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Incorporating Price and Inventory Endogeneity in Firm-Level Sales Forecasting

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Abstract

As numerous papers have argued, sales, inventory, and gross margin for a retailer are interrelated. We construct a simultaneous equation model to establish these interrelationships at a firm level. Using publicly available financial data we estimate the six causal effects among sales, inventory, and gross margin. Our results show that sales, inventory, and gross margin are mutually endogenous. In particular, we provide new evidence of the impact of inventory on sales and the interrelationship between gross margin and inventory. We also estimate the effects of exogenous explanatory variables such as store growth, proportion of new inventory, capital investment per store, selling expenditure, and index of consumer sentiment on sales, inventory, and gross margin. We show that our model can be used to benchmark retailers' performance in sales, inventory, and gross margin simultaneously. Finally, we show that our model can be used to generate sales forecasts even when sales were managed using inventory and gross margin. In numerical tests, sales forecasts from our model are more accurate than forecasts from time-series models that ignore inventory and price as well as forecasts from financial analysts.

* This is a preliminary draft. Please do not quote without the authors' consent. Comments are welcome.

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1. Introduction

The sales, inventory, and gross margin for a retailer are interrelated due to operational reasons. Retailers often use inventory and margin to increase sales. Conversely, sales provide input to the retailer's decisions on inventory and margins. Inventory and margin also influence each other. Procuring more inventory increases the probability of future markdowns, whereas higher margins increase the propensity to carry more inventory.

The theoretical literature in operations management has postulated several causes for the interrelationships among sales, inventory, and gross margin. An increase in sales leads to an increase in average inventory due to economies of scale as shown by the traditional EOQ model. An increase in inventory leads to an increase in expected sales by improving service levels, as is commonly known in stochastic inventory theory, as well as due to a demand stimulating effect studied by Balakrishnan et al. (2004), Dana and Petruzzi (2001), and Smith and Achabal (1998). An increase in gross margin (or price) increases the optimal inventory as shown in the joint pricing and inventory literature, see for example, Chen and Simchi-Levi (2004), Federgruen and Heching (1999), and Petruzzi and Dada (1999). On the flip side, an increase in inventory decreases the gross margin as shown in the markdown management and clearance pricing literature, see Gallego and van Ryzin (1994), Smith and Achabal (1998). The interrelationship between gross margin and sales is well-known from the familiar demand and supply curves in microeconomics.

While theoretical literature has studied each of the interrelations among sales, inventory, and gross margin in detail, it is often difficult to discern these relationships in practice. For example, Raman et al. (2005) illustrate some difficulties that arise due to the inability to distinguish these interrelationships in the case of Joseph A. Bank Clothiers, Inc. (Jos Bank; NYSE: JOSB), a men's clothing retailer. Jos Bank states that it carries higher inventory than its competitors in order to strategically use inventory to drive sales by providing higher service level. However, several financial analysts claim that Jos Bank carries more inventory than it should in order to generate the sales. So, while Jos Bank management argues that inventory drives sales, financial analysts question how sales are driving inventory at Jos

Bank[5]. Raman et al. (2005) also discuss examples of other retailers, such as Home Depot, Bombay Company, and Soucany, where the interrelationships between sales, inventory, and margin face similar difficulties. For example, in 2001-'02 when Home Depot lowered inventories to increase margins, analysts' blamed its strategy to reduce inventory to have caused the subsequent decline in sales.

One of the prime sources of difficulty in studying the interrelationships among these variables in practice is that the data obtained from practice are the joint outcome of all of these interrelationships being manifested simultaneously. This simultaneity suggests that sales, inventory, and margin are mutually endogenous and can be represented by a *triangular model* as shown in Figure 1. It has three implications for study of interrelationships using data: (i) Simple correlations among the three variables are insufficient to determine causation. For example, a positive correlation between sales and inventory does not help us identify whether sales drive inventory or inventory drives sales or the two variables are co-determined by other factors. (ii) A change to one of the variables will affect both the other variables, so that the validity of observed practices such as for Jos Bank or Home Depot cannot be ascertained easily. All three variables must be studied simultaneously in order to identify whether desired changes in their values take place. (iii) Any one of the three variables cannot be forecasted accurately while ignoring the other two. In particular, the triangular model can improve forecasting in two ways. It can enable forecasting of sales even when sales were managed using inventory and margin. Second it permits joint forecasting of all three variables as functions of historical and exogenous data.

Our paper presents an empirical study of this triangular model, and examines its implications stated above. Our analysis is conducted using firm-level annual and quarterly data for a large cross-section of U.S. retailers listed on NYSE, AMEX or NASDAQ. We represent the triangular model by a system of three simultaneous equations, namely, an aggregate sales equation, an aggregate inventory equation, and a gross margin equation. By estimating these equations, we test hypotheses on all six directions of causality represented in the triangular model. Thus, our analysis decomposes changes in

[5] We do not intend to settle the debate between Jos Bank management and financial analysts in this paper. However we test both effects (implied by the managements and financial analysts) in our sample of retailers.

sales, inventory, and gross margin into their various causal components. We then present an application of our model to simultaneously generate one-year-ahead forecasts of sales, inventory, and gross margin. We evaluate our method against traditional time-series forecasting methods as well as against forecasts of sales provided by equity analysts.

Our paper yields the following results which contribute to the literature. First, we determine the effects of sales, inventory, and margin on each other. We find that not only sales lead to an increase in inventory, but also inventory leads to an increase in sales. From our hypotheses, the causes for the effect of sales on inventory differ from that of inventory on sales. Sales could affect inventory through economies of scale or scope while inventory could affect sales through service level or a demand stimulating effect. We also find that an increase in gross margin leads to an increase in inventory while increase in inventory leads to a drop in gross margin. Finally, we find support for supply-demand model with increase in sales leading to an increase in margin and increase in margin resulting in lower sales. We term these six causal effects as price elasticity, inventory elasticity, stocking propensity to sales, stocking propensity to margin, markup propensity to sales, and markup propensity to inventory. Our results support the assumptions and analytical findings from the theoretical operations literature. Our results further show that the interactions among the three variables result from first and higher order effects driven by these relationships.

Second, we define curve shifters in each equation which enable us to identify each of the causal effects. Without these curve-shifters, it would not be possible to obtain joint forecasts of sales, inventory, and margin. Moreover, the effects of curve shifters and other predetermined variables on sales, inventory, and margins are of independent interest. For example, we find that selling and advertising expenditure has a direct effect on retailers' sales. Further, due to the triangular model, selling and advertising expenditure indirectly affects inventory and margin, which in turn has ripple effects on all three endogenous variables. The other predetermined variables considered are proportion of new inventory, store growth, capital investment per store, index of consumer sentiment, and lagged values of sales and margin.

