investment is an aspect of efficient inventory management. Our results above suggest that asymmetric inventory investment is a forward-looking resource adjustment and utilization decision that reflects managerial expectations of future demand and competitive forces in the product market. Thus, we test whether firms that efficiently deploy their productive resources are more likely to make asymmetric inventory investment in response to a decline in sales. The tension here is that the minimization of buffer stocks and holding costs is also an aspect of efficient inventory management. From Demerjian et al. (2012), we obtain a measure of firm efficiency based on the use of corporate resources in generating sales.[19] The results of untabulated tests suggest that asymmetric inventory investment is an increasing function of the firm efficiency score. We interpret this evidence as suggesting that, while the minimization of inventory holdings is an efficient strategy in general terms, asymmetric inventory investment in consideration of expected future demand and product market competition can also be viewed as efficient operating decisions.

Next, while asymmetric inventory investment may primarily reflect managers' expectations of future demand, it may also be subject to managers' financial reporting incentives. It is important to understand managers' rent-seeking behavior in production decisions because prior studies suggest that managers adjust production levels to meet earnings targets (Roychowdhury 2006). Following Roychowdhury (2006), we identify firms overproducing just to avoid reporting losses, based on whether net income scaled by total assets is greater than or equal to zero but less than 0.005 (i.e., small profit firms). We find no evidence of asymmetric inventory investment being more pronounced in such firms. The finding implies that the financial reporting incentives to overproduce play a limited role, if any, in the degree of asymmetric inventory investment.

Lastly, we suggest in the previous sections that stockout avoidance and demand uncertainty are important determinants of asymmetric inventory investment. We suspect that these factors are more salient for firms in the early stages of their life cycle, since incentives to avoid stockouts in competitive product markets are greater for these firms (Blazenko and Vandezande 2003). Dickinson (2011) uses cash flow patterns to classify firms into different stages of the life cycle.

[19] We thank the authors for making the data available.

We identify firms in the early stages of their life cycle as those falling in the introduction or growth stages of the Dickinson (2011) classification. In untabulated tests, we find that these firms in the early stages of life cycle exhibit a greater degree of asymmetric inventory investment than firms in the mature, shake-out, or declining stages of their life cycle. These findings are consistent with our results using relative stockout costs and demand uncertainty.

5. Conclusion

We explore whether managers respond asymmetrically to sales increases versus decreases when determining inventory production. Using a large sample of manufacturing firms, we find that managers make asymmetric inventory investment in response to sales changes, with inventory investment falling less for a sales decrease than rising for an equivalent amount of sales increase. Consistent with our hypotheses that managers' expectations of future demand and inventory stockouts are key determinants of the asymmetry, we find that asymmetric inventory investment increases with positive leading indicators of future demand and empirical proxies of inventory stockout costs. In our last set of analyses, we show that asymmetric inventory investment provides incrementally useful information for predicting future sales growth, and that both management sales guidance and analyst sales forecasts reflect asymmetric inventory investment to some extent. We find that forecasts of future sales growth based on a time-series model incorporating asymmetric inventory investment are associated with lower absolute forecast errors than benchmark forecasts.

In this paper, we highlight the information that inventory disclosure provides about managers' expectations of future business prospects and provide evidence on the incremental usefulness of asymmetric inventory investment in predicting future sales. In so doing, we combine related literature in operations management and accounting. Despite the importance of production and inventory decisions in the operations management literature, recent accounting research has rarely examined inventory behavior. The accounting literature on cost stickiness provides useful references by emphasizing the importance of incorporating the direction of changes in activity volumes in understanding managers' resource adjustment and utilization decisions based on economic optimization. Relying on this literature, we provide a large-sample evidence on asymmetric inventory investment, its determinants, and its implications for forecasting future demand. We stress that inventory disclosure reflects managers' expectations of business prospect and solicit future research on fundamental analysis that incorporates asymmetric inventory management.

We acknowledge that the implications of our findings are concentrated in the manufacturing industry where inventories are of strategic importance. Note that, in our analyses, we do not explicitly consider the potentially disruptive impact of innovative inventory management techniques (e.g., just-in-time, lean manufacturing, automation) that an emerging line of research focuses on (Acemoglu and Restrepo 2018; Bates et al. 2020). We call for future research on the implications of technological development for analysis of accounting information.

Appendix
Variable definitions

Variable		**Definition (COMPUSTAT variables where available)**
Main variables		
ΔINVENT	=	Change in total inventories divided by lagged total assets (ΔINVT/lagged AT).
1/A	=	Inverse of total assets (SALE).
SALES	=	Sales divided by lagged total assets (SALE/lagged AT).
ΔSALES		Change in sales divided by lagged total assets (ΔSALE/lagged AT).
DEC	=	An indicator variable indicates a sales decline.
SIZE	=	Natural logarithm of the market value of equity (PRCC_F*CSHO).
Q	=	Tobin's Q ([(PRCC_F*CSHO)+PSTK+DLTT+DLC]/AT).
ASSETINT	=	Asset intensity measured as net PPE divided by sales (PPENT/SALE).
EMPINT	=	Employment intensity measured as the number of employees divided by sales ([EMP*1000]/SALE).
RNOA	=	Return on net operating assets (Nissim and Penman 2001). Measured as operating income divided by lagged net operating assets.
OPLEV	=	Operating leverage (Nissim and Penman 2001). Measured as operating liabilities divided by net operating assets.
Cross-sectional determinants		
ΔOB	=	Percentage growth in order backlog (OB).
OUTLOOK	=	Annual mean response of CFOs in rating optimism about the future financial prospects of their firms from Duke CFO Global Business Outlook surveys.
SCIC	=	An indicator variable equals to one if gross margin of firm *i* in year *t* divided by the weighted average of cost of capital (sum of debt and equity costs) is higher than the industry-median value in a 2-digit SIC industry, and zero otherwise (Kesavan and Kushwaha 2014).
SGVOL	=	Standard deviation of sales growth for the last 5 years.
KZINDEX	=	Kaplan-Zingales financial constraint index initially measured as ([IB+DP]/PPENT) + 0.28**Q* + 3.13*([DLC+DLTT]/(DLC + DLTT + CEQ) – 39.36*(DVC/PPENT) – 1.31*(CHE/PPENT) and multiplied by –1 to make the measure increasing in financial constraints (Lamont et al. 2001).
ZINDEX	=	Altman's Z-score measured as 1.2*(Working Capital/Total Assets) + 1.4*(Retained Earnings/Total Assets) + 3.3*(Operating Income/Total Assets) + 0.6*(Market Value of Equity/Total Liabilities) + 1.0*(Sales/Total Assets) and multiplied by −1 to make the measure increasing in financial distress (Altman 1968; Zang 2012).
LEV	=	Sum of long-term debt and short-term debt divided by total assets ([DLC+DLTT]/AT).
CASH	=	Cash holdings scaled by total assets (CHE/AT).
ROA	=	Income before extraordinary items scaled by lagged total assets (IB/lagged AT).
Variables for future sales growth, management guidance and analyst forecast tests		
INVSIG	=	Difference between the ratio of total inventories to lagged total inventories and the ratio of sales to lagged sales in year t (INVT/lagged INVT – SALE/lagged SALE).
LNAGE	=	The natural logarithm of firm age in Compustat.
MFHIGHER	=	Difference between management sales guidance for year t+1 and actual sales in year t, divided by market value of equity at the beginning of year t.
MFERROR	=	Difference between management sales guidance for year t+1 and actual sales in year t+1, divided by market value of equity at the beginning of year t.
MFACCURACY	=	Absolute value of the difference between management sales guidance for year t+1 and actual sales in year t+1, divided by market value of equity at the beginning of year t.
MFHORIZON	=	The natural logarithm of 1 plus the number of days between the date of management sales guidance issuance and the date of fiscal year-end.

