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Saravanan Kesavan, Tarun Kushwaha
Kenan-Flagler Business School, University of North Carolina, Chapel Hill, North Carolina 27599
{saravanan_kesavan@unc.edu, tarun_kushwaha@unc.edu}

Vishal Gaur
Samuel Curtis Johnson Graduate School of Management, Cornell University,
Ithaca, New York 14850, vg77@cornell.edu

This paper examines the differences in the behaviors of high (HIT) and low inventory turnover (LIT) retailers in responding to demand shocks. We identify quantity and price responsiveness as two mediating mechanisms that distinguish how high and low inventory turnover retailers manage demand shocks. Using quarterly firm-level data of 183 U.S. retailers between 1985 and 2012, we find that HIT retailers are able to respond quickly by changing their purchase quantities in response to demand shocks, whereas LIT retailers primarily rely on price changes to manage demand shocks. In addition, we examine the differential implications of these mechanisms on the financial performance of HIT and LIT retailers. We find price responsiveness to be a less effective strategy, compared to quantity responsiveness, in reducing excesses and shortages of inventory. Finally, the negative financial impact of a given amount of excess and shortage of inventory is eight times more severe for LIT retailers compared to HIT retailers.

Keywords: inventory turnover; retailing; demand shock; supply chains; financial performance; econometric analyses
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1. Introduction

The virtues of high inventory turnover (HIT) have been expounded for decades. Yet, considerable heterogeneity in inventory turns across retailers can be observed even in narrowly defined segments. For example, the 80th and 20th percentiles of inventory turns in the apparel segment (Standard Industrial Classification (SIC) 56) in 2012 are 5.84 and 2.68. In other words, retailers in the 20th percentile require 120% more inventory to generate the same sales as retailers in the 80th percentile. Recent research in operations management has examined the differences in performance across high and low inventory turnovers (LITs). Researchers have benchmarked inventory turnover (Gaur et al. 2005), reconciled inventory variation in practice with analytical inventory theory (Rumyantsev and Netessine 2007a, Bray and Mendelson 2012, Jain et al. 2014, Rajagopalan 2013), and also correlated inventory productivity with financial performance (e.g., Chen et al. 2007, Rumyantsev and Netessine 2007b, Larson et al. 2015). However, little research has been done to understand the behavioral differences between high and low inventory turnover retailers that contribute to the observed performance differences. For example, it is unclear how these retailers manage demand-side risk and whether there are differences in the way they do so that could contribute to the observed performance differences in these two groups of retailers.

Consider the reactions of retailers in the top and bottom 20th percentiles of inventory turnover in the apparel segment (as previously discussed) during the economic recession of December 2007–June 2009. Prior to the recession, the consumer confidence index (CCI) had risen steadily from 2003 and peaked at 111.9 points in July 2007. In the next quarter, the CCI declined abruptly by 15%. Both groups of retailers experienced similar decline in sales of about 6.3% during that quarter. Thus, we would expect both groups to adjust to this downturn by decreasing their purchases. We calculate purchases using the accounting identity: purchases = ending inventory + cost of goods sold − beginning inventory. We find that the ratio of purchases to cost of goods sold (COGS) for retailers *above* the 80th percentile of inventory turns decreased by 30% in that quarter. However, for those retailers with turns in the *bottom* 20th percentile, this ratio increased by 30% in that quarter before declining by 44% in the next quarter. One potential explanation is that the purchases of these low inventory turnover retailers responded to the demand shock with a delay. In contrast, the gross margins of these low inventory turnover retailers declined by nearly twice the amount compared to their high inventory turnover counterparts, suggesting that low inventory turnover retailers may have reduced prices more aggressively than high inventory turnover retailers. Together, this example suggests that retailers with higher inventory turns were able to change their orders quickly (*quantity response*) to manage demand shocks, whereas low inventory turnover retailers changed prices (*price response*) to manage demand shocks.

Inventory theory offers an explanation for this observed difference in behavior. Specifically, the difference in responses to demand shocks between HIT and LIT retailers are consistent with the joint inventory pricing literature. This literature considers how firms can change their order quantity (quantity response) and/or pricing (price response) to manage demand uncertainty. Smaller ordering costs are generally associated with smaller, more frequent orders (Chen and Simchi-Levi 2004) and shorter lead time with fewer price changes (Bernstein et al. 2015). In the retail context, lead time is determined by not only the transportation time to retailers, but also the production lead time at suppliers. Since firms with lower setup costs and shorter lead times will have higher inventory turnover, ceteris paribus, the HIT retailers may have been able to change their orders in a timely fashion in response to demand changes. Thus, we expect HIT retailers to rely less on price responses compared to LIT retailers. Admittedly, lead time and setup costs are not reported by firms or observed in their public data. However, the implications of our arguments are testable. Thus, we address the following questions in this paper: (i) Do HIT retailers use more quantity response and less price response compared to LIT retailers when managing demand shocks? (ii) What are the resulting implications of such differences in behavior to the profitability of these two types of retailers?

Using 9,028 quarterly observations from 183 U.S. public retailers from the Compustat database for the period 1985–2012 and CCI from the Conference Board, and dividing retailers in each SIC segment into time-invariant high and low inventory turnover groups, we find the following:

(i) The inventory purchases of LIT retailers respond to demand shocks occurring two, three, and four quarters ago, whereas purchases of HIT retailers respond to demand shocks in the current quarter. Thus, HIT retailers appear to have more responsive supply chains than LIT retailers.

(ii) The total effect of a demand shock on the purchases of HIT retailers is smaller than the total effect on the purchases of LIT retailers. The total effect is measured using impulse response analysis as the total change in purchases attributed to that demand shock over the subsequent quarters.

(iii) LIT retailers change their gross margins by significantly larger amounts compared to HIT retailers in the quarter when a demand shock occurs. Thus, LIT retailers appear to use price response more actively than HIT retailers to manage demand shocks to compensate for their lagged quantity response.

(iv) The quantity response strategy of HIT retailers enables them to mitigate excesses and shortages of inventory (as measured by abnormal inventory growth (ABIG)) more effectively than LIT retailers. LIT retailers incur excesses and shortages in subsequent quarters after a demand shock and have a larger total impact than HIT retailers.

(v) Finally, excesses and shortages are much more detrimental to the financial performance of LIT retailers than HIT retailers. We find that a one-standard-deviation increase (from the mean) in ABIG leads to a 0.63% decline in return on assets (ROA) for HIT retailers, and a 2.44% decline in ROA for LIT retailers. A one-standard-deviation decrease (from the mean) in ABIG leads to a 1.08% decline in ROA for HIT retailers, and a much larger 9.95% decline in ROA for LIT retailers. Thus, LIT retailers face more severe penalty when there are excesses and shortages of inventory.

We use two methodologies with different measures of demand shocks for our analysis. In the first methodology, we use macroeconomic shocks as the proxy for demand shocks for each firm and utilize a vector autoregression (VAR) model to determine the effect of demand shocks on demand, purchases, gross margin, ABIG, and ROA. The VAR methodology is advantageous because it handles the simultaneity among different variables and permits the examination of contemporaneous as well as delayed effects of demand shocks on the variables using an impulse response function (IRF) analysis. In the second methodology, we estimate firm-level demand shocks by fitting a Martingale model of forecast evolution (MMFE) independently to each firm and examine their effects on purchases. Both methodologies and measures of demand shocks support our hypotheses.

This evidence is timely and relevant because demand uncertainty has been increasing in recent years, and supply chains are getting longer. Anecdotal evidence suggests that while retail managers are under competitive pressure to lower physical costs in their supply chains by sourcing from different parts of the world, they also worry about the cost of mismatches in supply and demand arising from uncertainty (Cave 2014). Our paper quantifies the implications of less responsive supply chains. It shows that the excesses and shortages of inventory are larger for lower inventory turnover retailers and hurt their profitability by much more compared to higher inventory turnover retailers.

Our paper contributes to the academic literature in the following ways. First, it contributes to the recent empirical research that has observed that high inventory turnover retailers have better financial performance (e.g., Alan et al. 2014, Chen et al. 2007, Rumyantsev and Netessine 2007b) by demonstrating one reason for the observed difference. It shows that higher inventory turnover retailers pursue more responsive inventory management that enables them to manage demand-side risk more effectively than lower inventory turnover retailers, who rely on changing prices to manage this risk.

Second, this paper offers a new explanation for the presence of the "*earns versus turns*" trade-off in retailing. The empirical evidence of this inverse relationship between inventory turns and gross margin has been well documented in prior research (Gaur et al. 2005). The reasons for the presence of this trade-off are usually argued based on the occurrence of competition, inherent differences in product characteristics across firms, and the newsvendor logic. According to the first explanation, firms with low inventory turns and low gross margin will exit the market, those with high inventory turns and high gross margin will erode their advantage over time, and the average firm in the marketplace will manifest a negative correlation between inventory turns and gross margin. According to the newsvendor logic, retailers with a higher margin have greater incentives to carry more inventory and will therefore have lower inventory turns. These arguments, however, assume that other aspects of retail inventory management, such as setup costs and lead time, do not vary across firms. Yet, we find contrasting examples of firms that source domestically, e.g., American Apparel, and those that source from faraway foreign locations, e.g., Gap, for the same market. Our paper offers a new explanation for this trade-off that is based on substitution of capabilities to respond to demand shocks with ordering or pricing changes motivated by the joint pricing and inventory management literature. LIT retailers who are unable to react to demand shocks due to their less responsive supply chains will need to change prices; sustaining greater price volatility would require higher margins (Pashigian 1988). Thus, the higher gross margins of LIT retailers observed in practice may be explained by their need to change prices more often to manage demand fluctuations compared to HIT retailers.

Third, this paper contributes to empirical research on inventory turnover performance by showing differences in the effect of abnormal inventory on financial performance across HIT and LIT retailers. Both the accounting and operations management literatures have highlighted the importance of ABIG as a predictor of earnings per share, ROA, and stock prices (Abarbanell and Bushee 1997, Thomas and Zhang 2000, Rumyantsev and Netessine 2007b, Kesavan and Mani 2013). Whereas Rumyantsev and Netessine (2007b) and Kesavan and Mani (2013) document a nonlinear relationship between ABIG and profitability, we show the nature of this relationship to be moderated by the type of retailer, namely, HIT or LIT. Therefore, whereas the prior literature has shown that financial performance of all retailers to be adversely impacted by excesses and shortages in inventory, our paper shows that this impact is much larger for LIT retailers compared to HIT retailers.