Third, we employ our model for forecasting future sales, inventory, and margin as functions of historical data and predetermined variables. Traditional forecasting models assume that sales are exogenous, and hence, espouse forecasting for sales and then using the sales forecast to determine inventory and margin. Our model significantly improves upon traditional forecasting methods because it accounts for sales being managed with inventory and margin and it forecasts for sales, inventory, and margin simultaneously taking into account their mutual interdependence and their co-determination by predetermined variables. In our evaluations, our model produces forecasts that are more accurate than those from two base models based on time-series historical data as well as forecasts from financial analysts. For the test dataset, mean absolute percent errors (MAPE) of forecast errors from our model are 5.82% and from the two base models are 8.62% and 6.41%. For firms for which forecasts from financial analysts are available, the MAPE of forecast errors from our model and from financial analysts are 2.45% and 6.36%, respectively.

Our results build on the previous empirical research on firm-level inventories both methodologically and by offering new insights. Several authors have studied firm level inventories but most have performed correlation studies between inventory turns and independent variables, e.g., Gaur et al. (2005), Gaur and Kesavan (2006), and Roumiantsev and Netessine (2005a, b). A notable exception is Kekre and Srinivasan (1990) which was one of the first papers to employ inventory as a variable in a simultaneous equations model, albeit to study a different issue. Methodologically, ours is the first causal model to conduct joint estimation of a system of equations to analyze simultaneous variations in sales, inventory, and margin. Instead of inventory turnover, we use inventory, sales, and margin as three distinct dependent variables. This enables us to decompose the variation in inventory turnover into its component variables, inventory and sales. Our data set is richer than in the previous literature since we expand the set of explanatory variables in the model to include the proportion of new inventory, selling expenditure, store growth, index of consumer sentiment, and lagged time-series variables. We also control for the number of stores, and redefine the metrics for gross margin and capital investment to obtain better statistical properties for our model. Finally, we show sales forecasting as a new application of empirical models of firm-level inventory.

The results of our paper have revelance to equity analysts as well as retail managers. Equity analysts typically forecast sales and earnings in order to determine equity valuation for a firm. Our model not only beats analysts' forecasts of sales, but also results in simultaneous forecasts for sales, inventory, and gross margin, which can be used in firm valuation. Retail managers can use our model to measure consumers' reactions such as price elasticity and inventory elasticity, as well as to examine their own past actions by measuring stocking propensity to sales and margin and markup propensity to sales and inventory. Retail managers also possess additional data that are not available to the equity analysts. They can augment our model with such data to forecast all three variables simultaneously for their corporate planning.

The rest of this paper is organized as follows: §2 presents our hypotheses; §3 describes the dataset and definitions of variables used in our study; §4 discusses the resulting model and the estimation methodology; the estimation results are presented in §5; §6 shows the application of our results to sales forecasting; and §7 discusses limitations of our study and directions for future work.

2. Hypotheses on Sales, Inventory, and Margin

We discuss the hypotheses between pairs of variables to differentiate the directions of causality. Though we motivate our hypotheses in the context of the retailing industry, they may apply to other industries as well. Our unit of analysis is a firm-year. By assuming that cost of items do not change with time, we define sales at cost so that cost of sales is a measure of volume of sales. This enables us to capture the effects of inventory and margin on unit sales rather than on revenue. We define inventory to be the average of total dollar inventory carried by a firm during the year. Finally, we measure margin by the ratio of revenue to cost of sales. Complete definitions of all variables and controls are provided in §3.

2.1 Hypotheses on Sales and Inventory

Increase in inventory could affect sales by increasing service level or by stimulating demand. The service level effect of inventory takes place by reducing the incidence of lost sales when demand is stochastic.

The demand stimulating effect can take place in several ways. Dana and Petruzzi (2001) show a model in which customers are more willing to visit a store when they expect a high service level. Hall and Porteus (2000) and Gaur and Park (2006) study models in which customers switch to competitors after experiencing stockouts. Balakrishnan et al. (2004) show the example of a retailer who follows a "*Stack them high and let them fly*" strategy in which presence of inventory enhances visibility and could also signal popularity of a product. Raman et al. (2005) discuss another retailer, Jos Bank, which has strategically increased inventory in order to drive an increase in sales. In its 10-K reports for the years 2002-2005, the company names 'inventory in-stock' as one of its four pillars of success. Since both effects described above are in the same direction, we hypothesize that increase in inventory causes an increase in sales.

Hypothesis 1: *Increase in inventory causes increase in sales.*

While Hypothesis 1 states that inventory causes sales to increase, we would also expect sales to cause an increase in inventory. This hypothesis is easy to argue from inventory theory, but notably different from Hypothesis 1. For example, the EOQ model implies that a retailer's average inventory is increasing in mean demand. The newsvendor model also implies this relationship under suitable assumptions on the demand distribution, e.g., normally distributed demand. Hence, we set up the following hypothesis.

Hypothesis 2: *Increase in sales causes increase in inventory.*

2.2 Hypotheses on Inventory and Margin

As inventory increases, the retailer may be forced to take larger markdowns on its merchandise or liquidate the merchandise through clearance sales. Hence, we expect margin to decrease with inventory. This hypothesis is consistent with the results for a linear demand model by Petruzzi and Dada (1999), who show that the optimal price is decreasing in inventory when demand is linear in price with an additive error term. This hypothesis is also consistent with Gallego and van Ryzin (1994) who consider dynamic pricing for a seasonal item whose demand rate is a function of price and show that the optimal price trajectory is decreasing in the level of inventory. Smith and Achabal (1998) obtain a similar result for a model with deterministic demand rate as a multiplicative function of price and inventory level. Hence we obtain the following hypothesis.

Hypothesis 3: *Increase in inventory causes decrease in margin.*

Margin has a direct effect on inventory because in the classical newsvendor solution, as margin increases, underage cost increases and results in a higher optimal safety stock. Hence, an increase in margin implies a higher average inventory level. Hence we expect increase in margin to result in higher inventory.

Hypothesis 4: *Increase in margin causes increase in inventory.*

2.3 Hypotheses on Sales and Margin

A retailer's margin depends on several factors including its pricing strategy, competitive position, demand for its products, cost of products, etc. For a given cost, margin increases with price. As margin increases, sales would be expected to decline because demand is generally downward sloping in price. This motivates Hypothesis 5. A change in cost without a change in price would change margin without affecting end-consumer demand. However, we assume that it is not possible to have a change in cost without a corresponding change in price because retailing is characterized by competition with low entry and exit barriers. We expect cost decreases to be passed on to consumers due to low entry barriers and cost increases to be passed on due to low exit barriers. Thus, we assume that retailers transfer changes in costs to consumers in order to maintain the margin.

Hypothesis 5: *Increase in margin causes decrease in sales.*

The supply equation in supply-demand model states that the price increases with demand. For a given inventory, we expect that as sales increases, the retailer would be willing to have a higher margin for its products due to lower clearance sales.

Hypothesis 6: *Increase in sales causes increase in margin.*

Note that some of our hypotheses are motivated by multiple drivers of causality. For example, inventory causes an increase in sales due to reduction in lost sales and/or demand stimulation. We restrict ourselves to measuring aggregate causality between pairs of variables without distinguishing amongst its various potential drivers. In order to measure these six causal effects we need to determine curve shifters that would enable us to decouple causalities between variables. The next section defines these curve shifters and other variables in detail, and describes the data used in our analysis.