AFHIGHER	=	Difference between consensus sales forecast for year t+1 and actual sales in year t, divided by market value of equity at the beginning of year t. Consensus sales forecast is computed as the mean forecast value using individual analysts' first forecasts in the first 180 days following the earning announcement date for year t.
AFERROR	=	Difference between consensus sales forecast for year t+1 and actual sales in year t+1, divided by market value of equity at the beginning of year t.
AFACCURACY	=	Absolute value of the difference between consensus sales forecast for year t+1 and actual sales in year t+1, divided by market value of equity at the beginning of year t.
AFDISPERSION	=	Standard deviation of individual analyst sales forecasts for year t+1 divided by consensus sales forecast.
STDREV	=	Standard deviation of quarterly sales scaled by assets in last 12 quarters in year t.
STDRET	=	Standard deviation of monthly stock returns in the last 12 months in year t.
BHAR	=	Buy-and-hold abnormal return (stock return minus value-weighted market return) in year t.
RDINT	=	R&D intensity measured as R&D expenditures scaled by assets as of the end of year t–1 (XRD/AT; missing XRD coded as zero).
ADINT	=	Advertising intensity (i.e., advertising expenditures scaled by assets) as of the end of year t–1 (XAD/AT).
RRCORR	=	The Spearman correlation of quarterly stock returns and seasonal revenue changes, scaled by the market value at the beginning of the quarter, in the 20 quarters before year t.
LOSS	=	An indicator variable equals to 1 if income before extraordinary items is negative in year t, and 0 otherwise.
ANALYSTS	=	The natural logarithm of 1 plus the number of analysts issuing annual sales forecasts during year t.
AFHORIZON	=	The natural logarithm of 1 plus the number of days between the date of analyst sales forecast issuance and the date of fiscal year-end.
GUIDANCE	=	An indicator variable indicates the presence of management sales guidance, and 0 otherwise.

References

Abarbanell, J. S., and B. J. Bushee. 1997. Fundamental analysis, future earnings, and stock prices. *Journal of Accounting Research* 35 (1):1-24.

Abarbanell, J. S., and B. J. Bushee. 1998. Abnormal returns to a fundamental analysis strategy. *The Accounting Review* 73 (1):19-45.

Abel, A. B. 1985. Inventories, stock-outs and production smoothing. *The Review of Economic Studies* 52 (2):283-93.

Acemoglu, D., and P. Restrepo. 2018. The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review* 108 (6):1488-1542.

Ak, B. K., and P. N. Patatoukas. 2016. Customer-base concentration and inventory efficiencies: Evidence from the manufacturing sector. *Production and Operations Management* 25 (2):258-72.

Alan, Y., G. P. Gao, and V. Gaur. 2014. Does inventory productivity predict future stock returns? A retailing industry perspective. *Management Science* 60 (10):2416-34.

Anderson, M. C., R. D. Banker, R. Huang, and S. N. Janakiraman. 2007. Cost behavior and fundamental analysis of SG&A costs. *Journal of Accounting, Auditing & Finance* 22 (1):1-28.

Anderson, M. C., R. D. Banker, and S. N. Janakiraman. 2003. Are selling, general, and administrative costs "sticky"? *Journal of Accounting Research* 41 (1):47-63.

Archibald, T. W., L. C. Thomas, J. M. Betts, and R. B. Johnston. 2002. Should start-up companies be cautious? Inventory policies which maximise survival probabilities. *Management Science* 48 (9):1161-74.

Ardalan, A. 1994. Optimal prices and order quantities when temporary price discounts result in increase in demand. *European Journal of Operational Research* 72 (1):52-61.

Balakrishnan, R., M. J. Petersen, and N. S. Soderstrom. 2004. Does capacity utilization affect the "stickiness" of cost? *Journal of Accounting, Auditing & Finance* 19 (3):283-300.

Banker, R. D., S. Basu, D. Byzalov, and J. Chen. 2016. The confounding effect of cost stickiness on conservatism estimates. *Journal of Accounting and Economics* 61 (1):203-20.

Banker, R. D., and D. Byzalov. 2014. Asymmetric cost behavior. *Journal of Management Accounting Research* 26 (2):43-79.

Banker, R. D., D. Byzalov, and L. Chen. 2013. Employment protection legislation, adjustment costs and cross-country differences in cost behavior. *Journal of Accounting and Economics* 55 (1):111-27.

Banker, R. D., D. Byzalov, M. Ciftci, and R. Mashruwala. 2014a. The moderating effect of prior sales changes on asymmetric cost behavior. *Journal of Management Accounting Research* 26 (2):221-42.

Banker, R. D., D. Byzalov, and J. M. Plehn-Dujowich. 2014b. Demand uncertainty and cost behavior. *The Accounting Review* 89 (3):839-65.

Banker, R. D., and L. Chen. 2006. Predicting earnings using a model based on cost variability and cost stickiness. *The Accounting Review* 81 (2):285-307.

Banker, R. D., I. Hwang, and H. Oh. 2015. Manufacturing capacity utilization and SG&A costs behavior. Working paper, Temple University and Seoul National University.

Bates, T. W., F. Du, and J. J. Wang. 2020. *Workplace Automation and Corporate Financial Policy*. Working paper, Arizona State University and California State University – Fullerton.