2. Hypotheses

In this section, we discuss differences in the responses of HIT and LIT retailers to demand shocks. An important challenge in theorizing about the differences in the behaviors of HIT and LIT retailers is that the primitives that drive the ability of a retailer to use quantity response or price response to demand shocks are unobservable. In particular, factors such as replenishment lead time, length of review cycle, and fixed ordering costs are important determinants of the ordering policy. These factors are unobservable from recorded data, but their outcomes, i.e., purchases, inventory turnover, and gross margin, are observed. To overcome this gap between theory and data, we assume that retailers with shorter lead time and lower ordering costs will have higher inventory turnover than retailers with longer lead time and higher ordering costs. Thus, we generate our hypotheses about the behaviors of HIT and LIT retailers implied by the underlying primitives. We test our assumption about the correlation between lead time and inventory turnover in §3.2 by imputing the lead time for each retailer using a structural model of an order-up-to policy. Moreover, other factors such as gross margin, sales growth, and firm size may differ between HIT and LIT retailers. Thus, we incorporate control variables from the previous literature in our model for testing the predictions from normative theory.

We use examples of inventory models with nonstationary demand to motivate the hypotheses on quantity response, and joint inventory–price optimization models for the hypotheses on price response. We measure quantity response through change in purchases, and price response through change in gross margin. Hypotheses 1–3 pertain to quantity response, Hypothesis 4 to price response, and Hypothesis 5 to the financial impact of demand shocks on HIT and LIT retailers

2.1. Quantity Response

The inventory purchase quantity in a periodic review model is determined by forecasting demand for the sum of the lead time L and the review cycle R. Therefore, a historical demand shock will affect purchases through the forecast of future demand over $L + R$. Intuitively, the longer the lead time or the length of the review cycle, the larger the effect of a demand shock will be on the forecast of demand, and thereby on the purchase quantities. Similarly, the higher the fixed ordering cost, the less frequent the orders, which then has a similar effect as the length of the review cycle. For the rest of our hypotheses' development, we focus on the effect of lead time. The effect of length of review cycle is similar.

Here, the replenishment lead time would consist of not only transportation but also production lead time. Transportation lead time is typically of the order of a few weeks, but production lead time can be a few months because of factors such as production capacity, setup changeovers, and product variety. Moreover, these two components add up across the tiers of the supply chain. For example, department stores are known to place orders about six months to a year in advance to their suppliers in East Asia (Fisher 1997).

Hypotheses 1 and 2 differentiate between HIT and LIT retailers with respect to purchases, whereas Hypothesis 3 formulates the post facto implication for their inventory levels.

Hypothesis 1 (H1) (Timeliness of Quantity Response). *The purchases of HIT retailers respond to relatively recent demand shocks, whereas purchases of LIT retailers respond to older shocks.*

Hypothesis 2 (H2) (Magnitude of Quantity Response). *The purchases of HIT retailers change by smaller amounts upon the occurrence of demand shocks than do those of LIT retailers.*

Hypothesis 3 (H3). *HIT retailers have less excesses and shortages in inventory due to demand shocks than LIT retailers.*

The intuition behind the above hypotheses can be seen through a consideration of the classic "beer game" simulation of supply chain management (Sterman 1989). Lee et al. (2004) describe forecast updating and order batching as two causes of the bullwhip effect simulated in the game. Shorter lead times and smaller batch sizes mitigate this effect. If shorter lead time and smaller batch size also lead to higher inventory turnover, then HIT retailers would be less susceptible to the bullwhip effect. They would see faster response to demand shocks (H1), smaller variations in purchases (H2), and less excess and shortage of inventory (H3). These hypotheses are also consistent with the predictions of the literature on the value of postponement. A postponement strategy, such as capacity reservation or warehousing, provides mechanisms to reduce lead time, which then enables better quantity response and smaller cost of excess and shortage of inventory (Van Mieghem and Allon 2008).

We illustrate the three quantity response hypotheses using the models by Lee et al. (2000) for auto regressive (AR(1)) demand and by Graves (1999) for auto regressive integrated moving average (ARIMA(0, 1, 1)) demand. Both of these models consider lead time without fixed ordering costs. In Lee et al. (2000), the demand D_t follows an AR(1) process, $D_t = d + \rho D_{t-1} + \varepsilon_t$, where $\rho \in (0, 1)$ and ε_t is a sequence of independent and identically distributed (i.i.d.) normally distributed random variables with mean zero and constant variance. Let the replenishment lead time be L. The order quantity Y_t after observing the demand in period t is

$$Y_t = \frac{1-\rho^{L+2}}{1-\rho} D_t - \frac{\rho(1-\rho^{L+1})}{1-\rho} D_{t-1}.$$

This order quantity is delivered in period $t+L$. Representing the delivered quantity as purchases, we obtain

$$\begin{aligned} Purchases_{t+L} &= \frac{1-\rho^{L+2}}{1-\rho} D_t - \frac{\rho(1-\rho^{L+1})}{1-\rho} D_{t-1} \\ &= \frac{1-\rho^{L+2}}{1-\rho} d + \rho^{L+2} D_{t-1} + \frac{(1-\rho^{L+2})}{1-\rho} \varepsilon_t. \end{aligned}$$

This expression shows that the observed impact of a demand shock ε_t at time t has two characteristics. First, the magnitude of the impact depends on the lead time. The longer the lead time, the larger the coefficient of ε_t, and the larger the impact on purchases. Therefore, LIT retailers will have larger changes in their purchases for a given demand shock than HIT retailers. Second, the impact of the shock on purchases will be realized only after the lead time. Thus, purchases of HIT retailers will respond to more recent demand shocks than will those of LIT retailers. These two effects motivate H1 and H2.

The same inference can be drawn from the ARIMA(0, 1, 1) demand model of Graves (1999). In this model, the retailer's demand during is represented as $D_1 = d + \varepsilon_1$ for period 1 and $D_t = D_{t-1} - (1-\alpha)\varepsilon_{t-1} + \varepsilon_t$ for $t = 2, 3, 4, \ldots$. Here, ε_t is a series of i.i.d. shocks with mean zero and variance σ^2, and $\alpha \in [0, 1]$ is the moving average coefficient. When α is zero, the demand follows a stationary i.i.d. process with mean d. As α increases, the demand during any time period depends more and more on the most recent demand realization. Again let the replenishment lead time from the manufacturer to the retailer be L periods. In this setup, Graves (1999) proposes a base-stock policy that yields the order quantity during period t as $Y_t = D_t + L\alpha\varepsilon_t$. The first component of the ordering quantity represents the amount of replenishment required to make up for the demand, and the second component adjusts the base-stock level for the change in forecast over the lead time. Graves (1999) notes that this policy is not optimal, but a reasonable extension of the base-stock policy to the case of nonstationary demand. This gives us

$$Purchases_{t+L} = D_t + L\alpha\varepsilon_t = D_{t-1} + (1+L\alpha)\varepsilon_t - (1-\alpha)\varepsilon_{t-1}.$$

Thus, we find that the effect of the demand shock ε_t in time period t increases with lead time. This implies that magnitude of changes in purchases of LIT retailers will be greater than HIT retailers upon a demand shock, which yields H1. Moreover, HIT retailers will respond to more recent demand shocks than LIT retailers leading to H2.

H3 follows in each of the above cases because retailers with a longer lead time will face more excess or shortage of inventory before they can recover from a demand shock. Thus, we would expect LIT retailers to have more excess and shortage in inventory than do HIT retailers following demand shocks.

2.2. Price Response

We next argue for a difference in the price responses of HIT and LIT retailers. As alternatives to adjusting their purchases, retailers can react to demand shocks by changing prices, which would then affect their gross margins. The theory on joint inventory–price optimization models predicts that retailers with higher fixed ordering costs who cannot adjust their purchases quickly will rely on price adjustments more than retailers with smaller fixed ordering costs. Therefore, we have the following hypothesis, comparing LIT and HIT retailers:

Hypothesis 4 (H4) (Magnitude of Price Response). *The gross margin of LIT retailers is more responsive to demand shocks than is that of HIT retailers.*

Chen and Simchi-Levi (2004) present an infinite-horizon periodic-review inventory model with fixed ordering cost, in which a retailer optimizes both price and order quantities to maximize the expected discounted profit. The authors show the optimality of a stationary (s, S, p) policy in which order quantities are determined based on the classical (s, S) policy, and the price in each period is determined based on the inventory position at the start of that period. Applying this model, if LIT retailers have higher fixed ordering costs than HIT retailers, then they would have a higher order-up-to level S. Correspondingly, they would place orders infrequently, have a larger variation in their inventory positions at the start of each period, and thus have more variation in their prices than HIT retailers on the occurrence of a demand shock. This yields H4.

Chen et al. (2006) consider the implications of setup cost on joint inventory and pricing optimization in periodic review systems with lost sales and find that the profit impact of dynamically changing prices increases with setup cost. Aguirregabiria (1999) uses data from supermarkets to show that fixed ordering costs are associated with greater price changes.

These papers support our arguments for differences in ordering costs across HIT and LIT retailers contributing to differences in changes in gross margin across these retailers. We note that the existing literature has considered fixed ordering cost, but not lead time, in multiperiod joint price–inventory optimization. According to Bernstein et al. (2015), the theory on joint inventory–price optimization typically ignores lead time for reasons of mathematical tractability. They employ a heuristic procedure and show that shorter lead time is associated with a more stable pricing policy. In summary, the theoretical literature has shown that longer lead time or higher ordering costs are associated with more price changes. Therefore, we expect LIT firms to have greater changes in gross margin compared to HIT firms.

2.3. Financial Performance

In H3, we argued that LIT retailers will have more excesses and shortages compared to HIT retailers. The current literature has shown that abnormal growth in inventory is detrimental to financial performance of retailers. Rumyantsev and Netessine (2007b) use ROA and Kesavan and Mani (2013) use earnings per share as measures of financial performance to provide evidence of nonlinearity in the relationship between ABIG and profitability. Neither paper examines whether this impact of ABIG on financial performance varies across retailers.

Excesses and shortages impact financial performance in different ways. Excess inventory increases direct costs for a retailer due to the capital tied to inventory and physical costs of holding inventory. Excesses could also force retailers to undertake steep discounting or clearance sales that will result in a decline in gross margin. In extreme cases, excess inventory can lead to write-offs. Larson et al. (2015) find that retailers with inventory write-down experienced an average decline in ROA of −15.4%. Shortages, on the other hand, affect financial performance primarily due to lost sales.