3. Data Description and Definition of Variables

We obtain financial data on retailers listed on the US stock exchanges, NYSE, NASDAQ and AMEX, from Standard & Poor's Compustat database using the Wharton Research Data Services (WRDS). We also collect data on the number of stores and total selling space[6] (in square feet) of each retailer in each year from 10-K statements with the help of a research associate. We collect data for the same set of firms as used in Gaur et al. (2005). From a complete list of 576 firms, Gaur et al. (2005) filter firms that had missing data or had their accounting practice changed during the study period to be left with 311 firms to perform their analysis. We collect data for 1994-2004 for the same set of firms as used in Gaur et al. (2005). Since GAAP (Generally Accepted Accounting Principles) does not mandate retailers to reveal store related information, many retailers do not provide this information. Of the 311 firms, about 205 firms had information on number of stores for at least one year. We consider all firms that have at least three years of data on number of stores to enable us to perform longitudinal analysis. We exclude jewelry firms from our dataset because we found in discussion with retailers familiar with this sector that many of the arguments used in our hypotheses (e.g., the EOQ model or the demand stimulating effect of inventory) do not apply to jewelry retail. For this reason, jewelry retailers could not be combined with the rest of the retailers, and further, since there were only seven jewelry firms we could not create a separate group to analyze them.

The Compustat database provides Standard Industry Classification (SIC) codes for all firms, assigned by the U.S. Department of Commerce based on their type of business. Our final dataset contains 149 firms spanning 5 retail sectors as shown in Table 1. All further analysis was performed on these 149 firms only.

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[6] There were fewer observations available for square-footage than for number of stores. Thus, we use square-footage data only to validate the results in the paper.

Besides financial data, we obtain index of consumer sentiment (ICS) collected and compiled by University of Michigan. The consumer sentiment index represents consumers' confidence and is collected every month. Finally, we obtain forecasts of annual sales made by equity analysts from Institutional Brokers Estimate System (I/B/E/S).

We use the following notation. From the Compustat annual data, for firm i in year t, let SR_{it} be the total sales revenue (Compustat field DATA12), $COGS_{it}$ be the cost of goods sold (DATA41), SGA_{it} be the selling, general and administrative expenses (DATA189), $LIFO_{it}$ be the LIFO reserve (DATA240), and $RENT_{it,1}$, $RENT_{it,2}$, …, $RENT_{it,5}$ be the rental commitments for the next five years (DATA96, DATA 164, DATA165, DATA166, DATA167, respectively). From the Compustat quarterly data, for firm i in year t quarter q, let PPE_{itq} be the net property, plant and equipment (DATA42), AP_{itq} be the accounts payable (DATA46), and I_{itq} be the ending inventory (DATA38). Let N_{it} be the total number of stores open for firm i at the end of year t. Hereafter, variable names without subscripts will be used as abbreviations for the variables.

We make the following adjustments to our data. The use of FIFO versus LIFO methods for valuing inventory produces an artificial difference in the reported ending inventory and cost of goods sold. Thus, we add back LIFO reserve to the ending inventory and subtract the annual change in LIFO reserve from the cost of goods sold to ensure compatibility between observations. The value of PPE could vary depending on the values of capitalized leases and operating leases held by a retailer. We compute the present value of rental commitments for the next five years using $RENT_{it,1},\ldots,RENT_{it,5}$, and add it to PPE to adjust uniformly for operating leases. We use a discount rate d = 8% per year for computing the present value, and verify our results with d = 10% as well.

From these data, we define the following variables:

Average sales per store, $$CS_{it} = \left[COGS_{it} - LIFO_{it} + LIFO_{i,t-1}\right] \Big/ N_{it}$$

Average inventory per store, $$IS_{it} = \left[\frac{1}{4}\sum_{q=1}^{4} I_{itq} + LIFO_{it}\right] \Bigg/ N_{it}$$

Margin, $MU_{it} = SR_{it} \Big/ \left[COGS_{it} - LIFO_{it} + LIFO_{i,t-1} \right]$

Average SGA per store, $SGAS_{it} = SGA_{it} / N_{it}$

Average capital investment per store, $CAPS_{it} = \left[\frac{1}{4} \sum_{q=1}^{4} PPE_{itq} + \sum_{\tau=1}^{5} \frac{RENT_{it\tau}}{(1+d)^{\tau}} \right] \Big/ N_{it}$

Store growth, $G_{it} = N_{it} / N_{it-1}$

Proportion of new inventory, $PI_{it} = \sum_{q=1}^{4} AP_{itq} \Big/ \left[\sum_{q=1}^{4} I_{itq} + 4LIFO_{it} \right]$

Here, average sales per store, average inventory per store, and margin are the three endogenous variables in our study, and average SGA per store, average capital investment per store, store growth and proportion of new inventory are exogenous variables. The last variable merits explanation. We define the proportion of new inventory in order to measure the fraction of inventory that has been purchased recently (see Raman et al. 2005 for the application of this measure to Jos Bank). Retailers typically pay their suppliers in a fixed number of days as defined in their contracts to take advantage of favorable terms of payment. Hence, accounts payable represents the amount of inventory purchased by the retailer within the credit period. Hence, the larger the value of this ratio, the more recent is the inventory. This measure differs from the average age of inventory which is defined as 365 divided by inventory turns. To illustrate this difference, consider two cases. In the first case, a retailer carries two units of inventory purchased one year ago, and in the second case, a retailer carries one unit of inventory purchased two years ago and a second unit purchased today. Assume that each unit costs a dollar and the credit period is less than one year. Then, the accounts payable is zero in the first case, and \$1 in the second case. Hence, proportion of new inventory is zero and 0.5 in the two cases whereas average age of inventory is 365 in both cases.

We use the annual time period as the unit of analysis because most retailers report store level data only at the annual level. Moreover, annual data are audited, and hence, of better quality than quarterly data. We also normalize our variables by the number of retail stores. An alternative would have been to study annual sales and annual inventory of a retailer. However, sales per store and inventory per store are better variables to use than total sales and inventory because they avoid correlations between sales and inventory that could arise due to scale effects caused by increase or decrease in the size of a firm.

Using the above definitions, we compute the logarithm of each variable in order to construct a multiplicative model. The variables obtained after taking logarithm are denoted by lower-case letters, i.e., cs_{it}, is_{it}, mu_{it}, $sgas_{it}$, $caps_{it}$, g_{it}, and pi_{it}, respectively.

4. Model

4.1 Structural Equations

We set up three simultaneous equations, one for each endogenous variable. We use a multiplicative or log-linear model for each equation because: (a) a multiplicative model of demand is used extensively in theoretical operations management and marketing literature; (b) use of a multiplicative model to study inventory turns is justified in Gaur et al. (2005); and (c) multiplicative models of supply equations are commonly used in economics.

We follow Gaur et al. (2005) in considering only within-firm variations in the variables of study because across-firm variations can be caused by variables omitted from our study such as differences across firms in accounting policies, management ability, firm strategy, store appearance, location, competitive environment in the industry, etc. We control for differences across firms by using time-invariant firm fixed effects in each equation.