Bernard, V. L., and J. Noel. 1991. Do inventory disclosures predict sales and earnings? *Journal of Accounting, Auditing & Finance* 6 (2):145-81.

Bernard, V. L., and T. L. Stober. 1989. The nature and amount of information in cash flows and accruals. *The Accounting Review* 64 (4):624-52.

Blanchard, O. J. 1983. The production and inventory behavior of the American automobile industry. *Journal of Political Economy* 91 (3):365-400.

Blazenko, G. W., and K. Vandezande. 2003. Corporate holding of finished goods inventories. *Journal of Economics and Business* 55 (3):255-66.

Blinder, A. S. 1981. Retail inventory behavior and business fluctuations. *Brookings Papers on Economic Activity* 2:443–505.

Bo, H. 2001. Volatility of sales, expectation errors, and inventory investment: Firm level evidence. *International Journal of Production Economics* 72 (3):273-83.

Buzacott, J. A., and R. Q. Zhang. 2004. Inventory management with asset-based financing. *Management Science* 50 (9):1274-92.

Caglayan, M., S. Maioli, and S. Mateut. 2012. Inventories, sales uncertainty, and financial strength. *Journal of Banking & Finance* 36 (9):2512-21.

Cannon, J. N. 2014. Determinants of "sticky costs": An analysis of cost behavior using United States air transportation industry data. *The Accounting Review* 89 (5):1645-72.

Carpenter, R. E., S. M. Fazzari, and B. C. Petersen. 1994. Inventory investment, internal-finance fluctuations, and the business cycle. *Brookings Papers on Economic Activity* 2:75-138.

Chen, H., M. Z. Frank, and O. Q. Wu. 2005. What actually happened to the inventories of American companies between 1981 and 2000? *Management Science* 51 (7):1015-31.

Chen, J. V., I. Kama, and R. Lehavy. 2019. A contextual analysis of the impact of managerial expectations on asymmetric cost behavior. *Review of Accounting Studies* 24 (2):665-93.

Chen, C. X., H. Lu, and T. Sougiannis. 2012. The agency problem, corporate governance, and the asymmetrical behavior of selling, general, and administrative costs. *Contemporary Accounting Research* 29 (1):252-82.

Corsten, D., and T. W. Gruen. 2004. Stock-outs cause walkouts. *Harvard Business Review* 82 (5):26-8.

Curtis, A. B., R. J. Lundholm, and S. E. McVay. 2014. Forecasting sales: A model and some evidence from the retail industry. *Contemporary Accounting Research* 31 (2):581-608.

Dasgupta, S., E. X. N. Li, and D. Yan. 2018. Inventory behavior and financial constraints: Theory and evidence. *The Review of Financial Studies* 32 (3):1188-233.

Dechow, P. M., S. P. Kothari, and R. L. Watts. 1998. The relation between earnings and cash flows. *Journal of Accounting and Economics* 25 (2):133-68.

Demerjian, P. R., B. Lev, and S. McVay. 2012. Quantifying managerial ability: A new measure and validity tests. *Management Science* 58 (7):1229-48.

Dickinson, V. 2011. Cash flow patterns as a proxy for firm life cycle. *The Accounting Review* 86 (6):1969-94.

Dierynck, B., W. R. Landsman, and A. Renders. 2012. Do managerial incentives drive cost behavior? Evidence about the role of the zero earnings benchmark for labor cost behavior in private Belgian firms. *The Accounting Review* 87 (4):1219-46.

Fairfield, P. M., R. J. Sweeney, and T. L. Yohn. 1996. Accounting classification and the predictive content of earnings. *The Accounting Review* 71 (3):337-55.

Feng, M., C. Li, S. McVay, and H. Skaife. 2015. Does ineffective internal control over financial reporting affect a firm's operations? Evidence from firms' inventory management. *The Accounting Review* 90 (2):529-57.

Gaur, V., M. L. Fisher, and A. Raman. 2005. An econometric analysis of inventory turnover performance in retail services. *Management Science* 51 (2):181-94.

Graves, S. C., A. H. G. Rinnooy Kan, and P. H. Zipkin. 2004. *Handbooks in operations research and management science, 3rd reprint*. *Vol. 4: Logistics of production and inventory*. North-Holland: Elsevier.

Guariglia, A., and S. Mateut. 2006. Credit channel, trade credit channel, and inventory investment: Evidence from a panel of UK firms. *Journal of Banking & Finance* 30 (10):2835-56.

Gunny, K. A. 2010. The relation between earnings management using real activities manipulation and future performance: Evidence from meeting earnings benchmarks. *Contemporary Accounting Research* 27 (3):855-88.

Hadley, G., and T. M. Whitin. 1963. *Analysis of inventory systems*. Englewood Cliffs, NJ: Prentice-Hall

Holzhacker, M, R. Krishnan, and M. D. Mahlendorf. 2015. Unraveling the black box of cost behavior: an empirical investigation of risk drivers, managerial resource procurement, and cost elasticity. *The Accounting Review* 90 (6):2305-35.

Hurley, S. F., and D. C. Whybark. 1999. Inventory and capacity trade-offs in a manufacturing cell. *International Journal of Production Economics* 59 (1–3):203-12.

Hutton, A. P., L. F. Lee, and S. Z. Shu. 2012. Do managers always know better? The relative accuracy of management and analyst forecasts. *Journal of Accounting Research* 50 (5): 1217-44.

Kashyap, A. K., O. A. Lamont, and J. C. Stein. 1994. Credit conditions and the cyclical behavior of inventories. *The Quarterly Journal of Economics* 109 (3):565-92.

Kesavan, S., V. Gaur, and A. Raman. 2010. Do inventory and gross margin data improve sales forecasts for U.S. public retailers? *Management Science* 56 (9):1519-33.

Kesavan, S., and T. Kushwaha. 2014. Differences in retail inventory investment behavior during macroeconomic shocks: Role of service level. *Production and Operations Management* 23 (12):2118-36.

Koo, D. S., and D. Lee. 2018. Influential chief marketing officers and management revenue forecasts. *The Accounting Review* 93 (4):253-81.

Lev, B., and S. R. Thiagarajan. 1993. Fundamental information analysis. *Journal of Accounting Research* 31 (2):190-215.

Lieberman, M. B., and L. Demeester. 1999. Inventory reduction and productivity growth: Linkages in the Japanese automotive industry. *Management Science* 45 (4):466-85.

Lieberman, M. B., S. Helper, and L. Demeester. 1999. The empirical determinants of inventory levels in high-volume manufacturing. *Production and Operations Management* 8 (1):44-55.