We argue that the impacts of excesses and shortages on financial performance can be mitigated if a retailer is able to quickly change its purchases. Retailers that have excess inventory in a period can reduce their replenishments for the next period, thereby limiting the impact of excess inventory to only one time period. Similarly, retailers who suffer a shortage of inventory can reduce its impact on financial performance by replenishing their stores during the next period. If HIT retailers have shorter lead times and smaller ordering costs compared to LIT retailers, then we argue that HIT retailers will be able to mitigate the impacts of excesses and shortages on financial performance better than LIT retailers.

Hypothesis 5 (H5). *The financial performance of LIT retailers is more negatively impacted by inventory excesses and shortages than is the financial performance of HIT retailers.*

3. Data and Methodology

We obtain data from two public sources: Compustat and the Conference Board. Quarterly data for retailer-level variables were obtained from Compustat for 28 years, 1985–2012. These data correspond to all retailers required to file financial statements with the Securities and Exchange Commission. These retailers belong to one of the eight two-digit SIC codes numbered 52 to 59, which correspond to the retail sector. These SIC codes cover the following segments within retail: construction and home improvement (SIC 52), department stores (SIC 53), groceries and produce (SIC 54), automobile dealers (SIC 55), clothing and accessories (SIC 56), furniture and white goods (SIC 57), restaurants and eating outlets (SIC 58), and others (SIC 59, drug stores, direct retailers, bookstores, stationery, florists, optical stores, news vendors, etc.). In keeping with Kesavan et al. (2010), we do not use retailers from SIC 58 (restaurants and eating outlets) and 55 (automobile dealers) in our analyses because retailers in these industries have a significant service component; consequently, inventory management is only partly related to their performance. Additionally, we drop retailers categorized as SIC 54 (grocery stores) from our analyses because we use macroeconomic shocks as proxy for unobservable demand shocks, and the grocery segment is acyclical.

Past research has measured macroeconomic shocks through several different approaches, each being appropriate for a given empirical setting: Lamey et al. (2007) use gross domestic product (GDP); Kesavan and Kushwaha (2014) use GDP, personal consumption expenditure, and CCI; and Doms and Morin (2004) and Lemon and Portniaguina (2006) use the University of Michigan's Index for Consumer Sentiment (ICS) as well as CCI. This research (see Bram and Ludvigson 1998, Ludvigson 2004) has shown that the CCI is better at predicting economic growth and expenditure behavior of consumers for most product categories vis-à-vis the ICS, and managers use it in their planning cycles (Carroll et al. 1994, Ludvigson 2004 and Souleles 2004). Thus, we calculate the average CCI for each quarter using the underlying monthly CCI series and use it to compute macroeconomic demand shocks.

For our analysis, we use only retailers with fiscal year end dates in December and January so that they are aligned in the release of macroeconomic information. Such retailers constitute about 68% of the overall population. We adjust all of the firm-level variables with consumer price index to control for inflation.

Table 1 summarizes the data sources and measurements of different variables. We generate the following independent and dependent variables for our analyses. *Inventory Turns* (IT_{it}) is measured as the ratio of cost of goods sold to average inventory. *Purchases* ($PURCH_{it}$) in a given quarter are obtained as ending inventory plus cost of goods sold minus beginning inventory. Although H1 and H2 deal with purchase quantity, we are limited by data availability to measure purchases in dollar amounts. This follows a standard approach in the literature (Cachon et al. 2007, Larson et al. 2015).

We use ABIG as a proxy for excesses and shortages, where $ABIG_{it}$ is defined as inventory growth (IG_{it}) minus sales growth (SG_{it}) with respect to the same quarter in the previous year, i.e., ABIG is the fourth-differenced time series $(IG_{it} - SG_{it}) - (IG_{i,t-4} - SG_{i,t-4})$. This measure has been used in the accounting literature (Lev and Thiagarajan 1993, Abarbanell and Bushee 1997) and operations management literature (Rumyantsev and Netessine 2007b, Kesavan and Mani 2013), and has

Table 1 **Variables Descriptions**

Variables	Measurement
Raw variables (data source: Compustat)	
CPI	Consumer price index as measure of inflation
$INVT_{it}$	CPI adjusted inventory (*INVTQ*)
$COGS_{it}$	CPI adjusted cost of goods sold (*COGSQ*)
$SALES_{it}$	CPI adjusted sales (*REVQ*)
NI_{it}	CPI adjusted net income in quarter (*NIQ*)
AT_{it}	CPI adjusted total assets (*ATQ*)
Endogenous variables	
Consumer Confidence Index	CCI_t
Macroeconomic Shock	ε_{it}^{CCI}
Demand	$LCOGS_{it} = \text{Log}(COGS_{it})$
Purchases	$LPURCH_{it} = \text{Log}[INVT_{it} + COGS_{iq} - INVT_{it-1}]$
Gross Margin	$\text{Log}[(SALES_{it} - COGS_{it})/COGS_{it}]$
Abnormal Inventory Growth	$ABIG_{it} = [(I_{it} - I_{it-4})/I_{it-4}] - [(COGS_{it} - COGS_{it-4})/COGS_{it-4}]$
Return on Assets	$ROA_{it} = NI_{it}/AT_{it}$
Mediating variable	
Inventory Turns	$IT_{it} = COGS_{it}/((INVT_{it} + INVT_{it-1})/2)$
HIT_i or LIT_i Classification	Retailer is classified as HIT_i if $IT_{i,t-5} > 75$th percentile for at least 3/4th of quarters Retailer is classified as LIT_i if $IT_{i,t-5} > 25$th percentile for at least 3/4th of quarters

been found to be used in practice (Raman et al. 2005). We treat $ABIG > 0$ as a proxy for excess inventory and $ABIG < 0$ as a proxy for shortages.

Finally, we use *Return on Assets* (ROA_{it}) as the measure of financial performance and *Gross Margin* (GM_{it}) as a proxy for price. Though gross margin can also change as a result of change in input costs, we assume that retailers' demand shocks do not have a differential impact on the input costs of HIT retailers compared to LIT retailers. Thus, we utilize the differences in gross margins across HIT and LIT retailers as a proxy for the relative changes in prices.

We trim the top 1% and bottom 1% of observations based on purchases, ABIG, and gross margin. This approach ensures that our analyses are not unduly influenced by extreme outliers.

3.1. Classification of HIT and LIT Retailers

To test our hypotheses using the VAR methodology, we group retailers into two time-invariant groups (HIT and LIT) and perform a split-sample analysis. We perform the grouping in the following way. First, we compute the percentile rank of each retailer in each quarter based on the distribution of inventory turnover in its SIC retail segment. Then we classify those retailers that appeared in the top 75th percentile for more than 75% of the quarters they were present as HIT retailers and those retailers that appeared in the bottom 25th percentile for more than 75% of the quarters they were present as LIT retailers. We do not use the rest of the retailers for our main analysis, but include them in robustness checks where we reclassify HIT and LIT retailers based on whether their inventory turn was above or below the median for the segment in that quarter. We begin with 13,227 quarterly observations from 357 retailers and use our sorting procedure to obtain 9,028 quarterly observations across 183 retailers. We summarize key variables in our data by each industry in Table 2 and by their inventory turn classification in Table 3. As seen in Table 3, the average quarterly inventory turn for HIT sample (1.65) is significantly greater than that for LIT sample (0.63).

There are two concerns with using a time-invariant classification of retailers into HIT and LIT groups: if retailers frequently switch between these groups and, more importantly, if this switching is driven by demand shocks, then this method of classification is neither appropriate nor exogenous to the dependent variables being examined. We examine for the presence of such confounding effects using the following tests. First, we examine whether past demand shocks explain whether a retailer is classified as HIT or LIT. We use a random effects panel data probit model to estimate the probability of a retailer belonging to the HIT classification as a function of its past financial performance, size, and lagged demand shocks. The results reported in Table 4 show that whereas past performance and assets are significant determinants of retailers' relative inventory turns classification in its segment, past demand shocks are not.

Second, we permit the HIT and LIT classification to vary over time and generate a transition matrix as shown in Table 5. We find that less than 1% of transitions are between HIT and LIT groups. Thus, retailers who may belong to both groups at different points in time do not unduly affect our analysis.

Finally, we test whether these transitions are driven by demand shocks. Again, we use a random effects panel data probit model to estimate the probability of a retailer transitioning between groups, as a function of past financial performance, size, and demand shocks. Table 6 reports the results of this analysis. We find that the impact of demand shocks on the probability of a retailer transitioning between groups is not statistically significant. These tests show that although demand shocks may impact inventory turns of the retailers, their relative positions among their peers remain unaffected. Therefore, our HIT and LIT classification is exogenous to the demand shocks.

3.2. Relationship Between Lead Time and Inventory Turnover

In this section, we estimate the lead times for retailers using their quarterly sales and purchases data and assess whether short lead time retailers have higher inventory turns. Bray and Mendelson (2012) use an MMFE process to model quarterly sales data, estimate demand shocks of different lead times, and apply a generalized order-up-to policy to assess the bullwhip for different lead times. Our method to estimate lead time is a special case of their model. We first establish a nonstationary demand process for each retailer by determining the best-fitting AR(p) model for the quarterly sales time series of each retailer. We find that an AR(2) model yields the best fit for 0.9% of the firms, AR(3) for 1.8%, AR(4) for 3.4%, AR(5) for 2.8%, and AR(6) for the remaining 91.1%. Moreover, the coefficients of lagged terms vary across firms.

The purchases time series for each retailer can be expressed as a function of its demand process as shown in §2.1 assuming an order-up-to policy with time-invariant costs. Lee et al. (2000) derive the order quantity as a function of lead time for AR(1) demand, and Gaur et al. (2005) derive this quantity for ARMA(p, q) demand. We use the coefficients from the best-fitting AR model in the expression from Gaur et al. (2005) for different values of lead time ranging between zero and four quarters. We then compare the predicted orders' time series thus obtained with actual purchases to determine the *best-fit lead time* for each retailer based on the Bayesian information criterion.