Based on Hypotheses 1-6, several control variables, and firm fixed effects, we specify the three equations as:

$$cs_{it} = F_i + \alpha_{11} is_{it} + \alpha_{12} mu_{it} + \alpha_{13} sgas_{it} + \alpha_{14} pi_{i,t-1} + \alpha_{15} g_{it} + \alpha_{16} ics_{t-1} + \varepsilon_{it} \quad (1)$$

$$is_{it} = J_i + \alpha_{21} cs_{it} + \alpha_{22} mu_{it} + \alpha_{23} cs_{i,t-1} + \alpha_{24} pi_{i,t-1} + \alpha_{25} g_{it} + \alpha_{26} caps_{it-1} + \eta_{it} \quad (2)$$

$$mu_{it} = H_i + \alpha_{31} cs_{it} + \alpha_{32} is_{it} + \alpha_{33} mu_{it-1} + \upsilon_{it} \quad (3)$$

Equation (1) models sales per store, (2) inventory per store and (3) margin. We name the equations as the *aggregate sales equation*, the *aggregate inventory equation*, and the *gross margin equation*, respectively. Each equation consists of firm fixed effects (F_i, J_i and H_i), coefficients of endogenous variables, coefficients of control variables and error terms (ε_{it}, η_{it}, and υ_{it}). The estimates of α_{11}, α_{12}, α_{21}, α_{22}, α_{31}, and α_{32} enable us to test our six hypotheses. We call these coefficients the inventory elasticity, the price elasticity, the stocking propensity to sales, the stocking propensity to margin, the markup propensity to sales, and the markup propensity to inventory, respectively.[7] It is useful to interpret the aggregate sales equation as measuring the consumers' response to retailer's actions and the aggregate inventory and aggregate gross margin equations as measuring the retailer's past actions on inventory and gross margin.

The set of control variables includes selling expenses per store, proportion of new inventory, capital investment per store, store growth, and index of consumer sentiment as exogenous explanatory variables, and lagged sales per store and lagged margin as additional time-series variables. Together, we call the exogenous and lagged variables as pre-determined variables because they shall be useful in forecasting the endogenous variables. We explain the use of control variables in each equation as follows:

Aggregate sales equation: We control for SGA per store, proportion of new inventory, store growth and macroeconomic factors. Selling, general and administrative expense per store depends on costs involved in building brand image, providing customer service and other operational activities that help to implement a retailer's competitive strategy (Palepu et al. 2004). We expect sales per store to increase with SGA per store since prior work has shown that improvement in customer service and increase in advertising expenses have both led to increase in sales (Bass and Clarke 1972).

We control for proportion of new inventory because a mere increase in average inventory would not increase sales if some of the inventory is stale or obsolete. Thus, we expect the sales per store to increase as proportion of new inventory increases. We use lagged value of proportion of new inventory instead of current value as the control variable because current value of proportion of new inventory is a function of current inventory, and thus, would be correlated with average inventory.

We control for store growth because the composition of new and old stores would affect total sales differently. Contribution of sales from new stores differs from old stores because they are opened

[7] We call the coefficients in the aggregate sales equation as inventory elasticity and price elasticity following common terminology. In the remaining equations, our terminology is motivated by Haavelmo (1943) who called the coefficients in a simultaneous equations model as *propensities*.

during the middle of the year, and hence, their sales contribution to total sales depends on the number of days for which the stores were open. Moreover, sales per day in new stores may be lower or higher than that in old stores depending on whether the stores take time to reach maturity or if they enjoy “fad” status, respectively (Lundholm and McVay 2004). Since we do not have information on when the stores were opened during a year and whether a retailer’s stores enjoy “fad” status or if they take time to gain maturity, we use an aggregate measure of change of stores at a retailer as a control variable.

Finally, we use index of consumer sentiment as a leading indicator of macroeconomic conditions. Carroll et al. (1994) find that the index of consumer sentiment is a leading indicator of change in personal consumption expenditures, a factor that would affect demand faced by a retailer.

Aggregate inventory equation: We control for proportion of new inventory because we expect average inventory per store to increase with the amount of older inventory carried in the store. We use lagged value of proportion of new inventory instead of its current value for the same reason as explained in §3.1. We control for capital investment per store since Gaur et al. (2005) show that inventory turns are positively correlated with capital intensity. Retailers make capital investments in warehouses, information technology, ERP or supply chain management systems, etc. Presence of warehouses enables a retailer to pool its inventory, thus resulting in a lower average inventory level throughout the chain. Cachon and Fisher (2000) cite several benefits of information technology including shorter lead times, smaller batch sizes and better allocation to stores that lower average inventory levels in the retail chain. Several other studies (Clark and Hammond 1997; Kurt Salmon Associates 1993) have suggested lower average inventory levels as one of the benefits of information technology. Thus, we expect that average inventory per store would decrease with increase in capital investment per store[8].

Since average inventory levels can be *sticky* we control for lagged sales per store to include the effect of sales from previous period on the persistence of inventory levels. Finally, we control for store

[8] As an alternate model specification, we included capital investment per store in the aggregate sales equation since some of the capital investment may lead to increased sales. However we found no statistical support for this variable in the aggregate sales equation.

growth since average inventory per store could vary across old and new stores. For example, the Annual Report of Jos Bank 2005 states that its new stores tend to carry lower inventory than old stores.

Aggregate gross margin equation: We use lagged margin as a control variable. Lagged margin is a proxy for the profitability drivers of the retailer.

Note that the set of pre-determined variables differs across equations. The variables that do not appear in each equation and vary across all observations are sga expenses, proportion of new inventory, index of consumer sentiment, lagged sales and lagged markup. We use these variables as curve-shifters in order to identify the coefficients of endogenous variables in the model. Without adequate curve shifters one cannot incorporate endogeneity of sales, inventory, and margin in sales forecasting. The ability of our chosen variables to serve as curve-shifters depends on the hypothesis that each of these variable directly affects only those endogenous variables in whose equations it appears. We perform tests of identification to test these hypotheses, and discuss their estimation methodology in §4.2.

4.2 Estimation of the Simultaneous System of Equations

Independent least square estimation of equations (1)-(3) would produce parameters that are inconsistent because sales per store, inventory per store, and margin are contemporaneously correlated (Greene 2003). Hence, we apply simultaneous equations modeling.