Lovell, M. 1961. Manufacturers' inventories, sales expectations, and the acceleration principle. *Econometrica* 29 (3):293-314.

Metzler, L. A. 1941. The nature and stability of inventory cycles. *The Review of Economics and Statistics* 23 (3):113-29.

Modigliani, F., and M. H. Miller. 1958. The cost of capital, corporation finance and the theory of investment. *American Economic Review* 48 (3):261-97.

Nissim, D., and S. H. Penman. 2001. Ratio analysis and equity valuation: From research to practice. *Review of Accounting Studies* 6 (1):109-54.

Petersen, M. A. 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies* 22 (1):435-80.

Pindyck, R. S. 1982. Adjustment costs, uncertainty, and the behavior of the firm. *The American Economic Review* 72 (3):415-27.

Roychowdhury, S. 2006. Earnings management through real activities manipulation. *Journal of Accounting and Economics* 42 (3):335-70.

Rumyantsev, S., and S. Netessine. 2007. What can be learned from classical inventory models? A cross-industry exploratory investigation. *Manufacturing & Service Operations Management* 9 (4):409-29.

Sherbrooke, C. C. 1968. METRIC: A multi-echelon technique for recoverable item control. *Operations Research* 16 (1):122-41.

Xu, X., and J. R. Birge. 2006. Equity valuation, production, and financial planning: A stochastic programming approach. *Naval Research Logistics* 53 (7):641-55.

Yang, S. A., and J. R. Birge. 2018. Trade credit, risk sharing, and inventory financing portfolios. *Management Science* 64 (8):3667-89.

Zang, A. Y. 2011. Evidence on the trade-off between real activities manipulation and accrual-based earnings management. *The Accounting Review* 87 (2):675-703.

TABLE 1
Descriptive statistics

Variable	N	Mean	Std	1P	25P	Median	75P	99P
Main variables								
$\Delta INVENT_{it}$	27,632	0.013	0.056	-0.141	-0.009	0.006	0.028	0.270
$1/A_{it}$	27,632	0.025	0.061	0.000	0.001	0.004	0.018	0.409
$SALES_{it}$	27,632	1.082	0.646	0.053	0.644	0.957	1.383	3.531
$\Delta SALES_{it-1}$	27,632	0.052	0.242	-0.860	-0.036	0.051	0.153	0.857
$\Delta SALES_{it}$	27,632	0.084	0.268	-0.652	-0.035	0.053	0.169	1.249
DEC_{it-1}	27,632	0.336	0.472	0.000	0.000	0.000	1.000	1.000
DEC_{it}	27,632	0.335	0.472	0.000	0.000	0.000	1.000	1.000
$SIZE_{it}$	27,632	5.859	2.430	0.643	4.082	5.822	7.473	11.659
Q_{it}	27,632	1.723	1.535	0.260	0.818	1.228	2.006	9.214
$ASSETINT_{it}$	27,632	0.303	0.426	0.007	0.093	0.178	0.334	2.963
$EMPINT_{it}$	27,632	5.466	6.318	0.344	2.513	3.896	5.897	46.433
$RNOA_{it}$	27,632	-0.026	1.677	-9.583	-0.072	0.080	0.193	8.722
$OPLEV_{it}$	27,632	0.603	1.349	-6.085	0.269	0.441	0.747	7.793
Variables in cross-sectional tests								
ΔOB_{it}	8,134	0.193	0.715	-0.806	-0.146	0.053	0.308	4.333
$OUTLOOK_{it}$	24,214	66.647	3.707	58.55	64.475	66.575	70.258	71.046
$SCIC_{it}$	16,804	0.486	0.500	0.000	0.000	0.000	1.000	1.000
$SGVOL_{it}$	24,618	0.369	0.491	0.027	0.126	0.226	0.407	3.549
$KZINDEX_{it}$	27,005	-9.114	27.221	-201.216	-7.212	-1.798	0.457	16.578
$ZINDEX_{it}$	26,932	-4.445	6.922	-37.189	-5.699	-3.260	-1.867	18.861
LEV_{it}	27,632	0.180	0.175	0.000	0.007	0.146	0.292	0.713
$CASH_{it}$	27,632	0.215	0.210	0.000	0.049	0.145	0.322	0.852
ROA_{it}	27,608	0.052	0.271	-1.399	0.017	0.106	0.172	0.571
Variables in management guidance and analyst forecasts tests								
$MFHIGHER_{it+1}$	14,532	0.066	0.158	-0.528	0.014	0.042	0.099	0.767
$MFERROR_{it+1}$	14,532	0.009	0.103	-0.331	-0.019	-0.001	0.018	0.554
$MFACCURACY_{it+1}$	14,532	-0.055	0.104	-0.694	-0.055	-0.019	-0.006	0.000
$AFHIGHER_{it+1}$	12,951	0.046	0.188	-0.916	0.010	0.041	0.092	0.746
$AFERROR_{it+1}$	12,951	0.015	0.148	-0.525	-0.026	0.002	0.040	0.731
$AFACCURACY_{it+1}$	12,951	-0.085	0.151	-1.001	-0.087	-0.033	-0.011	0.000
$AFDISPERSION_{it+1}$	12,533	0.046	0.058	0.003	0.014	0.026	0.051	0.354

Notes: This table present the descriptive statistics of variables used in analyses. The Appendix provides detailed definitions of variables.

TABLE 2
Asymmetric inventory investment and direction of sales changes

Indep. Variable =	Pred. Sign	Dep. Variable = $\Delta INVENT_{it}$ (1)	(2)
$1/A_{it-1}$		0.027*	0.026*
		(2.00)	(1.92)
$SALES_{it}$	(+)	0.010***	0.008***
		(7.07)	(5.94)
$\Delta SALES_{it-1}$	(+)	0.013***	0.009**
		(7.81)	(2.74)
DEC_{it-1}			-0.003**
			(-2.66)
$DEC_{it-1}*\Delta SALES_{it-1}$			0.000
			(0.07)
$\Delta SALES_{it}$	**(+)**	**0.087*** **	**0.098*** **
		(29.07)	**(25.17)**
DEC_{it}			-0.001
			(-1.34)
$DEC_{it}*\Delta SALES_{it}$	**(−)**		**-0.037*** **
			(-6.63)
$SIZE_{it}$		0.001***	0.002***
		(4.88)	(5.19)
Q_{it}		-0.000	-0.001
		(-1.01)	(-1.58)
$ASSETINT_{it}$		0.006***	0.006***
		(4.28)	(4.27)
$EMPINT_{it}$		0.001***	0.001***
		(6.14)	(6.48)
$RNOA_{it}$		-0.000	-0.000
		(-0.79)	(-0.67)
$OPLEV_{it}$		-0.000	-0.000
		(-1.25)	(-1.32)
Industry Fixed Effects		Yes	Yes
Year Fixed Effects		Yes	Yes
Observations		27,632	27,632
Adjusted R-squared		0.270	0.272

Notes: This table reports the results of estimating model (1) using the OLS. Detailed variable definitions are provided in the Appendix. Industry fixed effects are based on 3-digit SIC codes. Reported in parentheses are t-statistics based on standard errors adjusted for clustering by firm and year. Bolded variables represent our predictions. ***, ** and * denote significance at 1 percent, 5 percent, and 10 percent, respectively, using two-tailed t-tests.