We find that the average lead time across the entire data set is 0.95 quarters with a standard deviation

Table 2 Data Summary: Different Industries

	SIC 52	SIC 53	SIC 56	SIC 57	SIC 59	
Description	Building materials and hardware	General merchandise stores	Apparel and accessories stores	Home furniture and furnishing stores	Miscellaneous retailers	
Example of retailers	Home Depot, Lowe's, National Lumber and Supply, Tractor Supply & Co.	Kohl's, J.C. Penney, Macy's, Target	Aeropostale, Footlocker, Gap, Stein Mart	Bombay Co., Linen N Things, Restoration Hardware, Williams—Sonoma	Build-a-Bear, CVS, Staples, Toys"R"Us	Overall sample
No. of retailers	25	77	89	22	144	357
No. of observations	1,140	3,071	4,449	861	5,033	13,227
Inventory turn (IT_{it})	1.17	0.89	1.06	0.87	1.30	1.11
	(0.60)	(0.39)	(0.48)	(0.35)	(1.29)	(0.87)
Purchases ($PURCH_{it}$ in \$M)	652.42	876.99	258.84	104.54	271.23	414.78
	(1,801.11)	(1,909.34)	(513.28)	(116.62)	(779.16)	(1,175.81)
Cost of goods sold ($COGS_{it}$ in \$M)	638.78	865.01	255.59	101.41	265.99	408.20
	(1,772.99)	(1,887.28)	(511.58)	(114.44)	(762.83)	(1,160.12)
Ratio of $PURCH_{it}$ to $COGS_{it}$	1.02	1.05	1.04	1.05	1.06	1.05
	(0.20)	(0.30)	(0.25)	(0.21)	(0.30)	(0.28)
Gross margin (GM_{it})	0.28	0.30	0.36	0.37	0.35	0.34
	(0.12)	(0.08)	(0.11)	(0.10)	(0.13)	(0.12)
Abnormal inventory growth ($ABIG_{it}$)	0.00	0.02	0.01	0.01	0.02	0.01
	(0.28)	(0.36)	(0.26)	(0.15)	(0.15)	(0.14)
Return on assets (ROA_{iq})	0.0051	0.0004	0.0082	0.0046	−0.0027	0.0021
	(0.0680)	(0.0927)	(0.0661)	(0.0672)	(0.0932)	(0.0840)

Note. Means and standard deviations (in parentheses) are shown.

Table 3 **Data Summary: HIT vs. LIT**

	HIT sample	LIT sample
Example of retailers	Amazon, Claries, Gap, J.C. Penney, Mays Department Store, PetSmart, Office Depot, QVC, Target	Big Lots, Borders, Dicks Sporting Goods, Dillards, Eddie Bauer, Footlocker, Toys"R"Us
Number of retailers	81	102
Number of observations	4,208	4,820
Frequency distribution by industries (52, 53, 56, 57, 59)	6, 21, 23, 4, 27	5, 25, 29, 4, 39
Inventory turn (IT_{it})	1.65 (0.99)	0.63 (0.24)
Purchases ($PURCH_{it}$ in \$M)	512.78 (1,166.14)	204.26 (374.31)
Cost of goods sold ($COGS_{it}$ in \$M)	506.25 (1,151.81)	200.98 (385.09)
Ratio of $PURCH_{it}$ to $COGS_{it}$	1.02 (0.15)	1.07 (0.33)
Gross margin (GM_{it})	0.52 (0.15)	0.55 (0.14)
Abnormal inventory growth ($ABIG_{it}$)	0.01 (0.30)	0.01 (0.24)
Return on assets (ROA_{iq})	0.0075 (0.0622)	−0.0001 (0.0760)

of 0.49. The distribution of estimated lead times is as follows: 38% of the firms have lead times less than one quarter, 59% have lead times between one and two quarters, and the remaining 3% have lead times longer than two quarters. The correlation coefficient between the estimated lead time and inventory turnover is −0.34 ($p < 0.01$), implying that shorter lead time retailers have higher inventory turns. The average lead time for HIT retailers is 0.90 quarters, and that for LIT retailers is 1.08 quarters. A logit model to predict the HIT–LIT classification of retailers using estimated lead time as the input variable is statistically significant with $p = 0.03$ for the log likelihood. These tests support our assumption, used in the motivation of our hypotheses, that shorter lead time retailers have higher inventory turns.

Although our test results support our assumption, our estimates of lead time can likely be improved by using data that do not suffer from aggregation across stock-keeping units and time and by incorporating fixed ordering cost into the inventory model (Chen and Lee 2012).

3.3. Model Specification to Test Hypotheses H1–H4

We use a VAR model to determine the impact of demand shocks on demand, purchases, gross margin, abnormal inventory growth, and ROA. A VAR model is similar to a simultaneous equations model, but provides the following additional benefits: (a) it allows for dynamic interactions among variables, thereby improving model fit; (b) it allows us to examine the impact of shocks through an IRF analysis; and (c) it enables us to identify time-varying impacts such as delayed response and persistence. Stock and Watson (2001) provide additional details on VAR models.

VAR models are extensively used in economics, finance, and marketing for modeling multivariate time series. In economics, the methodology has been applied to study relationships between macroeconomic variables such as interest rates, unemployment, inflation, exchange rates, and economic growth. (See the seminal paper by Sims 1980 or Stock and Watson 2001 for a review.) In finance, the methodology has been used for understanding relationships between stock

Table 4 **Probability of Classification in HIT (vs. LIT) Group**

Dependent variable: $P(HIT_{it})$	Coeff.	S.E.
ROA_{it-1}	***0.9070***	0.3848
$ASSETS_{it-1}$ (in \$M)	***0.0512***	0.0189
CCI_{t-1}	0.0011	0.0012
Intercept	***1.0073***	0.5426
Quarter Effects	None significant	
Industry Segment Effects	One significant	
Sample Size N	9,052	
No. of Retailers	183	

Note. All bold and italicized coefficients have $p < .05$.

Table 5 **Transition Between Different Inventory Turn Classification**

Transition matrix	LIT (Low)	MIT (Medium)	HIT (High)
LIT (Low)	3,819	61	0
MIT (Medium)	780	3,778	790
HIT (High)	70	824	4,432

Table 6 Probability of Transition Between Different Inventory Turn Classifications

Dependent variable: $P(TRANSITION_{it})$	Coeff.	S.E.
ROA_{it-1}	$-$***0.4191***	0.1878
$ASSETS_{it-1}$ (in \$M)	-0.6670	0.6170
CCI_{t-1}	-0.0002	0.0006
Intercept	$-$***0.6833***	0.1505
Quarter Effects	Two significant	
Industry Segment Effects	One significant	
Sample Size N	13,983	
No. of Retailers	357	

Note. All bold coefficients have $p < 0.05$ and italicized coefficients have $p < 0.10$.

prices, dividends, and earnings (Campbell and Shiller 1988); international transmission of stock market movements (Eun and Shim 1989); information content of stock trades (Hasbrouck 1991); and monetary policy and stock returns (Thorbecke 1997). In marketing, the methodology has been adopted to examine the relationships between consumer demand, advertising spending, promotional expenditure, and customer profitability (see Dekimpe and Hanssens 1999); product quality and profitability (Jacobson and Aaker 1987); new product introduction, sales promotion, and firm value (Pauwels et al. 2004); and word of mouth and social networking (Trusov et al. 2009). More recently, the technique has found utility in the operations management literature for studying relationships between inventory investment and other firm decisions (see Wu and Chen 2010, Kesavan and Kushwaha 2014).

The first step in model specification is to determine whether to specify the VAR model in levels or changes. Most of our variables are autocorrelated time-series data, which suggests that a change specification is more appropriate. Consistent with Levin et al. (2002), we perform panel unit root tests to identify whether variables are stationary or evolving. We work with the logarithmic transformations for purchases (*LPURCH*), gross margin (*LGM*), and demand (*LCOGS*) to account for scale differences (Gaur et al. 2005). The unit root tests suggest that all the variables except The customer confidence index and ABIG are not stationary (see Online Appendix A (available as supplemental material at http://dx.doi.org/10.1287/msom.2015.0571) for detailed results). ABIG is already fourth differenced by definition. Therefore, we specify all remaining variables, except CCI and ABIG, as fourth differenced to account for autocorrelation and the strong quarterly seasonality in the retail sector. Our tests show that the fourth-differenced variables are stationary.

The second step in model specification involves identifying the endogenous variables. We use the Granger causality test to determine the choice of endogenous variables (Enders 1995); see Online Appendix B for details. Our results indicate that sales ($\Delta LCOGS_{it}$), purchases ($\Delta LPURCH_{it}$), gross margin (ΔLGM_{it}), abnormal inventory growth ($ABIG_{it}$), and return on assets (ΔROA_{it}) are Granger-caused by the other variables in the system and are therefore endogenous.

The third step is determining the optimal number of lags of the variables to be included in the model. These lags act as instruments for identifying the system of equations specified above. To determine the optimal lag length, we use the Schwarz Bayesian information criterion to consistently estimate the lag structure that minimizes the sum of squared errors by taking into account model complexity (Schwarz 1978); see Online Appendix C for details. We find the optional number of lags to use in our VAR model to be four.

In matrix notation, the VAR model for each retailer i from industry segment j can be written as

$$\begin{bmatrix} CCI_t \\ \Delta \mathrm{LCOGS}_{it} \\ \Delta \mathrm{L}P\mathrm{URCH}_{it} \\ \Delta \mathrm{LGM}_{it} \\ ABIG_{it} \\ \Delta ROA_{it} \end{bmatrix} = \begin{bmatrix} \lambda_{10} \\ \lambda_{20} \\ \lambda_{30} \\ \lambda_{40} \\ \lambda_{50} \\ \lambda_{60} \end{bmatrix} + \sum_{l=1}^{4} \begin{bmatrix} \lambda_{11}^l & \lambda_{12}^l & \lambda_{13}^l & \lambda_{14}^l & \lambda_{15}^l & \lambda_{16}^l \\ \lambda_{21}^l & \lambda_{22}^l & \lambda_{23}^l & \lambda_{24}^l & \lambda_{25}^l & \lambda_{26}^l \\ \lambda_{31}^l & \lambda_{32}^l & \lambda_{33}^l & \lambda_{34}^l & \lambda_{35}^l & \lambda_{36}^l \\ \lambda_{41}^l & \lambda_{42}^l & \lambda_{43}^l & \lambda_{44}^l & \lambda_{45}^l & \lambda_{46}^l \\ \lambda_{51}^l & \lambda_{52}^l & \lambda_{53}^l & \lambda_{54}^l & \lambda_{55}^l & \lambda_{56}^l \\ \lambda_{61}^l & \lambda_{62}^l & \lambda_{63}^l & \lambda_{64}^l & \lambda_{65}^l & \lambda_{66}^l \end{bmatrix}$$