Due to the presence of firm fixed effects, our model should be estimated by first-differencing or mean-centering the observations for each firm. We use first-differencing due to its usefulness for sales forecasting and superior statistical properties. First differencing expresses year-to-year changes in sales, inventory and margin as functions of lagged and exogenous variables. Thus, changes in sales, inventory and margin can be forecasted using estimates from our model. In contrast, a mean-centered model[9] cannot be used for sales forecasting without assuming that mean of each variable remains unchanged when a new year is added - an assumption that is violated by the non-stationarity of our variables. Mean-centering is

[9] For completeness, we estimated the mean-centered model as well. We found all hypotheses to be supported ($p < 0.05$).

also problematic because it produces inconsistent estimates in the presence of lagged endogenous variables (Wooldridge 2002). Hence, first differencing equations (1)-(3) gives us:

$$\Delta cs_{it} = \alpha_{10} + \alpha_{11}\Delta is_{it} + \alpha_{12}\Delta mu_{it} + \alpha_{13}\Delta sgas_{it} + \alpha_{14}\Delta pi_{i,t-1} + \alpha_{15}\Delta g_{it} + \alpha_{16}\Delta ics_{t-1} + \Delta\varepsilon_{it} \tag{4}$$

$$\Delta is_{it} = \alpha_{20} + \alpha_{21}\Delta cs_{it} + \alpha_{22}\Delta mu_{it} + \alpha_{23}\Delta cs_{i,t-1} + \alpha_{24}\Delta pi_{i,t-1} + \alpha_{25}\Delta g_{it} + \alpha_{26}\Delta caps_{i,t-1} + \Delta\eta_{it} \tag{5}$$

$$\Delta mu_{it} = \alpha_{30} + \alpha_{31}\Delta cs_{it} + \alpha_{32}\Delta is_{it} + \alpha_{33}\Delta g_{it} + \alpha_{34}\Delta mu_{i,t-1} + \Delta\upsilon_{it} \tag{6}$$

Here, Δ prefix for each variable is denotes first difference. Equations (4)-(6) are the *structural equations* and their coefficients are the *structural parameters* of the model. We solve this simultaneous system to obtain the *reduced form* of the equations by expressing each endogenous variable as a function of predetermined variables only. Hence, we get three *reduced form equations* as shown in (7)-(9), with coefficients denoted as $\beta_{10}, \ldots, \beta_{37}$ which are functions of the structural parameters, $\alpha_{10}, \ldots, \alpha_{34}$.

$$\Delta cs_{it} = \beta_{10} + \beta_{11}\Delta cs_{i,t-1} + \beta_{12}\Delta mu_{i,t-1} + \beta_{13}\Delta sgas_{it} + \beta_{14}\Delta pi_{i,t-1} + \beta_{15}\Delta g_{it} + \beta_{16}\Delta caps_{i,t-1} + \beta_{17}\Delta ics_{t-1} + \nu_{it} \tag{7}$$

$$\Delta is_{it} = \beta_{20} + \beta_{21}\Delta cs_{i,t-1} + \beta_{22}\Delta mu_{i,t-1} + \beta_{23}\Delta sgas_{it} + \beta_{24}\Delta pi_{i,t-1} + \beta_{25}\Delta g_{it} + \beta_{26}\Delta caps_{i,t-1} + \beta_{27}\Delta ics_{t-1} + \theta_{it} \tag{8}$$

$$\Delta mu_{it} = \beta_{30} + \beta_{31}\Delta cs_{i,t-1} + \beta_{32}\Delta mu_{i,t-1} + \beta_{33}\Delta sgas_{it} + \beta_{34}\Delta pi_{i,t-1} + \beta_{35}\Delta g_{it} + \beta_{36}\Delta caps_{i,t-1} + \beta_{37}\Delta ics_{t-1} + \omega_{it} \tag{9}$$

In order to estimate the model, we first conduct a test of endogeneity to determine if average sales per store, average inventory per store, and margin are endogenous in each of the equations. The test of endogeneity is based on Wooldridge (2002: page 121). The test results show that the variables are endogenous in all three equations at $p<0.001$.

Next we determine if it is possible to recover the structural parameters, $\alpha_{10}, \ldots, \alpha_{34}$, from the coefficients of the reduced form equations by performing the order test for identification. We find that all three equations are over-identified, and thus, all structural parameters can be recovered from the coefficients of the reduced form equations. We consider different estimation techniques such as three stage least squares (3SLS), 2SLS, and IVGLS (Instrument Variable Generalized Least Squares Method). While 3SLS is efficient in the presence of over-identification and correlated errors across equations in the system, this method requires errors to be homoscedastic. However, the errors in our model can be both heteroscedastic and autocorrelated because shocks to sales, inventory, and margin can be both contemporaneously correlated as well as correlated across time periods. For example, a shock to sales in a year could cause inventory to be high or low in that year as well as in the next year resulting in correlations between residuals in the aggregate sales equation and aggregate inventory equation. Hence, we rule out both 3SLS and 2SLS and choose IVGLS procedure that takes into account both heteroscedasticity and (AR1) autocorrelation among observations within each firm.

5. Estimation Results

5.1 Endogenous Variables

Table 2 presents estimation results for the three structural equations (4)-(6) using pooled data for all 149 firms. The structural equations capture the effects of the endogenous variable on each other, and thus, enable us to test our hypotheses. We find that all six hypotheses are supported by the coefficients' estimates at $p<0.001$.

Our results broadly support findings from operations management theory. They show that sales, inventory and margin aggregated at the firm level follow causality relationships that are consistent with theory developed at the item level. First, consider the aggregate sales equation and the aggregate inventory equation. The *inventory elasticity* is 0.29, showing that increase in inventory causes an increase in sales. It implies that if a retailer increases inventory in order to increase sales then its inventory turns decrease since a 1% increase in inventory per store causes an increase of 0.29% increase in sales per store. The *stocking propensity to sales* is 0.76, showing that increase in sales also causes an increase in inventory. Since this estimate is less than 1, it supports economies of scale in inventory. It implies that an increase in consumers' purchases increases the inventory turns of the retailer. Next, consider the aggregate inventory equation and the gross margin equation. The *stocking propensity to margin* is 1.81 and *markup propensity to inventory* is -0.14. Thus, an increase in margin causes an increase in inventory consistent with results from stochastic inventory theory. And an increase in inventory causes a decrease in margin, which supports findings from dynamic pricing literature (Gallego and van Ryzin 1994; Smith and Achabal 1998) that show that optimal pricing trajectory decreases with inventory. Finally, in the aggregate sales equation and the gross margin equation, *price elasticity* is -1.51 and retailers' *markup propensity to sales* is 0.14. Thus, an increase in margin causes a decrease in sales whereas an increase in sales causes an increase in margin as expected according to the demand-supply model in microeconomics. Besides being consistent with theory, these results provide new evidence of the impact of inventory on sales and the interrelationship between margin and inventory.

Our model distinguishes between direct and indirect effects of sales, inventory and margin on each other. We find that inventory directly affects sales through inventory elasticity, i.e., by reducing lost sales and stimulating demand. Additionally, inventory indirectly affects sales through margin: an increase in inventory leads to a decrease in margin, which in turn leads to a further increase in sales. The sum of first and second order effects of inventory on sales is equal to 0.288 + (-0.14)(-1.51) = 0.50. In the reverse direction, sales directly lead to an increase in inventory through stocking propensity to sales. Sales also indirectly lead to an increase in inventory since higher sales leads to higher margins, which increase the propensity to carry inventory. The sum of first and second order effects of sales on inventory is 0.76 + (0.14)(1.81) = 1.01. Likewise, for the remaining pairs of variables we get:

Effect of margin on inventory = 1.81 + (-1.51)(0.76) = 0.662,

Effect of inventory on margin = -0.14 + (0.29)(0.14) = 0.10,

Effect of margin on sales = -1.51 + (1.81)(0.29) = -0.99,

Effect of sales on margin = 0.14 + (0.76)(-0.14) = 0.03.

