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ANALYZING THE EFFECTS OF DEMAND UNCERTAINTY ON INVENTORY IN SIX U.S. RETAIL SECTORS USING MULTIVARIATE GARCH-M MODELS AND LIFE AND PROPERTY-CASUALTY INSURANCE INDUSTRY COMPARISONS FOUR YEARS AFTER THE ENACTMENT OF GLBA

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A DISSERTATION APPROVED FOR THE
DEPARTMENT OF ECONOMICS

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ABSTRACT

Chapter 1

This study examines the relationship between inventory and demand uncertainty in six retail sectors and compares the results with previous studies that focused on the more aggregate retail data. Using the constant correlation bivariate GARCH-in-Mean with the vector error correction model (VECM) as the form of mean equation and assuming the GARCH(1,1) process as the measure of demand uncertainty, previous studies find no significant relationships between inventory and demand volatility in aggregate retail. Using the same model for six retail sectors, this study finds the same results. This study shows positive effects of demand uncertainty on inventory holdings by replacing the VAR for VECM as the form of mean equation, particularly in building material, furniture, auto dealers and general merchandise, using both constant correlation and diagonal-BEKK models and in food using the diagonal-BEKK model. A significantly negative relation exists in food retail using a constant correlation model. A mixed result is observed in apparel and general merchandise between different scenarios within the VAR diagonal models. In food, furniture, auto-dealers, and general merchandise retailers, the demand volatilities are time-varying across models. In building material retail, the time-varying demand volatility is not observed in the VECM with a constant correlation. In apparel, the time-varying demand volatility is not observed in both the VAR and VECM with constant correlation. In addition, interrelationships exist between inventory and sales in all six retail sectors in one or in a combination of these forms: (1) their

dependence on each other's level, (2) their being influenced by each other's volatility, and (3) their significant coefficient of correlations. Previous studies show that aggregate retail inventory and demand are cointegrated and the same results are shown in this study in the six retail sectors.

Chapter 2

Following GLBA of 1999, previous studies recommended that banks enter the life insurance industry rather than property casualty insurance based on their prediction that the combined firm would have a less volatile return. Their recommendations are based on industry return and volatility data before the enactment of GLBA in which the life insurance firms had less volatile returns than property-casualty insurance. The theoretical background links a higher revenue or demand for financial institution's products with a safer or lower-risk financial institution. This study uses different data and finds that the return and volatility in each and between these two industry segments do not differ significantly upon the enactment of GLBA. This study uses regression models to analyze the premiums earned by the company and the loss ratio to see whether life insurance is more attractive for entrants than the property-casualty industry. The regression results show that during the four-year period after the enactment of GLBA, premiums earned by a life insurance company are higher than premiums earned by property-casualty insurance. The loss ratio equations show that during the four-year period, the loss ratio experienced by life insurance is higher than that experienced by property-casualty insurance.

Chapter 1. ANALYZING THE EFFECTS OF DEMAND UNCERTAINTY ON INVENTORY IN SIX U.S. RETAIL SECTORS USING MULTIVARIATE GARCH-M MODELS

1. INTRODUCTION

This study focuses on the relationship between monthly inventory and sales, particularly between monthly inventory and uncertainty in demand. The importance of inventories to a firm cannot be ignored. For example, Blinder (1981, p.11-12) notes that many opportunities are available for a firm from the existence of inventories. The author divides a firm's output into storable and un-storable and states that firms have an additional degree of freedom with storable output. According to the author, with storable output, firms are able to make current production differ from current sales and in particular circumstances are advisable to do so; they may use inventories of finished goods to speculate against future price changes or to absorb short-run shocks to demand; and they may use inventory holdings to spur demand by reducing delivery lags or to reduce production costs through improved scheduling. In macro levels, from 1959-1979, changes in inventory investment accounted for 37 percent of the variance of changes in GNP, and retail inventories are the predominant type of inventories accounting for variations (Blinder 1981, p. 12).

The literature suggests three motives for holding inventories, which include production smoothing, production cost smoothing, and stock avoidance motives. In the production smoothing motive, the objective of a firm is to minimize production cost. In a situation when sales vary predictably over time so that the firm produces a constant amount of output resulting in accumulating inventories during low sales and depleting inventories during high sales, (Guasch and Kogan, 1993), inventories absorb the change in sales (Lee and Koray, 1994). In production cost smoothing, firms may profit by increasing production or building inventories when costs are low and the opposite when costs are high (Lee and Koray, 1994). Guasch and Kogan (1993) suggest minimizing "transaction cost motive" due to certain fixed costs in placing an order or due to economies of scale for a large order. In this case, inventory decisions are made by weighing inventory holding costs and savings from large orders and firms following an (S,s) strategy when facing uncertain demand by placing an order of appropriate size to bring it back to S level when inventory falls below s level. Thirdly, the stockout avoidance model is discussed by Lee and Koray who refer to Kahn (1987). If the firm can backlog excess demand, that is, it has the ability to reproduce output when demand turns out to be higher than expected so that output is always available upon customers' arrival, then volatility in production exceeds that of sales. Because stockouts are costly, firms hold inventories instead of smoothing production, so that inventory increases with the risk of stockouts as a result of unpredictable variation in demand. The costs of stockout include the loss of goodwill and the loss of potential sales if it cannot satisfy demand immediately out of inventory (Guasch and Kogan, 1993).