$$\cdot \begin{bmatrix} CCI_{t-l} \\ \Delta \mathrm{LCOGS}_{it-l} \\ \Delta \mathrm{LPURCH}_{it-l} \\ \Delta \mathrm{LGM}_{it-l} \\ ABIG_{it-l} \\ \Delta ROA_{it-l} \end{bmatrix} + \begin{bmatrix} \mu_{j1} \\ \mu_{j2} \\ \mu_{j3} \\ \mu_{j4} \\ \mu_{j5} \\ \mu_{j6} \end{bmatrix} + \begin{bmatrix} \varepsilon_{it}^{CCI} \\ \varepsilon_{it}^{\Delta \mathrm{LCOGS}} \\ \varepsilon_{it}^{\Delta \mathrm{LPURCH}} \\ \varepsilon_{it}^{\Delta \mathrm{LGM}} \\ \varepsilon_{it}^{ABIG} \\ \varepsilon_{it}^{\Delta ROA} \end{bmatrix}, \quad (1)$$

where l stands for number of lags of each endogenous variable to be included. We are primarily interested in examining the impact of demand shock (ε_{it}^{CCI}) on the rest of the variables. The second and third rows explain changes in demand (measured as change in log cost of goods sold, $\Delta LCOGS_{it}$) and in purchases (measured as change in log purchases, $\Delta LPURCH_{it}$), respectively. The fourth, fifth, and sixth rows explain changes in gross margin (ΔLGM_{it}), abnormal inventory growth, and change in return on assets (ΔROA_{it}), respectively. We control for industry segment-specific fixed effects (μ_j) in our system of equations. The ε's are white noise residuals that are assumed to be distributed multivariate normal $(0, \Sigma)$. The lag terms act as instruments to identify the system. In the above system, λ_{11}, λ_{22}, λ_{33}, λ_{44}, λ_{55}, and λ_{66} are the carryover effects (lag terms) for the endogenous variables.

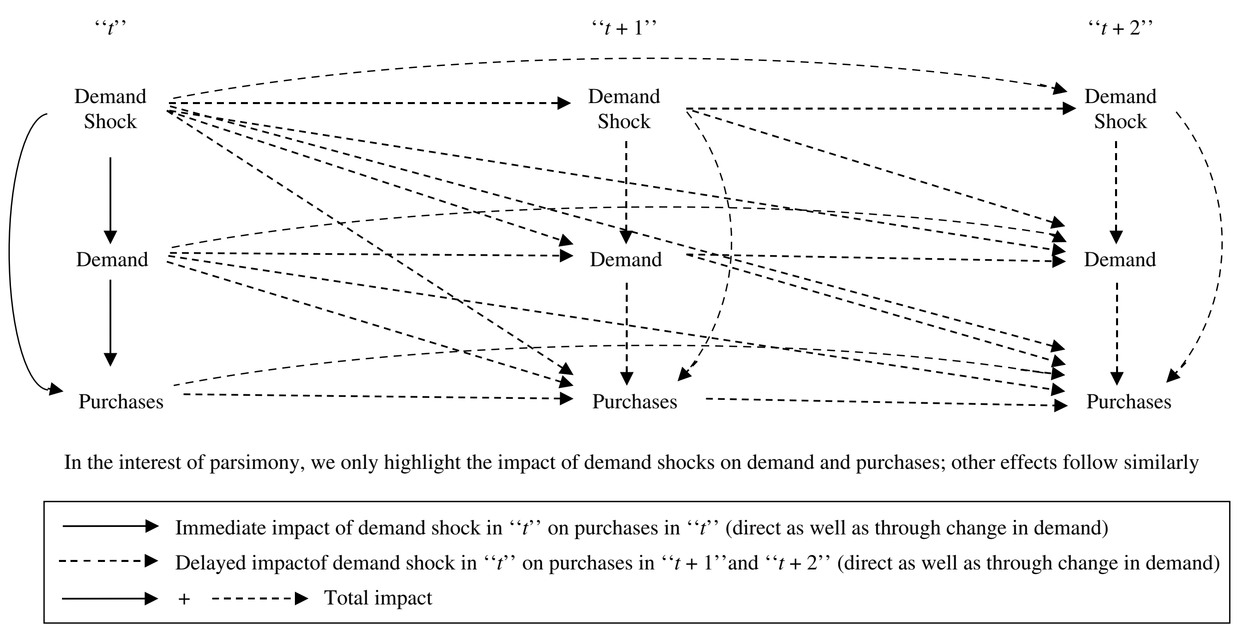
The last step in the VAR methodology is the use of IRFs to examine the impact of demand shock (ε_{it}^{CCI}) on the rest of the variables. An impulse response analysis is frequently undertaken after model estimation since interpreting the coefficients of a VAR model is often problematic due to severe multicollinearity among lags of variables (Sims 1980). An impulse response is the forecasted response of a system of variables to a unit (or one standard deviation) exogenous shock in another variable. The procedure for the IRF analysis is as follows. We first estimate the system of equations as specified in the VAR model. Next, we predict the changes in the values of other endogenous variables over the next 10 quarters due to a *one-standard-deviation shock* to CCI in the current quarter. The statistical significance of the impulse response weights are assessed by examining the t-statistics associated with the forecasted values of the dependent variable (Sims 1980). We use Cholesky's degrees of freedom adjusted decomposition to generate relevant IRFs. We use analytical standard errors to test the significance of impulse responses. We use a conservative plus or minus two standard deviation band for evaluating the statistical significance of impulse responses (Sims and Zha 1999).

We present details of the calculations of forecasted responses for the system of equations in Online Appendix D. The Granger causality test results reported in Online Appendix B suggest that (a) demand shocks Granger-cause all firm specific variables; (b) change in demand Granger-causes change in purchases, but not the other way around; (c) change in purchases Granger-cause change in gross margin; (d) change in demand, purchases, and gross margin Granger-cause ABIG; and (e) ABIG Granger-causes ROA and not vice versa. Consistent with these results, we specify following causal ordering for generating IRFs:

$$\textit{Demand Shock} \rightarrow \textit{Demand} \rightarrow \textit{Purchases} \rightarrow \textit{Gross Margin}$$
$$\rightarrow \textit{Abnormal Inventory Growth} \rightarrow \textit{Return on Assets}.$$

We calculate the *immediate* and *persistent* impact of demand shock on other variables in the system using the IRFs. The *immediate* impact is operationalized as the impulse response weight in the concurrent time period, i.e., impact in time period t. The *persistent* impact is the sum of effects of impulse response weights from time period t until mean reversion or new trend is reached. The sum total of immediate and persistent impact is the total impact. We exemplify these impacts using Figure 1. In the interest of parsimony, we only highlight the impact of demand shocks on purchases. The solid lines represent the immediate impact of demand shock in time period t on purchases in time period t. This impact includes the direct impact as well as the one that permeates through change in demand. The dashed lines represent the delayed impact of demand shock in time period t on purchases in time periods $t+1$ and $t+2$. Again, this effect includes the direct impact as well as the one that permeates through demand as well as recursive relationships between demand shocks, demand, and purchases.

Figure 1 **Graphical Representation of Impulse Response Functions from the VAR Specification**



In the interest of parsimony, we only highlight the impact of demand shocks on demand and purchases; other effects follow similarly

We examine the moderating effect of inventory turnover by using a split-sample approach and estimating the VAR model separately for the HIT and LIT subsamples and then comparing results.

3.4. Model Specification to Test Hypothesis 5

H5 predicts that the impact of ABIG on profitability would be different for HIT and LIT retailers. Because such an impact is likely to be nonlinear (Rumyantsev and Netessine 2007b, Kesavan and Mani 2013), we estimate a separate equation using linear and quadratic terms for ABIG in the following model specification:

$$ROA_{it} = \alpha_0 + \alpha_1 ABIG_{it} + \alpha_2 ABIG_{it}^2 + Z_{it}\Sigma + \mu_i + \sigma_t + \vartheta_{it}. \tag{2}$$

Here, α's are response parameters, and Z_{it} is the vector of control variables including linear and quadratic terms for gross margin, CCI, and lagged ROA. To account for retailer and quarter-industry-specific unobserved heterogeneity in the above equation, we include retailer fixed effects (μ_i) and quarter-industry (σ_t) fixed effects. Since we hypothesize a nonlinear impact of *ABIG* on *ROA*, and *ABIG* takes both positive and negative values, comparing statistical significance of coefficients α_1 and α_2 across the HIT and LIT subsamples may not reveal the range of *ABIG* values in which ROA differs across the two types of retailers. Bollen and Stine (1990) find that in a large sample the bootstrap distribution of an estimator is close to that assumed with classical methods. They also suggest that such bootstrap distribution of an estimator is appropriate for nonlinear and indirect effects. We formally test the difference in the impact of *ABIG* on *ROA* between HIT and LIT retailers by performing 1,000 bootstraps of linear and quadratic coefficients from their two-standard-deviation asymptotic intervals. We compare the mean of fitted *ROA* values across the 1,000 bootstraps between the two subsamples in the observed *ABIG* range, and test for the statistical significance of the difference between the means to evaluate the range of *ABIG* values in which HIT and LIT retailers are different from each other. This constitutes the test of H5.

4. Results

4.1. Hypotheses 1–4

Figure 2, (a)–(j), presents the IRFs and their associated impact on our key variables of interest. For completeness, we report the coefficients from the estimation of the VAR models for HIT and LIT firms in Online Appendix E. These coefficients' estimates along with the variance–covariance matrix are used for generating the IRFs discussed below.

4.1.1. *Demand Shock → Demand*. We find that a one standard deviation (1σ) increase in demand shock leads to 0.0049 ($p < 0.05$) and 0.0050 ($p < 0.05$) increases in the realized demand (i.e., cost of goods sold) in the HIT and LIT samples, respectively. These coefficients imply that demand increases by 0.49% and 0.50% for HIT and LIT retailers compared to their demand four quarters back, respectively. These effects are immediate, with no significant persistence. In other words, the demand change quickly reverts to zero after the quarter in which the demand shock occurs. Since the demands of both HIT and LIT retailers are affected similarly by demand shocks, any difference in purchase behavior across these retailers may not be attributed to differences in demand shifts.