The first and second order effects of sales, inventory and margin show that sales and inventory are very sensitive to changes in each other and in margin. In contrast, margin is less sensitive to changes in sales and inventory. Thus, we see that small changes in margin in our dataset lead to large changes in sales and inventory. Changes in sales and inventory also lead to large changes in each other, but do not affect margins by much. Regardless of the magnitude of these changes, a retailer needs to be cognizant of the mechanism by which the second order effect propagates and should take that effect into account while planning.

The magnitudes of coefficients can also be used to compare our results with prior research on firm-level inventory turnover. Gaur et al. (2005) show that inventory turnover is negatively correlated with gross margin. This conclusion of Gaur et al. is supported by our results since an increase in margin leads to a decrease in sales and an increase in inventory.

To test our hypotheses at segment level and to determine if the coefficients vary across segments, we also estimate the structural equations separately for different industry segments. Table 3 reports the coefficient estimates obtained. Since we test six hypotheses on five segments, we obtain a total of thirty tests of hypotheses. Of these thirty tests, we find that our hypotheses are statistically supported in 16 cases ($p<0.05$). In the remaining cases, the coefficients are not statistically significant. For example, in the food, miscellaneous, and general sectors we find that margin is not sensitive to sales or inventory. Further, even when the coefficients were significant, they are found to differ considerably across segments. For example, inventory elasticity varies between 0.205 for "Miscellaneous" retail segment to 0.663 for "Apparel". This implies that customers' purchases increased by about 3 times more in "Apparel" than in "Miscellaneous" in response to retailers' increase in inventory. Future research could study different factors such as purchasing behavior among customers, product characteristics, lead time, etc. that might affect these coefficient estimates.

5.2 Predetermined Variables

We use both structural and reduced form equations to interpret the coefficients of predetermined variables. Estimates from reduced form equations are useful because they capture the overall effect of the predetermined variables on all endogenous variables whereas the structural equations capture only first order effects of predetermined variables. These equations are also useful for forecasting sales per store, inventory per store, and markup. Table 2 shows the coefficients' estimates for structural equations and Table 4 for reduced form equations. We summarize some of the insights from these estimates as below. All coefficients are statistically significant at $p<0.001$ unless otherwise noted.

Consider the effect of SGA per store on the endogenous variables as shown in Table 4. A 1% increase in spending on SGA per store increases sales per store by 0.77%, inventory per store by 0.58%

and margin by 0.03%. This shows that when a retailer increases spending in SGA per store, it can expect to increase sales and margin while carrying more inventory. We note that while SGA per store appears only in the equation for sales per store in the structural form, it is found to have second and higher order effects on inventory per store and margin. Further, the coefficient of SGA per store in the reduced form equation for sales is 0.77, whereas its coefficient in the structural equation is 0.64 as shown in Table 2. Thus, the higher order effects enhance the effect of SGA per store on sales.

We find that a 1% increase in lagged capital investment per store increases both sales per store (0.02%) and inventory per store (0.03%) while decreasing margin (-0.01%). In §4.1, we expected capital investment per store to cause a decrease in the average inventory per store but our results indicate otherwise. We think that this might be happening because capital investment and inventory may serve as complementary inputs into the business, i.e., when retailers make capital investments, they are able to expand their business due to the ability to use inventory more efficiently. Gaur et al. (2005) found that inventory turnover was negatively correlated with capital intensity. Similar to them, we find that inventory turnover and capital intensity computed from our estimates of the structural equations model are negatively correlated with each other even though inventory increases with capital investment.

The rest of the coefficients' estimates for predetermined variables are as expected and support the reasoning in §4.1. In particular, we find that increase in store growth leads to a decrease in sales per store (-0.13%), decrease in inventory per store (-0.26%), and increase in margin (0.02%). We also find that lagged proportion of new inventory leads to an increase in sales per store (0.02%) and decreases in inventory per store (-0.12%) and margin (-0.003%). We also find that increase in the index of consumer sentiment is associated with increase in sales per store (0.04%), increase in inventory per store (0.08%), and increase in margin (0.04%).

5.3 Example: Home Depot 2000-2004

In §1, we noted that Home Depot's decline in sales during 2001-2002 could not be attributed to decline in its inventory without analyzing the contemporaneous change in margin. In this example, we illustrate the usefulness of our model for benchmarking Home Depot's performance for the years 2000-2004.

Our methodology is as follows. The reduced form model (7)-(9) yields predicted values of sales per store, inventory per store, and margin as functions of predetermined variables. Hence, residuals from the reduced form model can be used to measure unexpected changes in the values of these variables. Likewise, each structural equation (4)-(6) gives the predicted value of an endogenous variable as a function of predetermined variables and actual values of remaining endogenous variables. Thus, the residuals from a structural equation, say for sales per store, give the unexplained variation in sales per store after controlling for the effects of changes in inventory per store and margin.

Table 5 reports the residuals from reduced form equations (7)-(9) and the structural equation of sales (4) for Home Depot for the years 2000-2004. From the residuals for the reduced form equations, we observe that Home Depot's sales were less than the predicted values in each year, inventories were higher than the predicted values in 3 out of 5 years, and margins were higher than the predicted values in each year. This shows that the effect of inventories on sales cannot be ascertained without accounting for the unexpected increase in margins. Moreover, the residuals for the structural equation for sales are negative in 4 out of 5 years. This shows that Home Depot's sales declined in these years even after taking into account the *actual* changes in inventory and margin. This example illustrates that our model presents a way to control for changes in predetermined and endogenous variables in measuring performance with respect to sales, inventory, and margin. These controls are based on coefficients estimated across all retailers. Thus, an individual retailer may then investigate possible reasons for its observed residuals.

6. Application to Sales Forecasting

In this section, we discuss the application of our model to forecast sales and evaluate its performance. Forecasts from our model are generated using the reduced form equations. These equations use exogenous variables and lagged endogenous variables to forecast sales per store, inventory per store and margin per store simultaneously. Since sales per store are computed at cost, we combine forecasts of sales per store and margin in order to obtain a forecast of sales revenue per store.

$$\hat{cs}_{it} = cs_{it-1} + \hat{\beta}_{10} + \hat{\beta}_{11}\Delta cs_{it-1} + \hat{\beta}_{12}\Delta mu_{it-1} + \hat{\beta}_{13}\Delta sgas_{it} + \hat{\beta}_{14}\Delta pi_{it-1} + \hat{\beta}_{15}\Delta g_{it} + \hat{\beta}_{16}\Delta caps_{it-1} + \hat{\beta}_{17}\Delta ics_{it-1} \quad (10)$$

$$\widehat{mu}_{it} = mu_{it-1} + \hat{\beta}_{30} + \hat{\beta}_{31}\Delta cs_{it-1} + \hat{\beta}_{32}\Delta mu_{it-1} + \hat{\beta}_{33}\Delta sgas_{it} + \hat{\beta}_{34}\Delta pi_{it-1} + \hat{\beta}_{35}\Delta g_{it} + \hat{\beta}_{36}\Delta caps_{it-1} + \hat{\beta}_{37}\Delta ics_{it-1} \quad (11)$$

$$\widehat{srs}_{it} = \widehat{cs}_{it} + \widehat{mu}_{it} \quad (12)$$

Here, $\widehat{srs}_{it}$ denoted the forecast of sales revenue per store. Note that all variables are logarithms.