TABLE 3
Cross-sectional tests: Managers' expectations of future demand

Panel A: Expectations of future demand

		Dep. Variable = $\Delta INVENT_{it}$		
	Pred.	*EXPECTATION*		
Indep. Variable =	Sign	ΔOB_{it}	$OUTLOOK_{it}$	$\Delta SALES_{it+1}$
		(1)	(2)	(3)
$1/A_{it-1}$		0.012	0.029*	0.036**
		(0.83)	(1.88)	(2.74)
$SALES_{it}$	(+)	0.011***	0.007***	0.007***
		(4.94)	(5.29)	(5.67)
$\Delta SALES_{it-1}$	(+)	0.015**	0.010**	0.008***
		(2.59)	(2.30)	(2.96)
DEC_{it-1}		0.000	-0.003**	-0.002**
		(0.34)	(-2.60)	(-2.28)
$DEC_{it-1}*\Delta SALES_{it-1}$		-0.000	-0.003	0.004
		(-0.02)	(-0.41)	(0.82)
$\Delta SALES_{it}$	**(+)**	0.067***	-0.033	0.079***
		(4.55)	(-0.77)	(11.16)
DEC_{it}		0.002	-0.001	-0.001
		(1.02)	(-1.21)	(-0.72)
$DEC_{it}*\Delta SALES_{it}$	**(−)**	**0.017**	**0.109**	**-0.000**
		(0.98)	**(1.61)**	**(-0.02)**
EXPECTATION		0.019***	-0.000	0.015***
		(8.74)	(-0.04)	(9.57)
$EXPECTATION*\Delta SALES_{it}$		0.046***	0.002***	0.029***
		(3.14)	(3.12)	(3.20)
$EXPECTATION*DEC_{it}*\Delta SALES_{it}$	**(−)**	**-0.074****	**-0.002***	**-0.070*****
		(-2.75)	**(-2.06)**	**(-3.82)**
$SIZE_{it}$		0.001**	0.001***	0.001***
		(2.21)	(5.12)	(4.40)
Q_{it}		0.001	-0.001*	-0.001***
		(1.64)	(-1.77)	(-3.52)
$ASSETINT_{it}$		0.009**	0.005***	0.006***
		(2.91)	(4.07)	(4.31)
$EMPINT_{it}$		0.000	0.001***	0.000***
		(1.68)	(6.90)	(5.20)
$RNOA_{it}$		0.001	-0.000	-0.000
		(0.99)	(-1.02)	(-1.03)
$OPLEV_{it}$		-0.002**	-0.000	-0.000
		(-2.77)	(-1.26)	(-0.67)
Industry Fixed Effects		Yes	Yes	Yes
Year Fixed Effects		Yes	Yes	Yes
Observations		8,134	24,214	24,914
Adjusted R-squared		0.313	0.269	0.297

Panel B: Multi-period models using path of prior sales changes

		Dep. Variable = $\Delta INVENT_{it}$	
Indep. Variable =	Pred. Sign	*Two-period*	*Three-period*
		(1)	(2)
$1/A_{it-1}$		0.025*	0.027*
		(1.92)	(2.06)
$SALES_{it}$	(+)	0.009***	0.009***
		(5.95)	(6.07)

$\Delta SALES_{it-1}$	(+)	0.008**	0.009***
		(2.82)	(3.09)
DEC_{it-1}		-0.002*	-0.002*
		(-1.88)	(-2.02)
$DEC_{it-1}*\Delta SALES_{it-1}$		-0.000	-0.001
		(-0.05)	(-0.20)
$INC_{it-1}*\Delta SALES_{it}$	(+)	0.097***	
		(30.20)	
$\boldsymbol{INC_{it-1}*DEC_{it}*\Delta SALES_{it}}$	**(−)**	**-0.031*** **	
		(-5.65)	
$DEC_{it-1}*\Delta SALES_{it}$	(+)	0.096***	
		(14.13)	
$\boldsymbol{DEC_{it-1}*DEC_{it}*\Delta SALES_{it}}$	**(−)**	**-0.016** **	
		(-2.43)	
$INC_{it-2}*INC_{it-1}*\Delta SALES_{it}$	(+)		0.098***
			(28.31)
$\boldsymbol{INC_{it-2}*INC_{it-1}*DEC_{it}*\Delta SALES_{it}}$	**(−)**		**-0.035*** **
			(-5.16)
$DEC_{it-2}*INC_{it-1}*\Delta SALES_{it}$	(+)		0.087***
			(13.48)
$\boldsymbol{DEC_{it-2}*INC_{it-1}*DEC_{it}*\Delta SALES_{it}}$	**(−)**		**-0.013***
			(-1.79)
$INC_{it-2}*DEC_{it-1}*\Delta SALES_{it}$	(+)		0.097***
			(11.77)
$\boldsymbol{INC_{it-2}*DEC_{it-1}*DEC_{it}*\Delta SALES_{it}}$	**(−)**		**-0.019** **
			(-2.87)
$DEC_{it-2}*DEC_{it-1}*\Delta SALES_{it}$	(+)		0.093***
			(14.89)
$\boldsymbol{DEC_{it-2}*DEC_{it-1}*DEC_{it}*\Delta SALES_{it}}$	**(−)**		**-0.012**
			(-1.34)
$SIZE_{it}$		0.002***	0.001***
		(5.02)	(5.07)
Q_{it}		-0.001	-0.000
		(-1.44)	(-1.38)
$ASSETINT_{it}$		0.006***	0.006***
		(4.26)	(4.26)
$EMPINT_{it}$		0.001***	0.001***
		(6.39)	(6.35)
$RNOA_{it}$		-0.000	-0.000
		(-0.71)	(-0.60)
$OPLEV_{it}$		-0.000	-0.000
		(-1.37)	(-1.28)
Test of differences		***F-statistic***	***P-value***
$INC_{it-1}*DEC_{it}*\Delta SALES_{it} = DEC_{it-1}*DEC_{it}*\Delta SALES_{it}$		3.84*	(0.067)
$INC_{it-2}*INC_{it-1}*DEC_{it}*\Delta SALES_{it} = DEC_{it-2}*DEC_{it-1}*DEC_{it}*\Delta SALES_{it}$		4.25*	(0.056)
Industry Fixed Effects		Yes	Yes
Year Fixed Effects		Yes	Yes
Observations		27,632	27,632
Adjusted R-squared		0.272	0.270