This study particularly focuses on the relationship between inventory and uncertainty of demand in 6 retail sectors: apparel, building materials and hardware, food stores, furniture, general merchandise stores, and automotive dealers. This study uses seasonally-adjusted monthly inventory and sales retail data from 1981 to 2000 and examines empirically the following hypotheses drawn from theoretical background and previous studies discussed in the other section of this paper: (1) The theoretical backgrounds suggest that there are inter-correlations between inventory and sales so that a long term relationship should exist between inventory and sales. In this case Lee and Koray (1994) had shown that a cointegration is present between aggregate retail sales and inventories. Since the aggregate series is a summation of its less aggregate components, the characteristics of the aggregate series can be decomposed through analyzing its less aggregate components. Because this study uses VAR and VEC Models, in which each of six retail series is regressed only on its own lagged values without the influence of any other retail series, these models imply that each retail series is independent from any of the others. This leads to a hypothesis that if aggregate retail sales and inventory are cointegrated, each retail sales and inventory should also be cointegrated. (2) The stock-out avoidance motive suggests that uncertainty in sales increases the risk of stockout so that if this motive prevails in retail inventory (for example, Guasch and Kogan, 2003) this study hypothesizes that volatility in sales should positively affect retail inventory holdings. Feldstein and Auerbach (1976) decompose the change in finished goods inventories into two components that reflect unanticipated sales and intended inventory accumulation. This suggests that inventory increases with unanticipated sales. If sales expectations are correct, all of the observed change in finished goods inventories will be intended. (3) The practice pricing decision in retail industry, such as markups, markdowns, and price deals, may result in fluctuation in sales value; and technical (graphical) analysis shows no clear trend in the series and leads to a hypothesis that volatilities in inventory or sales are time-varying, that is, they are not constant over time.

As analytical tools, this study employs multivariate GARCH models that consist of two equations: mean equations and variance equations. This study uses a vector error correction model (VECM) and vector autoregressive (VAR) as the alternative mean equations. The use of theVECM is to compare the results to a previous study which employed this model. These two models allow inventory to depend on previous sales and sales to depend on previous inventories, but these models differ from simultaneous equations in that there is no endogenous variables in the right hand side of VAR or VECM model. In this study, demand uncertainty, which is represented by sales volatility, that is, the unexplained part of sales called residuals, is hypothesized to be time varying so that the GARCH process is used. This study employs the GARCH(1,1) process to represent the conditional volatility. The use of GARCH(1,1) will make this study comparable to the specification made by Lee and Koray, who also used GARCH(1,1). This demand uncertainty will enter the mean equations, which will allow this study to see if the relationship between inventory and demand uncertainty exists. These analytical tools are called multivariate and, in this case, bivariate GARCH-in-Mean. The use of the VECM requires that inventory and sales are cointegrated. The long-term relationship between inventory and sales, called the cointegrating equation, will have an error term, called cointegrating error, and this error will be included as regressors in the VECM. The use of VAR does not require that the cointegrating residuals be included in the VAR, but inventory and sales should be cointegrated. Another difference is that in the VECM, the variables used are the changes in inventory and sales, while in VAR the variables used are the levels of inventory and sales.

Using the VAR as the mean equation for the multivariate GARCH-in-Mean, this study finds that the interrelationship between inventory and sales are significant in each of the 6 retail sectors in one or combinations of the following forms: (1) The current levels of inventory are significantly influenced by previous levels of sales and the current levels of sales are significantly influenced by previous levels of inventory. (2) Inventories are influenced by the volatility of sales and sales are influenced by volatility of inventory, and (3) spill-over volatilities occur between inventory and sales.

Long-term relationships between inventory and demand in 6 retail sectors is found in this study while Lee and Koray (1994) reported the same result for the aggregate retail series. Statistically, in these 6 retail sectors, inventory and demand are cointegrated with order one, the same order as in the aggregate retail found by Lee and Koray (1994).