4.1.2. *Demand Shock → Purchases*. We find that a 1σ increase in demand shock increases purchases of HIT retailers by 0.0080 ($p < 0.05$). This effect is immediate with no significant persistence. On the contrary, for a 1σ increase in demand shock, the immediate increase in purchases is not statistically significant in the LIT sample (0.0097, $p > 0.10$). Instead, the effect of demand shock on purchases in the LIT sample is felt beyond the first quarter and is persistent for up to four quarters. As seen in the IRF in Figure 2(d), the impact of this demand shock is statistically significant in the second through fourth quarters. This supports H1 that the impact of demand shocks on purchases will be delayed for LIT retailers because the orders from LIT retailers are delivered (as purchases) with a longer lag due to a slower responsiveness of their supply chain compared to HIT retailers.

Additionally, the persistence of this effect suggests that the response time of LIT retailers can be potentially as long as four quarters. The total effect of a 1σ demand shock on purchases in the LIT sample (0.0529, $p < 0.01$) is greater (Diff $= 0.0449$, $p < 0.01$) than that in the HIT sample. Thus, LIT retailers appear to change their purchases by 4.6% more than their HIT counterparts when demand shocks occur. These two results support H2.

4.1.3. *Demand Shock → Gross Margin.* The impact of a 1σ increase in demand shock on gross margin is positive but not significant for HIT retailers (see Figure 2(e)). However, LIT retailers increase their gross margin in response to demand shocks (0.0043, $p < 0.01$). This impact is only immediate (i.e., concurrent quarter) with no persistence. These findings support H4.

4.1.4. *Demand Shock → ABIG*. Figure 2, (g) and (h), suggests that both HIT and LIT retailers do not face immediate increase in ABIG in response to demand shocks. This suggests that even though LIT retailers are able to respond slowly in changing their purchases, their larger change in gross margin enables them to avoid ABIG in the current quarter. However, our results for H2 indicate that orders flow into purchases after at least one quarter. Thus, LIT retailers may exhibit ABIG due to a demand shock in subsequent

Figure 2 **(Color online) Impulse Response Function of Demand Shocks on Retailer Outcomes**

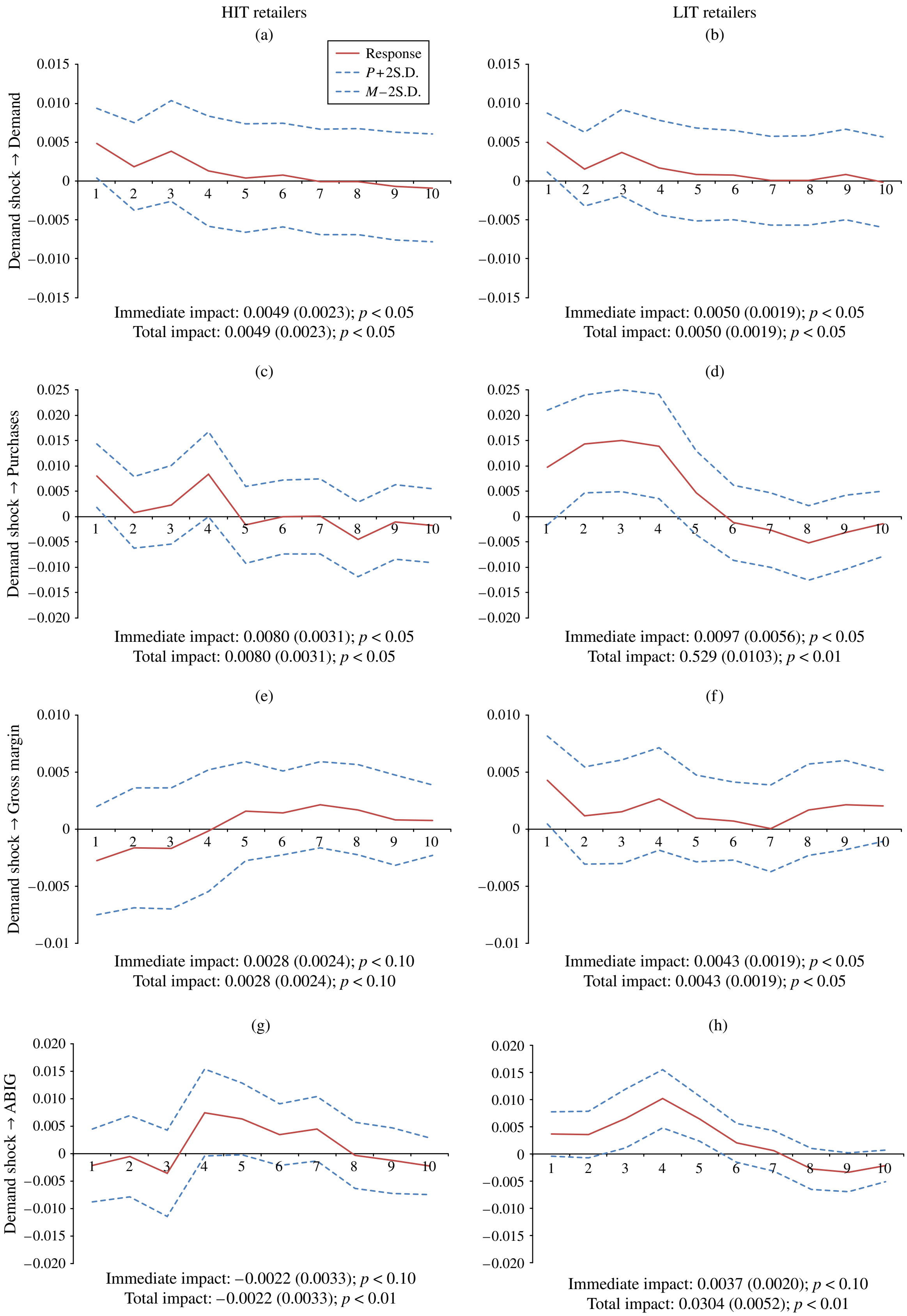
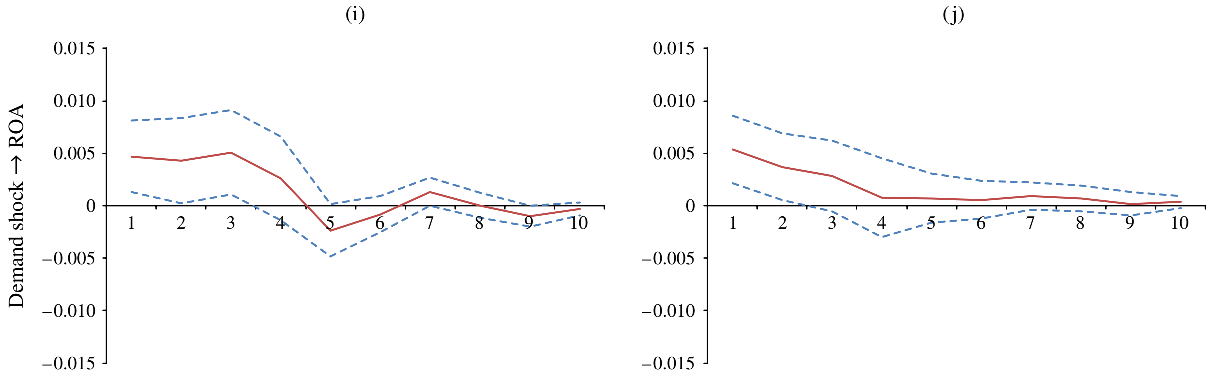


Figure 2 (Color online) (Continued)



Immediate impact: 0.0047 (0.0017); $p < 0.01$
Total impact: 0.0141 (0.0033); $p < 0.1$

Immediate impact: 0.0053 (0.0016); $p < 0.01$
Total impact: 0.0119 (0.0028); $p < 0.1$

Notes. The x-axes show quarters; the y-axes show sales ((a) and (b)), purchases ((c) and (d)), gross margin ((e) and (f)), ABIG ((g) and (h)), and ROA ((i) and (j)). The solid lines represent response to a one S.D. increase in demand shocks. The dotted lines represent a $+/-2$ S.D. band.

quarters. Consistent with this expectation, we observe abnormal inventory growth in subsequent quarters for LIT retailers, as shown in Figure 2(h). Thus, the impact of demand shocks on the ABIG of LIT retailers occurs after the current quarter but persists up to the fourth quarter. The total resulting impact of demand shocks on the ABIG of LIT retailers is significant (0.0304, $p < 0.01$) and greater than that for HIT retailers (Diff $= 0.0326$, $p < 0.01$). HIT retailers do not have abnormal inventory growth in the current or subsequent quarters. Thus, a quantity responsiveness mechanism adopted by HIT retailers for mitigating the impact of demand shocks appears to be more effective in preventing ABIG compared to the price responsiveness mechanism adopted by the LIT retailers.

4.1.5. *Demand Shock → ROA*. Figure 2, (i) and (j), suggests that both HIT and LIT retailers face immediate changes in firm performance, measured as return on asset, in response to demand shocks. The immediate (i.e., HIT $= 0.0047 \approx$ LIT $= 0.0053$) and total (i.e., HIT $=$ $0.0141 \approx$ LIT $= 0.0119$) effects of demand shocks on ROA for the two samples are similar. Thus, the baseline impact of demand shocks on ROA is consistent across both HIT and LIT retailers, after controlling for ABIG. In other words, demand shocks impact the financial performance of HIT and LIT retailers similarly, once we account for the effect of ABIG. Next, we consider the impact of ABIG on ROA.

The impulse response to demand shocks measured from the VAR model yields larger estimates of lead times than those obtained in §3.2 from an AR(p) demand model and an order-up-to policy. We can identify two potential reasons for this difference. The first is the time difference between order placement and shipments. In §3.2, we impute orders as a function of lead time and the AR(p) demand specification and then assess the fit between the imputed orders and actual purchases. It is likely that the order lead time thus obtained would be shorter than the purchases lead time because orders are placed earlier than the occurrence of material flows in the inventory data. The second is methodological differences between the two approaches. The model used in §3.2 does not allow for any control variables or covariates, and, furthermore, provides a single "best fit" estimate of lead time. In contrast, the VAR model concurrently estimates the impulse response of purchases to demand signals of different lags. These methodological differences could lead to different estimates of lead time. In particular, autocorrelation in the purchase time series is not incorporated in §3.2. Time series data have high autocorrelation, so this could affect the estimates in §3.2. We address autocorrelation in the VAR model by using first-differenced variables and including lagged values of purchases in the equation.

In our opinion, the VAR model provides more accurate empirical results for purchases because it employs fewer assumptions and directly measures the response of purchases to demand shocks. It is, however, noteworthy that the imputed lead times in §3.2 are directionally consistent with those from the VAR model.