Notes: This table reports the cross-sectional results of estimating model (1) using the OLS in Panel A and the multi-period versions of model (1) using the OLS in Panel B. Detailed variable definitions are provided in the Appendix. Industry fixed effects are based on 3-digit SIC codes. Reported in parentheses are t-statistics based on standard errors adjusted for clustering by firm and year. Bolded variables represent our predictions. ***, ** and * denote significance at 1 percent, 5 percent, and 10 percent, respectively, using two-tailed t-tests.

TABLE 4
Cross-sectional tests: Stockout costs and demand uncertainty

		Dep. Variable = $\Delta INVENT_{it}$		
		STOCKOUT		
Indep. Variable =	Pred. Sign	***$SCIC_{it}$***	***Q_{it}***	***$SGVOL_{it}$***
		(1)	(2)	(3)
$1/A_{it-1}$		0.074**	0.017	0.010
		(2.21)	(1.24)	(0.63)
$SALES_{it}$	(+)	0.006***	0.008***	0.008***
		(3.82)	(6.00)	(5.88)
$\Delta SALES_{it-1}$	(+)	0.006	0.008**	0.009***
		(1.64)	(2.63)	(3.35)
DEC_{it-1}		-0.002**	-0.003**	-0.002**
		(-2.38)	(-2.57)	(-2.57)
$DEC_{it-1}*\Delta SALES_{it-1}$		0.003	0.001	0.001
		(0.49)	(0.27)	(0.21)
$\Delta SALES_{it}$	**(+)**	**0.097*** **	**0.109*** **	**0.130*** **
		(15.17)	**(14.17)**	**(19.49)**
DEC_{it}		-0.001	-0.001	0.001
		(-0.51)	(-0.70)	(1.43)
$DEC_{it}*\Delta SALES_{it}$	**(−)**	**-0.027** **	**-0.029*** **	**-0.017* **
		(-2.94)	**(-3.12)**	**(-2.04)**
STOCKOUT		0.001	0.002	0.003**
		(0.95)	(1.03)	(2.13)
$STOCKOUT*\Delta SALES_{it}$		0.013	-0.018	-0.047***
		(1.42)	(-1.68)	(-6.60)
$STOCKOUT*DEC_{it}*\Delta SALES_{it}$	**(−)**	**-0.037* **	**-0.028** **	**-0.014* **
		(-1.98)	**(-2.24)**	**(-1.91)**
$SIZE_{it}$		0.002***	0.001***	0.001***
		(4.05)	(4.20)	(4.79)
Q_{it}		-0.001**		-0.001***
		(-2.96)		(-3.05)
$ASSETINT_{it}$		0.006***	0.006***	0.005***
		(4.25)	(4.55)	(3.20)
$EMPINT_{it}$		0.001***	0.000***	0.001***
		(5.86)	(6.13)	(6.27)
$RNOA_{it}$		-0.000	-0.000	0.000
		(-0.79)	(-0.54)	(0.48)
$OPLEV_{it}$		-0.000	-0.000	-0.000
		(-1.07)	(-1.19)	(-1.15)
Industry Fixed Effects		Yes	Yes	Yes
Year Fixed Effects		Yes	Yes	Yes
Observations		16,804	27,632	24,618
Adjusted R-squared		0.293	0.274	0.265

Notes: This table reports the cross-sectional results of estimating model (1) using the OLS. Detailed variable definitions are provided in the Appendix. Industry fixed effects are based on 3-digit SIC codes. Reported in parentheses are t-statistics based on standard errors adjusted for clustering by firm and year. Bolded variables represent our predictions. ***, ** and * denote significance at 1 percent, 5 percent, and 10 percent, respectively, using two-tailed t-tests.

TABLE 5
Inventory signal and future sales growth

Indep. Variable =	Pred. Sign	Dep. Variable = $\Delta SALES_{it+1}$		
		(1)	(2)	(3)
$INVSIG_{it}$	(+)	**0.053*** **	**0.065*** **	**0.072*** **
		(9.34)	**(11.48)**	**(12.38)**
DEC_{it}		-0.015***	-0.014**	-0.013**
		(-3.33)	(-2.66)	(-2.71)
$DEC_{it}*INVSIG_{it}$	(+)	**0.056***	**0.057***	**0.054***
		(2.89)	**(2.84)**	**(2.69)**
$INVSIG_{it-1}$			0.010*	0.011*
			(2.10)	(1.85)
DEC_{it-1}			-0.005	-0.005
			(-0.99)	(-0.97)
$DEC_{it-1}*INVSIG_{it-1}$			0.011	0.022**
			(1.49)	(2.37)
$INVSIG_{it-2}$				-0.001
				(-0.20)
DEC_{it-2}				-0.003
				(-0.40)
$DEC_{it-2}*INVSIG_{it-2}$				0.000
				(0.05)
$\Delta SALES_{it}$	(+)	0.155***	0.156***	0.152***
		(5.91)	(5.99)	(5.35)
Q_{it}		0.024***	0.024***	0.025***
		(9.16)	(8.76)	(9.80)
$LNAGE_{it}$		-0.012***	-0.011***	-0.010***
		(-4.13)	(-3.79)	(-3.66)
$SIZE_{it}$		0.001	0.001	0.000
		(0.61)	(0.67)	(0.27)
LEV_{it}		-0.009	-0.011	-0.007
		(-0.84)	(-1.05)	(-0.61)
$CASH_{it}$		-0.044***	-0.044**	-0.042***
		(-3.09)	(-2.90)	(-3.02)
ROA_{it}		0.026*	0.020	0.033**
		(1.89)	(1.45)	(2.49)
Industry Fixed Effects		Yes	Yes	Yes
Year Fixed Effects		Yes	Yes	Yes
Observations		21,802	21,518	20,591
Adjusted R-squared		0.150	0.155	0.153

Notes: This table reports the results of estimating the relation between asymmetric inventory investment and future sales growth using the OLS. Detailed variable definitions are provided in the Appendix. Industry fixed effects are based on 3-digit SIC codes. Reported in parentheses are t-statistics based on standard errors adjusted for clustering by firm and year. Bolded variables represent our predictions. ***, ** and * denote significance at 1 percent, 5 percent, and 10 percent, respectively, using two-tailed t-tests.