The time varying volatility of sales is found in all 6 retail sales, either in the VAR with constant correlation models or in the VAR with diagonal models. In most scenarios, using VAR with constant correlation and diagonal specifications, this study observes positive relationships between inventory and sales uncertainty which are shown by positively significant coefficients of the conditional variance or conditional standard deviation of sales in the inventory mean equations. Some negative results are observed in a small number of scenarios for food, general merchandise and apparel retails. Using the VECM as the mean equation for the multivariate GARCH-in-Mean, this study finds the same results as those reported by Lee and Korey (1994) using the same scenario. That is, no significant relationship is observed between inventory and demand uncertainty. However, the differences exist when using VECM with different scenarios.

2. INVENTORY AND DEMAND

2.1. Inventory and Uncertainty of Demand

Because one of the motives of holding inventory relates to the uncertainty of demand, this chapter will examine the effect of uncertainty of demand on retail inventory holdings. The demand uncertainty is defined as a situation when the distribution of demand exhibits significant variation and the realization of demand is unknown at the moment all strategic decisions are made (Deneckere, Marvel, and Peck, 1996), or when there is a volatility of the firm's demand with respect to the general market movement (Kim and Chung, 1989). The impact of demand uncertainty is that it imposes a probable cost of unsold production (Driver and Moreton, 1991). In studies of inventories, the term "demand" and "sales" are used interchangeably. Inventories may be set as a choice variable while sales are set exogenously by demand. Mills (1957, 223) separated demand into two additive components: a known component and an uncertainty component. In the language of regression, Mills refers to the known component as the part of demand which is "explained" by other variables, and the uncertainty component are the residual. Hong Bo (2001) offers some reasons why the volatility of sales matters for inventory investment decision. Hong Bo discusses two relevant information categories used by firms to forecast future sales: information on economic-wide uncertainty and information that is specific to the firm. According to Hong Bo, even though the firm can only observe specific shocks to itself and not those specific to other firms, both the expectations formed and expectation errors made by other firms are relevant for correcting forecast errors and adjusting inventories. Specifically Hong Bo refers to Pesaran (1989), who states that the relevance of expectation errors made by other firms is for forecasting prices. To correct the errors in future sales forecasts, the firm needs to know the unexpected changes in industry sales when adjusting inventories.

The following literature review suggests that inventory and uncertainty are related. A firm behaves differently under uncertainty than in a world of certainty. Under uncertainty the competitive firm will produce a higher level of output than a non-competitive firm selling at the same price (Hawawini 1978, p.195). Thus we expect inventory increases with uncertainty. Capacity is insufficient to satisfy demand when it is peaked. A firm with non constant demand needs to build large inventories of seasonal products early to satisfy peak demand (Arntzen and Bradlev, 1999). Firms, on average, overstate future sales, leading them to accumulate inventories, partially due to concern of avoiding stockout in the case of highly unexpected demand (Hong Bo, 2001). Deneckere, Marvel, and Peck (1996) show that a manufacturing firm facing uncertain demand and selling through a competitive retail market may wish to support adequate retail inventories by preventing the emergence of discount retailers. Full price retailers are compensated for a higher probability of unsold inventories by a higher retail price when they sell. They show that preventing discounting increases the manufacturer's wholesale demand and profits.

With stochastic demand, firms with multi-product inventories will benefit because demand from Class A can be satisfied using stock of product B, $A \neq B$. This implies a positive relation between the amount of inventory and uncertainty (Bassok, Anupindi, and Akella, 1999). The larger the inventory, the lower the probability of shortages that cost the firm missed current sales and customer goodwill (Irvine 1984, p.158). Thus there will be a positive relationship between inventory and sales. The buffer motive is the implicit motive for holding inventories that involves a firm's consideration of uncertain future demand, and since profit is lost if sales have to be missed or postponed, it is worthwhile for the firm to hold inventories of its products (Mills 1957, p. 222)

According to Lee and Koray (1994), if the stockout-avoidance motive is a reason for holding inventories, an increase in the risk of stockouts will make the firm increase its inventories. Therefore, uncertainty in sales and increased risk of stockouts may lead to an increase in the level of inventories. Guash and Kogan (2003) describe the occurrence of stockout-avoidance motive when demand varies unpredictably and a firm wants to avoid penalties, such as loss of goodwill and loss of potential sales as a result of its inability to meet unanticipated demand. According to the authors, the stockout-avoidance motive explains the existence of retail inventories and raw material inventories as well. Callen, Hall, and Henry (1990) argue that the expected costs associated with a stockout-avoidance increase with the level and variance of sales and decrease with the level of the stock. The authors show a positive relation between a firm's holdings of inventory and its variance of sales.