4.2. Hypothesis 5

Table 7 reports the implications of ABIG for ROA. In both subsamples, we find support for an inverted-U relationship between ABIG and ROA. This is consistent with the nonlinear relationships demonstrated in Rumyantsev and Netessine (2007b) and Kesavan and Mani (2013). For the LIT sample, the coefficients of the linear (0.1071, $p < 0.01$) and quadratic terms (-0.8712, $p < 0.01$) for ABIG are significant. For the HIT sample, only the coefficient for the quadratic term is significant (-0.0693, $p < 0.01$).

To quantify the impact of ABIG on the ROAs of HIT and LIT retailers, we examine the effect of a 1σ change

Table 7 Results: Retailer Performance Model

Dependent variable: ROA_{it}	Coefficient	HIT full model Coeff.	HIT full model S.E.	LIT full model Coeff.	LIT full model S.E.
CCI_t	α_1	−0.0001	0.0001	0.0000	0.0002
$ABIG_{iqt}$	α_2	0.0032	0.0076	***0.1071***	0.0184
$(ABIG_{it})^2$	α_3	***−0.0693***	0.0105	***−0.8712***	0.0456
ΔGM_{it}	α_4	***0.5305***	0.0631	***0.4655***	0.1209
$(\Delta GM_{it})^2$	α_5	***−4.2094***	0.7338	−1.7303	1.6465
ROA_{it-1}	α_6	***−0.2149***	.0139	***−0.2858***	0.0199
Intercept	α_0	***0.0199***	0.0056	0.0102	0.0101
Quarter ∗ SIC Dummies		Yes		Yes	

Notes. All bold coefficients have $p < 0.05$, and italicized coefficients have $p < 0.10$. HIT and LIT Classifications are based on $t - 2$.

in ABIG from its mean values on the ROAs of both types of retailers. The mean and standard deviation of ABIG for HIT retailers in our sample are −0.023 and 0.349, respectively. For HIT retailers, a 1σ increase in ABIG at the mean leads to a decrease in ROA of 0.63%. Similarly, for these retailers, a 1σ decline in ABIG at the mean leads to a decrease in ROA of 1.08%. The mean and standard deviation of ABIG for LIT retailers in our sample are −0.021 and 0.261, respectively. For LIT retailers, a 1σ increase in ABIG leads to a 2.44% decrease in ROA, and a 1σ decline in ABIG leads to a 9.95% decrease in ROA. Thus, for a 1σ increase (decrease) in ABIG, the ROA of LIT retailers is 1.81% (8.87%) less than that of their HIT counterparts.

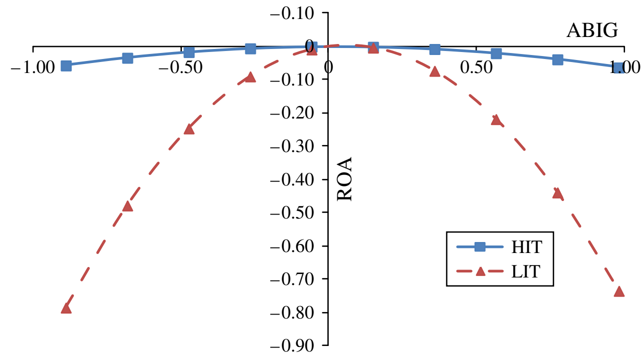
We formally test these differences in the impact of ABIG on HIT and LIT retailers by performing 1,000 bootstraps of linear and quadratic coefficients from their 2σ asymptotic intervals. The mean values and associated standard errors for these bootstraps are reported in Table 8 and plotted in Figure 3. As shown in Table 8, the differences in the impact of ABIG on the ROAs of HIT and LIT retailers are statistically significant ($p < 0.10$). Thus, we find support for H5.

Table 8 Results: Bootstraps for Comparing Nonlinear Effects

ABIG	HIT Mean	HIT S.E.	LIT Mean	LIT S.E.	Difference (HIT − LIT) Mean	Difference (HIT − LIT) S.E.
−0.89	***−0.0571***	0.0118	***−0.7847***	0.0455	***−0.7276***	0.0332
−0.68	***−0.0340***	0.0079	***−0.4778***	0.0283	***−0.4438***	0.0208
−0.47	***−0.0169***	0.0048	***−0.2463***	0.0155	***−0.2294***	0.0115
−0.27	***−0.0057***	0.0024	***−0.0900***	0.0068	***−0.0844***	0.0051
−0.06	−0.0004	0.0005	***−0.0091***	0.0012	***−0.0087***	0.0009
0.15	−0.0011	0.0013	−0.0035	0.0034	−0.0025	0.0025
0.36	***−0.0077***	0.0034	***−0.0733***	0.0100	***−0.0656***	0.0075
0.57	***−0.0202***	0.0061	***−0.2183***	0.0203	***−0.1981***	0.0150
0.77	***−0.0387***	0.0095	***−0.4387***	0.0348	***−0.4000***	0.0255
0.98	***−0.0631***	0.0139	***−0.7343***	0.0538	***−0.6712***	0.0393

Notes. All bold coefficients have $p < 0.05$, and italicized coefficients have $p < 0.10$. HIT and LIT Classifications are based on $t - 1$.

Figure 3 (Color online) Abnormal Inventory Growth and Return on Assets



Notes. We remove top and bottom 1% of data before plotting. The graph is based on bootstrap values from Table 8.

Together, these results suggest the following: (a) HIT and LIT retailers, on average, face similar demand expansion (or contraction) in uncertain economic times. (b) Shorter response times permit HIT retailers to make smaller changes in purchases to mitigate the uncertainty of demand shocks. On the contrary, LIT retailers have to make larger changes to their purchases because of their longer response time. (c) Whereas HIT retailers primarily use quantity responsiveness to mitigate the impact of demand shocks, LIT retailers use price responsiveness to do the same. (d) LIT retailers experience more excesses and shortages when faced with demand shocks. These excesses and shortages are sticky and can persist for as long as four quarters. (e) Not only do LIT retailers experience more excesses and shortages, but the impact of a given amount of excess and shortage of inventory on the financial performance of LIT retailers is also more negative compared to their HIT counterparts.

5. Robustness Checks

5.1. Alternative Methodology

We replace the VAR methodology used to test Hypotheses 1–4 with an alternate methodology to validate the robustness of our results. In the alternate methodology, we generate firm-level demand shocks directly based on an MMFE model (Hausman 1969, Heath and Jackson 1994), in which the difference in successive forecasts for a time period is used as a measure of demand shock. We generate demand signals of different quarterly lead times using these shocks and examine the signal(s) to which HIT and LIT retailers react. In recent research, Bray and Mendelson (2012) use a similar MMFE methodology to decompose the bullwhip into a series of bullwhips based on information lead time of the demand signals. We use these demand shocks to examine Hypotheses H1–H4. The detailed methodology and the results are provided in

Online Appendix F. We find support for all Hypotheses H1–H4. One advantage of this methodology is that we can interpret the magnitude of the impact of demand shocks on different variables, which was harder in the case of VAR models. For example, we find that the impact of 1% demand shock at the mean values on change in purchases amounts to increases of $1.68 million and $6.61 million in year-over-year purchases for HIT and LIT retailers, respectively. Thus, LIT retailers increase their purchases four times as much as their HIT counterparts. We also find that LIT retailers change their gross margin 2.5 times more than HIT retailers.

In summary, we find that even with an alternate methodology that employs a different model specification and a different measure of demand shock, we find support for our claim that HIT and LIT retailers differ in their use of quantity and price responses to demand shocks.

5.2. Alternate Classification of Retailers in the High and Low Groups

Recall that we classify retailers as HIT or LIT based on quartile cutoffs. To ensure a conservative test of our hypotheses, we utilize the entire sample by classifying retailers into the high (low) inventory turn group if they are above (below) the median inventory turns in their industry for at least three-fourths of the quarters that they are present in the sample. This permits us to utilize data from more than 300 retailers (vis-à-vis 183 before) to test our hypotheses. The immediate and total impact from the IRFs from this sample are reported in Online Appendix G. The results are directionally consistent with, albeit slightly weaker than, those reported in Figure 2. Thus, our results are not sensitive to alternate classification schemes.

5.3. Face Validity of Findings

When faced with demand shocks, LIT retailers accumulate higher ABIG that subsequently has stronger detrimental impact on financial performance. Thus, it is likely that LIT retailers will have inferior long-term stock returns and survival rates than HIT retailers. Therefore, we compute long-term stock returns and survival rate statistics for HIT and LIT retailers to test the face validity of our findings. First, for stock returns, we generate monthly equal-weighted portfolio returns of HIT and LIT retailers for a 10-year window (2003–2012), with rebalancing at the end of each month. We compute abnormal monthly portfolio returns using the Fama and French (1993) three-factor model. Online Appendix H shows the cumulative value of $100 invested in each portfolio on January 1, 2003. Over the 10-year window, the HIT portfolio outperforms the LIT portfolio by a significant margin. By December 31, 2012, the values of HIT and LIT portfolios are $205 and $132, respectively. This result is consistent with Alan et al. (2014).

Second, we examine rates of bankruptcy for the two types of retailers using the UCLA-LoPucki Bankruptcy Database. We extract bankruptcies filed by publicly traded U.S. retailers between 1985 and 2011. We find 36 instances of bankruptcies, of which 18 are from LIT retailers and 7 are from HIT retailers. The remaining 11 are filed by medium inventory turn retailers. Thus, one-half of all bankruptcies are filed by LIT retailers, which constitute 29% of our sample, whereas HIT retailers, which constitute 23% of the sample, yield only 19% of the bankruptcies filed. The inferior stock market returns and lower survival rate of LIT retailers compared to HIT retailers provide additional evidence in support of our findings.

6. Conclusions, Limitations, and Future Work

We use a VAR methodology to discern differences in inventory purchase and pricing behavior across HIT and LIT retailers. We find that HIT retailers are able to quickly respond to demand shocks by changing their purchase quantity. LIT retailers appear to depend primarily on price changes to manage demand shocks. Though LIT retailers are able use price response to mitigate their inability to adjust purchase quantities under demand shocks, we find that the price response strategy is a less effective approach because it results in relatively more abnormal inventory growth compared to the quantity response strategy. Furthermore, a given amount of abnormal inventory growth can have more than eight times the detrimental effect on the financial performance of LIT retailers compared to HIT retailers.