TABLE 6
Asymmetric inventory investment and management sales guidance

Indep. Variable =	Dep. Variable =		
	MFHIGHER$_{it+1}$	***MFERROR$_{it+1}$***	***MFACCURACY$_{it+1}$***
	(1)	(2)	(3)
INVSIG$_{it}$	**0.061*** **	**-0.002**	**-0.001**
	(6.17)	**(-0.42)**	**(-0.29)**
DEC$_{it}$	-0.044***	0.001	-0.004
	(-4.92)	(0.11)	(-1.51)
DEC$_{it}$*INVSIG$_{it}$	**0.059** **	**-0.010**	**-0.006**
	(2.16)	**(-0.65)**	**(-0.49)**
STDREV$_{it}$	0.100**	0.011	0.003
	(2.46)	(0.65)	(0.17)
STDRET$_{it}$	0.056	0.021	-0.233***
	(0.49)	(0.48)	(-4.72)
SIZE$_{it}$	-0.006*	0.000	0.005***
	(-2.05)	(0.01)	(3.73)
ROA$_{it}$	-0.090**	0.052**	0.023
	(-2.47)	(2.30)	(1.51)
BHAR$_{it}$	0.038***	-0.020***	0.010*
	(5.01)	(-5.42)	(1.91)
Q$_{it}$	-0.011***	-0.000	0.008***
	(-5.13)	(-0.04)	(7.56)
RDINT$_{it}$	-0.137*	-0.092***	0.153***
	(-1.90)	(-3.62)	(5.04)
ADINT$_{it}$	-0.034	-0.012	-0.004
	(-0.32)	(-0.19)	(-0.08)
RRCORR$_{it}$	-0.022**	-0.005	0.016***
	(-2.43)	(-0.91)	(3.19)
LOSS$_{it+1}$	-0.040***	0.058***	-0.032***
	(-4.05)	(8.35)	(-5.06)
ANALYSTS$_{it}$	-0.013*	-0.004	0.004
	(-2.01)	(-1.22)	(1.27)
MFHORIZON$_{it+1}$	-0.000	0.006	-0.029***
	(-0.08)	(1.36)	(-11.88)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	14,532	14,532	14,532
Adjusted R-squared	0.1678	0.1106	0.2370

Notes: This table reports the results of estimating the relation between asymmetric inventory investment and management sales guidance using the OLS. Detailed variable definitions are provided in the Appendix. Industry fixed effects are based on 3-digit SIC codes. Reported in parentheses are t-statistics based on standard errors adjusted for clustering by firm and year. Bolded variables represent our predictions. ***, ** and * denote significance at 1 percent, 5 percent, and 10 percent, respectively, using two-tailed t-tests.

TABLE 7
Asymmetric inventory investment and analyst sales forecasts

	Dep. Variable =			
Indep. Variable =	***AFHIGHER$_{it+1}$***	***AFERROR$_{it+1}$***	***AFACCURACY$_{it+1}$***	***AFDISPERSION$_{it+1}$***
	(1)	(2)	(3)	(4)
INVSIG$_{it}$	**0.076*** **	**-0.006**	**0.004**	**-0.002**
	(13.05)	**(-1.34)**	**(1.19)**	**(-1.01)**
DEC$_{it}$	-0.042***	-0.010*	0.009**	0.001
	(-3.01)	(-1.81)	(2.64)	(0.66)
DEC$_{it}$*INVSIG$_{it}$	**0.059***	**-0.025**	**-0.013**	**0.014*** **
	(2.10)	**(-1.27)**	**(-1.47)**	**(2.93)**
STDREV$_{it}$	0.067*	0.022	0.019	0.047***
	(1.80)	(1.53)	(1.00)	(6.64)
STDRET$_{it}$	-0.177	0.008	-0.169***	0.032*
	(-1.27)	(0.18)	(-3.49)	(2.05)
SIZE$_{it}$	-0.007**	-0.003	0.011***	-0.000
	(-2.14)	(-1.54)	(5.64)	(-0.73)
ROA$_{it}$	-0.066	0.029**	0.042**	-0.013
	(-1.19)	(2.21)	(2.22)	(-1.65)
BHAR$_{it}$	0.049***	-0.015	0.040***	-0.003
	(4.22)	(-1.65)	(6.55)	(-1.62)
Q$_{it}$	-0.007**	0.000	0.004***	0.001*
	(-2.38)	(0.29)	(3.30)	(1.96)
RDINT$_{it}$	-0.072	-0.091**	0.129***	0.060***
	(-0.82)	(-2.43)	(3.50)	(3.94)
ADINT$_{it}$	-0.017	0.084	-0.113*	-0.063***
	(-0.26)	(1.27)	(-1.77)	(-3.07)
RRCORR$_{it}$	-0.021	0.001	0.005	-0.003
	(-1.70)	(0.23)	(0.83)	(-1.18)
LOSS$_{it+1}$	-0.045***	0.076***	-0.035***	0.012***
	(-6.25)	(9.02)	(-5.55)	(4.59)
ANALYSTS$_{it}$	-0.006	-0.008**	-0.003	0.002**
	(-0.94)	(-2.15)	(-0.71)	(2.75)
AFHORIZON$_{it+1}$	-0.027**	0.055***	-0.060***	-0.031***
	(-2.42)	(4.72)	(-7.75)	(-5.07)
GUIDANCE$_{it}$	-0.007*	0.005*	-0.006	-0.005***
	(-1.77)	(1.81)	(-1.74)	(-3.88)
AFDISPERSION$_{it}$	0.067	-0.106**	0.184***	0.231***
	(1.12)	(-2.78)	(5.09)	(7.82)
AFHIGHER$_{it}$	0.118			
	(1.47)			
AFERROR$_{it}$		0.143***		
		(3.18)		
AFACCURACY$_{it}$			0.336***	
			(11.41)	
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	12,951	12,951	12,951	12,533
Adjusted R-squared	0.2121	0.1451	0.3266	0.4008

Notes: This table reports the results of estimating the relation between asymmetric inventory investment and analyst consensus sales forecasts using the OLS. Detailed variable definitions are provided in the Appendix. Industry fixed effects are based on 3-digit SIC codes. Reported in parentheses are t-statistics based on standard errors adjusted for clustering by firm and year. Bolded variables represent our predictions. ***, ** and * denote significance at 1 percent, 5 percent, and 10 percent, respectively, using two-tailed t-tests.