We compare forecasts from our model against forecasts from two base models and forecasts provided by financial analysts. The first base model is a time series model which assumes that sales per store and margin follow independent ARIMA (1,1,1) processes. Thus, we use lagged sales per store and lagged margin to predict current sales per store and current margin. We then compute a forecast for sales revenue per store from forecasted sales per store and margin as before. The time series models are:

$$\widehat{cs}_{it} = cs_{it-1} + \hat{\gamma}_{10} + \hat{\gamma}_{11}\Delta cs_{it-1} \quad (13)$$

$$\widehat{mu}_{it} = mu_{it-1} + \hat{\gamma}_{20} + \hat{\gamma}_{21}\Delta mu_{it-1} \quad (14)$$

The second base model is an augmented time series model in which we add exogenous variables such as SGA per store, store growth and index of consumer sentiment to the time series model. The motivation for this model is that it is a reduced form model derived by ignoring the simultaneity with inventory per store and margin. It is specified as:

$$\widehat{cs}_{it} = cs_{it-1} + \hat{\tau}_{10} + \hat{\tau}_{11}\Delta cs_{it-1} + \hat{\tau}_{12}\Delta sgas_{it} + \hat{\tau}_{13}\Delta g_{it} + \hat{\tau}_{14}\Delta ics_{it-1} \quad (15)$$

$$\widehat{mu}_{it} = mu_{it-1} + \hat{\tau}_{20} + \hat{\tau}_{21}\Delta mu_{it-1} \quad (16)$$

Since the coefficients of the estimates for our model are found to vary significantly across segments, we use segment-wise coefficients' estimates to generate forecasts from our model. Likewise, we estimate the base models with separate coefficients for each segment using the generalized least squares method to incorporate heteroscedastic and autocorrelated (AR(1)) disturbances.

We follow the methodology provided by Pindyck and Rubenfeld (1997) to compare forecasts from our model against forecasts from base models. We use data for 1994 to 2003 to fit our model, leaving out observations for 2004 as the test sample. We present results from *ex-post simulations*, i.e., by evaluating forecasts for the fit dataset, and from *ex-post forecasts*, i.e., by evaluating forecasts for the test dataset. Finally, we compare forecasts from our model against forecasts from financial analysts.

6.1 Ex-post Simulations

The results of the ex-post simulation are given in Table 6. The reported forecast errors are based on dollar figures, not the logged forecasts obtained from the models. The MAPE, MAD and RMSE of errors from simulations of reduced form are 27.50%, 3.66% and 65.70% while those of the time series model are 66.89%, 7.82% and 227.34% and those of the augmented time series model are 27.86%, 3.75%, and 65.62%. Hence, we see that the forecasts from the reduced form model are more accurate than those from the time series model. The augmented time series model produces similar accuracy measures as that of the reduced form model, possibly due to over-fitting. However, the evaluation of ex-post forecasts from these two models might provide a better comparison between the reduced form model and the augmented time series model.

6.2 Ex-post Forecasts

Table 7 provides the accuracy measures computed for the reduced form model and the base models. The MAPE, MAD and RMSE values for the reduced form, time series and augmented time series models are (5.82%, 37.45%, 83.33%), (8.62%, 61.10%, 130.20%), and (6.41%, 48.48%, 127.92%) respectively. We find that the ex-post forecasts from our model outperform ex-post forecasts from both the base models in all three metrics.

6.3 Forecasts from Equity Analysts

Next we compare forecasts from the reduced form model against those from financial analysts. We use analyst forecasts from I/B/E/S database made thirteen months before the fiscal year end date. For example, if the end date of fiscal year 2004 was January 31, 2005, then we use forecasts made on or before December 31, 2003 for this year. Since analysts do not cover all firms, only 42 firms in our sample had analysts' forecasts. Further analysts forecast directly for sales revenue. Hence we divide their forecasts by number of stores to obtain sales revenue per store which is then used for computing forecast errors. Table 8 presents the results of this analysis. The MAPE, MAD and RMSE for forecasts from our model are 2.45%, 19.97%, and 39.94% while those for forecasts from equity analysts are 6.36%, 26.37%, and 42.06%. Hence, we find that forecasts from the reduced form model outperform equity analysts' forecasts in all three metrics.

While we do not know the methodology employed by equity analysts to forecast sales, there are suggestions in the literature that they may not be forecasting sales, inventory, and margin simultaneously. For example, Palepu et al. (2004) state that sales forecasts should be used as input to forecast line items in balance sheet. Our methodology suggests improvements to such a sequential forecasting process by not only producing sales forecasts that are more accurate but also forecasting two other variables that are used by equity analysts to track the performance of a firm.

7. Conclusions, Limitations, and Future Work

In this paper, we construct a simultaneous equations system to examine the interrelationships among sales per store, inventory per store and margin. We define curve shifters that permit us to determine the directions of causality among these variables. We show that sales per store, inventory per store, and margin are mutually endogenous. We also show that the structural equations and the reduced form models can be used to benchmark a retailer's performance in sales, inventory, and margin. Finally, we show that the reduced form model enables us to forecast sales, inventory and margin jointly from historical data after accounting for the interrelationships among them. Our tests show the sales forecasts thus generated to be more accurate than forecasts from two base models and from financial analysts.

Our analysis has some limitations due to the use of financial data which contain noise. Hence, it is possible to enrich our analysis with more accurate or detailed data obtained from firms. Examples of such data include selling and advertising expenditure, capital investment, distribution of the age of inventory, store openings, square footage of stores, and cost-of-goods-sold without overhead expenses. Additional data may also be helpful for the interpretation of coefficients in our model.

We identify the study of inventory elasticity and various propensities measured in this paper as one of the areas of future research. Our study shows that inventory elasticity is about 1/5th of price elasticity in the aggregate dataset with considerable heterogeneity among retail segments. While the magnitude of inventory elasticity indicates the importance of this measure, the heterogeneity among retail segments provides opportunities for future research to examine the drivers of these differences. Also, our study is the first to measure the different propensities of retailers and the results indicate that these propensities are not only high in magnitude but also exhibit variability across the retail segments. Some of the factors that can be studied to analyze the differences in these estimates are substitutability of products, lead times for procurement, product characteristics, competition etc. Further, with sufficient data, it may be possible to repeat the analysis for each firm and determine the drivers of elasticities and propensities at firm level.

Another direction for future research may be availed by applying our model for predicting earnings. We showed that our model is superior to traditional forecasting since it yields joint forecasts for sales, inventory and margin. We may use these forecasts to predict future earnings of firms and determine whether the resulting method yields more accurate forecasts than provided by financial analysts. Finally, this methodology may be tested for manufacturers and wholesalers.