Our analysis suggests areas for future work in theoretical and empirical research. First, lead time may be an important predictor in the choice of price and quantity response to demand shocks. Most theoretical papers in the joint price–inventory optimization assume zero lead time. Incorporating lead time in these models would be useful to help bridge the gap between theoretical research and practical application. Whereas we estimate lead times for high and low inventory turnover retailers and show that they are different across these retailers, future research may develop structural models that incorporate additional primitives such as review time and fixed ordering costs and account for possible aggregation bias with firm-level data to obtain better estimates of lead time and other primitives. Once these underlying primitives have been estimated, it may be possible to test the differential effects of each of these factors on the ability of retailers to respond to demand shocks.

Our paper has implications for managers who are considering decisions that will result in an increase or decrease in inventory turnover. First, consider those retailers who face decisions that might decrease their inventory turns, such as an increase in lead time or increase in ordering costs. Since supply chain responsiveness is likely to decline for these retailers, our results suggest that these retailers should first evaluate whether they would be able to respond by changing prices when there are demand shocks. Sustaining higher price volatilities would require them to have a higher margin (Pashigian 1988) that may or may not be possible with their market position and the segment they serve. Furthermore, even if their margins were high enough to allow them to become price responsive, they may need to build capability to implement rapid price changes in their chain. Such capabilities would require organizational changes and investments in information technology that might be time consuming and expensive.

At the same time, there are many retailers who are considering reducing the lead time in their supply chain, which could result in an increase in inventory turns. For example, a recent article in the *New York Times* (Cave 2014) discusses the growing trend of companies considering sourcing closer to home and how managers are evaluating the higher margins from sourcing from faraway destinations against speed of response. As managers consider the losses from lower margins, they should also consider the large financial advantage that accrues from being able to quantity respond during demand shocks, as documented in this paper.

Supplemental Material
Supplemental material to this paper is available at http://dx.doi.org/10.1287/msom.2015.0571.

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References
Abarbanell J, Bushee B (1997) Fundamental analysis, future earnings, and stock prices. *J. Accounting Res.* 35(1):1–24.
Aguirregabiria V (1999) The dynamics of markups and inventories in retailing firms. *Rev. Econom. Stud.* 66(2):275–308.
Alan Y, Gao GP, Gaur V (2014) Does inventory productivity predict future stock returns? A retailing industry perspective. *Management Sci.* 60(10):2416–2434.
Bernstein F, Li Y, Shang K (2015) A simple heuristic for joint inventory and pricing models with lead time and backorders. *Management Sci.*, ePub ahead of print November 25, http://dx.doi.org/10.1287/mnsc.2015.2227.
Bollen KA, Stine R (1990) Direct and indirect effects: Classical and bootstrap estimates of variability. *Sociol. Methodology* 20(1):115–140.
Bram J, Ludvigson SC (1998) Does consumer confidence forecast household expenditure? A sentiment index horse race. *Econom. Policy Rev.* 4(2):59–78.
Bray R, Mendelson H (2012) Information transmission and the bullwhip effect. *Management Sci.* 58(5):860–875.
Cachon GP, Randall T, Schmidt GM (2007) In search of the bullwhip effect. *Manufacturing Service Oper. Management* 9(4):457–479.
Campbell JY, Shiller RJ (1988) Stock prices, earnings, and expected dividends. *J. Finance* 43(3):661–676.
Carroll CD, Fuhrer JC, Wilcox DW (1994) Does consumer sentiment forecast household spending: If so why? *Amer. Econom. Rev.* 84(5):1397–1408.
Cave D (2014) As ties with China unravel, U.S. companies head to Mexico. *New York Times* (May 31), http://www.nytimes.com/2014/06/01/world/americas/as-ties-with-china-unravel-us-companies-head-to-mexico.html.
Chen H, Frank MZ, Wu OQ (2007) U.S. retail and wholesale inventory performance from 1981 to 2004. *Manufacturing Service Oper. Management* 9(4):430–456.
Chen Li, Lee HL (2012) Bullwhip effect measurement and its implications. *Oper. Res.* 60(4):771–784.
Chen X, Simchi-Levi D (2004) Coordinating inventory control and pricing strategies with random demand and fixed ordering cost: The infinite horizon case. *Oper. Res.* 52(6):887–896.
Chen Y, Ray S, Song Y (2006) Optimal pricing and inventory control policy in periodic-review systems with fixed ordering cost and lost sales. *Naval Res. Logist.* 53(2):117–136.
Dekimpe MG, Hanssens DM (1999) Sustained spending and persistent response: A new look at long-term marketing profitability. *J. Marketing Res.* 36(4):397–412.
Doms ME, Morin NJ (2004) Consumer sentiment, the economy, and the news media. Working Paper 2004-09, Federal Reserve Bank of San Francisco, San Francisco.
Enders W (1995) *Applied Econometric Time Series* (John Wiley & Sons, New York).
Eun CS, Shim S (1989) International transmission of stock market movements. *J. Financial Quant. Anal.* 24(2):241–256.
Fama EF, French KR (1993) Common risk factors in the returns on stocks and bonds. *J. Financial Econom.* 33(1):3–56.
Fisher ML (1997) What is the right supply chain for your product? *Harvard Bus. Rev.* 75(2):105–116.
Gaur V, Fisher ML, Raman A (2005) An econometric analysis of inventory turnover performance in retail services. *Management Sci.* 51(2):181–194.
Gaur V, Giloni A, Seshadri S (2005) Information sharing in a supply chain under ARMA demand. *Management Sci.* 51(6):961–969.
Graves SC (1999) A single-item inventory model for a nonstationary demand process. *Manufacturing Service Oper. Management* 1(1):50–61.
Hasbrouck J (1991) Measuring the information content of stock trades. *J. Finance*. 46(1):179–207.
Hausman WH (1969) Sequential decision problems: A model to exploit existing forecasters. *Management Sci.* 16(2):93–111.
Heath DC, Jackson PL (1994) Modeling the evolution of demand forecasts with application to safety stock analysis in production/distribution systems. *IIE Trans.* 26(3):17–30.
Jacobson R, Aaker DA (1987) The strategic role of product quality. *J. Marketing* 51(4):31–44.
Jain N, Girotra K, Netessine S (2014) Managing global sourcing: Inventory performance. *Management Sci.* 60(5):1202–1222.
Kesavan S, Kushwaha T (2014) Differences in retail inventory investment behavior during macroeconomic shocks: Role of service level. *Production Oper. Management* 23(12):2118–2136.
Kesavan S, Mani V (2013) The relationship between abnormal inventory growth and future earnings for U.S. public retailers. *Manufacturing Service Oper. Management* 15(1):6–23.
Kesavan S, Gaur V, Raman A (2010) Do inventory and gross margin data improve sales forecasts for U.S. public retailers? *Management Sci.* 56(9):1519–1533.
Lamey L, Deersnyder B, Dekimpe MG, Steenkamp JBEM (2007) How business cycles contribute to private-label success: Evidence from the U.S. and Europe. *J. Marketing* 71(1):1–15.
Larson CR, Turcic D, Zhang F (2015) Inventory write-downs, sales growth, and ordering policy: An empirical investigation of dynamic ordering policies. *Management Sci.* 61(9):2118–2138.

Lee H, Padmanabhan P, Whang S (2004) Information distortion in a supply chain: The bullwhip effect. *Management Sci.* 50(12): 1875–1886.

Lee HL, So KC, Tang CS (2000) The value of information sharing in two-level supply chain. *Management Sci.* 46(5):626–643.

Lemon M, Portniaguina E (2006) Consumer confidence and asset prices: Some empirical evidence. *Rev. Financial Stud.* 19(4): 1499–1529.

Lev B, Thiagarajan SR (1993) Fundamental information analysis. *J. Accounting Res.* 31(2):190–190.

Levin A, Lin CF, Chu CSJ (2002) Unit root tests in panel data: Asymptotic and finite-sample properties. *J. Econometrics* 108(1): 1–24.

Ludvigson SC (2004) Consumer confidence and consumer spending. *J. Econom. Perspect.* 18(2):29–50.

Pashigian BP (1988) Demand uncertainty and sales: A study of fashion and markdown pricing. *Amer. Econom. Rev.* 78(5): 936–953.

Pauwels K, Silva-Risso J, Srinivasan S, Hanssens DM (2004) New products, sales promotion, and firm value: The case of automobile industry. *J. Marketing*. 68(4):142–156.

Rajagopalan S (2013) Impact of variety and distribution system characteristics on inventory levels at U.S. retailers. *Manufacturing Serivce Oper. Management* 15(2):191–204.

Raman A, Gaur V, Kesavan S (2005) David Berman. Case 605-081, Harvard Business School, Boston.

Rumyantsev S, Netessine S (2007a) What can be learned from classical inventory models? A cross-industry exploratory investigation. *Manufacturing Service Oper. Management* 9(4):409–429.

Rumyantsev S, Netessine S (2007b) Should inventory policy be lean or responsive? Evidence for U.S. public companies. SSRN working paper, http://dx.doi.org/10.2139/ssrn.2319834.

Schwarz G (1978) Estimating dimensions of a model. *Ann. Statist.* 6(2):461–464.

Sims CA (1980) Macroeconomics and reality. *Econometrica* 48(1):1–48.

Sims CA, Zha T (1999) Error bands for impulse responses. *Econometrica* 67(5):1113–1155.

Souleles NC (2004) Expectations, heterogeneous forecast errors, and consumption: Micro evidence from the Michigan consumer sentiment surveys. *J. Money Credit Banking*. 36(1):39–72.

Sterman JD (1989) Modeling managerial behavior: Misperceptions of feedback in a dynamic decision making experiment. *Management Sci.* 35(3):321–339.

Stock JH, Watson MW (2001) Vector autoregressions. *J. Econom. Perspect.* 15(4):101–115.

Thomas J, Zhang XJ (2000) Identifying unexpected accruals: A comparison of current approaches. *J. Accounting Public Policy* 19(4–5): 347–376.

Thorbecke W (1997) On stock market returns and monetary policy. *J. Finance* 52(2):635–654.

Trusov M, Bucklin RE, Pauwels K (2009) Effect of word-of-mouth versus traditional marketing: Findings from a Internet social networking site. *J. Marketing* 73(September):90–102.

Van Mieghem JA, Allon G (2008) *Operations Strategy* (Dynamic Ideas, Belmont, MA).

Wu OQ, Chen H (2010) Optimal control and equilibrium behavior of production-inventory systems. *Management Sci.* 56(8): 1362–1379.