TABLE 8
Asymmetric inventory investment and sales forecasting models

Panel A: Distributions of absolute forecast errors (AFE)

Forecasting Model	**Obs**	**Median**	**Mean**	**Std. Dev.**	**Q1**	**Q3**
RW Model	14,100	0.080	0.128	0.144	0.033	0.167
BC Model	14,100	0.054	0.098	0.127	0.013	0.130
ASYINV Model	14,100	0.024	0.064	0.099	0.000	0.083
AF	8,592	0.049	0.086	0.107	0.022	0.105
MF	3,173	0.046	0.084	0.107	0.019	0.102

Panel B: Pair-wise improvements in AFE

Comparison Model	**Base Model**	**Obs**	**Median Diff.**	**Mean Diff.**
ASYINV Model	*RW* Model	14,100	0.055***	0.065***
AF	*RW* Model	8,592	0.027***	0.034***
MF	*RW* Model	3,173	0.020***	0.023***
ASYINV Model	*BC* Model	14,100	0.030***	0.034***
AF	*BC* Model	8,592	0.004***	0.007***
MF	*BC* Model	3,173	0.004***	0.002
ASYINV Model	*AF*	8,592	0.023***	0.022***
ASYINV Model	*MF*	3,173	0.016***	0.020***

Notes: This table reports the results on absolute forecast errors (AFE) of random-walk model (*RW* Model), Banker and Chen (2006) model (*BC* Model), asymmetric inventory model (*ASYINV* Model), analyst sales forecasts (*AF*) and management sales guidance (*MF*). In Panel A, we report the descriptive statistics for AFE. Refer to the text for details on the estimation of individual models. In Panel B, we test pair-wise improvements in AFE between comparison models and base models. Pair-wise improvement is defined as AFE of Base Model minus AFE of Comparison Model. ***, ** and * denote significance at 1 percent, 5 percent, and 10 percent, respectively, using two-tailed t-tests for difference in means (Wilcoxon signed rank tests for difference in medians).

TABLE 9
Asymmetric inventory investment: Financial constraints

		Dep. Variable = $\Delta INVENT_{it}$				
		FC				
Indep. Variable =	Pred. Sign	***KZINDEX$_{it}$***	***ZINDEX$_{it}$***	***LEV$_{it}$***	***CASH$_{it}$***	***ROA$_{it}$***
		(1)	(2)	(3)	(4)	(5)
$1/A_{it-1}$		0.022	0.032**	0.026*	0.027*	0.030**
		(1.74)	(2.36)	(1.92)	(2.04)	(2.21)
$SALES_{it}$	(+)	0.010***	0.007***	0.008***	0.010***	0.006***
		(6.79)	(5.32)	(6.09)	(6.42)	(4.25)
$\Delta SALES_{it-1}$	(+)	0.008**	0.008**	0.009**	0.008**	0.006*
		(2.32)	(2.37)	(2.63)	(2.33)	(1.79)
DEC_{it-1}		-0.003**	-0.002**	-0.003**	-0.003**	-0.002**
		(-2.59)	(-2.47)	(-2.69)	(-2.77)	(-2.15)
$DEC_{it-1}*\Delta SALES_{it-1}$		-0.001	-0.002	0.001	0.003	-0.001
		(-0.17)	(-0.29)	(0.10)	(0.50)	(-0.16)
$\Delta SALES_{it}$	**(+)**	**0.096*** **	**0.111*** **	**0.095*** **	**0.114*** **	**0.099*** **
		(22.54)	**(19.13)**	**(16.24)**	**(20.53)**	**(16.17)**
DEC_{it}		-0.002	-0.001	-0.001	-0.001	-0.001
		(-1.72)	(-1.20)	(-1.35)	(-1.41)	(-1.35)
$DEC_{it}*\Delta SALES_{it}$	**(−)**	**-0.069*** **	**-0.074*** **	**-0.049*** **	**-0.026** **	**-0.016**
		(-9.47)	**(-10.34)**	**(-6.18)**	**(-2.73)**	**(-1.66)**
FC		-0.009***	-0.009***	-0.005***	0.013***	0.008***
		(-3.65)	(-5.17)	(-3.73)	(7.10)	(3.68)
$FC*\Delta SALES_{it}$		0.001	-0.022*	0.006	-0.034***	0.003
		(0.11)	(-2.02)	(0.90)	(-5.21)	(0.42)
$FC*DEC_{it}*\Delta SALES_{it}$		**0.059*** **	**0.067*** **	**0.025***	**-0.022***	**-0.051*** **
		(3.59)	**(4.30)**	**(1.82)**	**(-1.98)**	**(-4.33)**
$SIZE_{it}$		0.001***	0.001***	0.002***	0.002***	0.001***
		(4.44)	(4.77)	(5.73)	(5.52)	(3.21)
Q_{it}		-0.001*	-0.001***	-0.001*	-0.001**	-0.000
		(-2.10)	(-3.87)	(-1.85)	(-2.33)	(-1.33)
$ASSETINT_{it}$		0.008***	0.006***	0.006***	0.007***	0.006***
		(5.16)	(4.26)	(4.47)	(4.90)	(4.17)
$EMPINT_{it}$		0.001***	0.001***	0.001***	0.000***	0.001***
		(6.74)	(6.61)	(6.23)	(5.84)	(6.89)
$RNOA_{it}$		-0.000	-0.000	-0.000	-0.000	-0.000
		(-0.46)	(-0.63)	(-0.67)	(-0.42)	(-1.32)
$OPLEV_{it}$		-0.000*	-0.000	-0.000	-0.000	-0.000
		(-1.75)	(-0.91)	(-1.38)	(-1.62)	(-0.92)
Industry Fixed Effects		Yes	Yes	Yes	Yes	Yes
Year Fixed Effects		Yes	Yes	Yes	Yes	Yes
Observations		27,005	26,932	27,632	27,632	27,608
Adjusted R-squared		0.269	0.271	0.273	0.278	0.275

Notes: This table reports the cross-sectional results of estimating model (1) using the OLS. Detailed variable definitions are provided in the Appendix. Industry fixed effects are based on 3-digit SIC codes. Reported in parentheses are t-statistics based on standard errors adjusted for clustering by firm and year. Bolded variables represent our predictions. ***, ** and * denote significance at 1 percent, 5 percent, and 10 percent, respectively, using two-tailed t-tests.