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Figure 1: Triangular model of endogeneity among sales, inventory, and margin

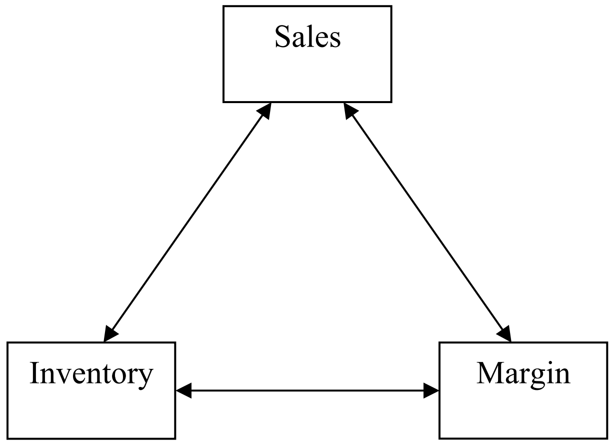

Table 1 Variable Definitions and Summary Statistics

Variable	Definition	Mean	Standard Deviation	Min	Max
Δcs_{it}	Sales per store	0.017	0.180	-2.471	2.434
Δis_{it}	Inventory per store	0.006	0.150	-1.392	0.962
Δmu_{it}	Margin	0.002	0.032	-0.165	0.174
$\Delta cs_{i,t-1}$	Lagged sales per store	0.019	0.185	-2.471	2.434
$\Delta mu_{i,t-1}$	Lagged margin	0.002	0.031	-0.165	0.140
Δsga_{it}	SGA per store	0.024	0.132	-1.310	1.053
$\Delta caps_{i,t-1}$	Lagged capital investment per store	0.045	0.235	-2.109	2.348
Δg_{it}	Store growth	-0.013	0.219	-2.040	2.188
$\Delta pi_{i,t-1}$	Lagged proportion of new inventory	0.001	0.159	-1.219	0.920
Δics_{t-1}	Index of consumer sentiment	0.006	0.059	-0.102	0.075

Note: 1249 firm-year observations. All variables are logged and first differenced.

Table 2: Estimation Results of Structural Equations

	Aggregate Sales Equation Δcs_{it}	Aggregate Inventory Equation Δis_{it}	Gross Margin Equation Δmu_{it}
Δcs_{it}		0.685** (0.041)	0.136** (0.007)
Δis_{it}	0.326** (0.024)		-0.143** (0.005)
Δmu_{it}	-1.193** (0.313)	2.370** (0.687)	
Δcs_{it-1}		0.111** (0.028)	
$\Delta sgas_{it}$	0.598** (0.026)		
Δpi_{it-1}	0.035** (0.004)	-0.135** (0.011)	
Δg_{it}	-0.028** (0.006)	-0.192** (0.021)	
Δics_{i-1}	0.059** (0.022)		
$\Delta caps_{it-1}$		0.038** (0.009)	
Δmu_{it-1}			0.106** (0.011)
Constant	0.002 (0.001)	-0.018** (0.002)	0.001* (0.000)
Wald χ^2	292298.71**	22260.02**	1498.61**

Notes: *,** denote statistically significant at 0.05 and < 0.001, respectively. The numbers in brackets below the parameter estimates are the respective standard errors. Wald test statistic compares fit of model including explanatory variables to fit of model after excluding all variables.

Table 3: Summary Results of Structural Equations for Different Retail Segments

Retail Industry Segment	SIC Code	Examples of Firms	Number of Firms	Number of Observations	Price Elasticity	Inventory Elasticity	Stocking Propensity to Sales	Stocking Propensity to Margin	Markup Propensity to Sales	Markup Propensity to Inventory
Apparel	56	J Crew, Casual Male, Goodys Family Clothing etc.	54	412	-1.150** (0.307)	0.663** (0.095)	0.922** (0.069)	-0.192 (0.462)	0.153** (0.037)	-0.132** (0.045)
Home Furniture and Accessories	57	Bed Bath & Beyond, Radioshack, Home Depot etc.	24	164	-0.851 (1.267)	0.519* (0.082)	1.061** (0.229)	-3.341 (3.078)	0.167** (0.017)	-0.181** (0.016)
General	53	Ames Dept., Dollar General, Federated, Walmart etc.	21	148	-5.277** (1.492)	-0.234 (0.239)	0.537** (0.031)	4.873** (0.966)	0.026 (0.028)	0.012 (0.028)
Miscellaneous	59	Walgreen, Staples etc.	25	188	1.778 (3.03)	0.205* (0.347)	0.731** (0.170)	3.223 (2.001)	0.054 (0.034)	-0.031 (0.023)
Food Stores	54	Safeway, Winn-Dixie, Whole Foods Market etc.	17	134	-0.134 (2.336)	0.408** (0.171)	0.427** (0.058)	-2.570 (1.686)	0.009 (0.017)	-0.023 (0.022)

Note: *,** denote statistically significant at 0.01 and <0.001 respectively. The numbers in brackets below the parameter estimates are the respective standard errors.

Table 4: Estimation Results of Reduced Form Equations

	Δcs_{it}	Δis_{it}	Δmu_{it}
Δcs_{it-1}	0.072** (0.004)	0.161** (0.017)	-0.021** (0.003)
$\Delta sgas_{it}$	0.762** (0.008)	0.576** (0.012)	0.032** (0.004)
Δpi_{it-1}	-0.019** (0.003)	-0.119** (0.009)	0.010** (0.002)
Δg_{it}	-0.136** (0.007)	-0.257** (0.013)	0.025** (0.002)
$\Delta caps_{it-1}$	0.017** (0.004)	0.033** (0.011)	-0.003 (0.002)
Δmu_{it-1}	0.215** (0.022)	0.724** (0.064)	0.016* (0.007)
Δics_{t-1}	0.033* (0.011)	0.075** (0.026)	0.039** (0.006)
Constant	-0.007** (0.001)	-0.017** (0.002)	0.002** (0.000)
Wald χ^2	-603095.27**	-15604.83**	-498.70**

Note: *,** denote statistically significant at 0.05 and <0.001. The numbers in brackets below the parameter estimates are the respective standard errors.

Table 5: Benchmarking Home Depot's performance in Sales, Inventory, and Margin during 2000-2004

Year	Residuals from the Reduced Form Model			Residuals from the Structural Equations Model (Abnormal Sales)
	Abnormal Sales	Abnormal Inventory	Abnormal Margin	
2000	-0.041	0.000	0.005	-0.034
2001	-0.007	-0.043	0.008	0.018
2002	-0.034	0.038	0.016	-0.017
2003	-0.014	0.029	0.006	-0.013
2004	-0.061	-0.011	0.020	-0.027

Table 6: Evaluation of Forecast Accuracy using Ex-post Simulations

	Reduced Form Model	Time Series Model	Augmented Time Series Model
MAPE	27.50%	66.89%	27.86%
MAD	3.66%	7.82%	3.75%
RMSE	65.70%	227.34%	65.62%

Table 7: Evaluation of Forecast Accuracy using Ex-post Forecasts

	Reduced Form Model	Time Series Model	Augmented Time Series Model
MAPE	5.82%	8.62%	6.41%
MAD	37.45%	61.10%	48.48%
RMSE	83.33%	130.20%	127.92%

Table 8: Comparison of Forecast Accuracy with Financial Analysts

	Reduced Form Model	Financial Analysts
MAPE	2.45%	6.36%
MAD	19.97%	26.37%
RMSE	38.94%	42.06%