2.2. Demand Uncertainty Measurement

Mills (1957, p. 223) measures demand uncertainty from regression of demand on other variables, that is, as the part of demand which is unexplained by other variables called residual. In empirical studies, several measures of demand uncertainty have been applied which include a firm's beta (Harris, 1986), standard deviation of sales (Irvine, 1984), and conditional heteroscedasticity (Lee and Koray, 1994) using bivariate GARCH(1,1). Cuthbertson and Gasparro (1993) also use this GARCH(1,1) as a measure of conditional variance of sales, and they seem to assume that output is equal to sales. Other measures of uncertainty are lead time uncertainty (Song, 1994), serially correlated demand (Kahn, 1987), variation in profitability (Bean, 1989), as well as coefficient of variation of demand (Bartezzaghi, et.al, 1999).

The volatility in inventory and sales correlated over time is shown by Lee and Koray (1994). If we adapt the intuitive explanation of time varying volatility by Jones, et. al. (1998), the explanation includes that such autocorrelation is plausible because events do not occur independently over time. Thus, if the news generating process has autocorrelated volatility, we would expect the inventory holding and sales also to have autocorrelated volatility. Autocorrelated volatility could arise because of random sentiment shocks that may slow the incorporation of news into inventory holdings or into customer demand. Perhaps inventory holdings or customer demands respond immediately to news but incorrectly; that is, there may be under or overreaction.

2.3. Interrelation between Inventory and Sales

Inventory and sales may be linked together through some economic or financial relationships. The relationship between inventory decisions and sales is inferred from the following theoretical backgrounds. The level of sales is universally recognized as an important determinant of the level of inventories a firm holds (Irvine 1984, p. 156). Using intrafirm data, the author found that in addition to profitability, inventory carrying costs, and standard deviation of sales, inventory holdings by each department depend on the level of sales. Empirical evidence (Feldstein and Auerbach, 1976) indicates a positive correlation between inventory and sales. The authors focus on durable goods inventory. As previously stated, the authors separate the change in finished goods inventories; the first reflects unanticipated sales and the second, intended inventory accumulation. If sales expectations are perfect, all of the observed change in finished goods inventories will be intended. Using the stock adjustment model, the authors regress the actual change in inventory on sales and sales forecast errors. The results show a positive relation between the change in inventory with sales and with sales forecast errors. The authors also introduce the target adjustment model to analyze the distribution of the change of inventory. They found that target inventory adjusts very slowly to respond to the changing level of sales and that the impact of unanticipated sales was corrected as much as 95 percent in the same period.

A firm may use inventories of finished goods to speculate on future price movements or to absorb short-run shocks to demand (Blinder 1981, p. 11). Inventory holdings may be used to spur demand by reducing delivery lags (Blinder 1981, p. 12). Blinder (1981) argues that output, sales, and inventory carryover depend on the stock of current inventory. According to Blinder, the higher inventories lead to lower prices so that sales are an increasing function of inventories.

A retailer can use inventory holdings in its interaction with consumers to lead to sales by practicing price deals or price specials (Eppen and Liebermann 1984, p. 519). According to these authors, price deals occur when a retailer offers an item for sale for a short period of time at prices below its going market rate. Price deals on nonperishable goods can benefit both the retailer and the consumer by transferring part of the inventory carrying cost from the former to the latter in return for an unusually low price. The price deal incorporates inventory considerations.

The relative size of inventory maintained may be due to the larger variety of products available for sale. In addition to price deals, B. Peter Pashigin (1988) argues that increases and differences between merchandise groups due to the growing importance of variety in merchandising, particularly since 1970, affects sales behavior through increases in percentage markups and markdowns taken by department stores relative to dollar revenues. This finding implies that the larger the inventory maintained in terms of more variety, the greater its influence on sales behavior. With multiproduct inventories with stochastic demands, there might be the occurrence of substitution. That is, demand for Class A can be substituted using stocks of product B, for $A \neq B$ (Bassok, Anupindi, and Akella, 1999).

Another situation where inventory leads to sales is through dynamic pricing decisions as explained by Rajan, Rakesh, and Steinberg (1992). The decay of inventories can affect price changes during the inventory cycle; that is, in the situation in which the product exhibits (i) physical decay or deterioration of inventory, and a (ii) decrease in market value called value drop associated with each unit of inventory on hand. This leads to changes in prices over the inventory cycle. This dynamic pricing in turn leads to a fluctuation in sales values. The authors refer to this situation as decaying inventory and decaying demand. This implies a time-varying cost of inventory and price. How inventory generates sales is explained by Arcelus and Srinivasan (1987, p. 756). These authors relate inventory and sales through pricing policies especially in retailing; that is, inventory is evaluated in the same way as any other investment, namely on its ability to generate profits, rather than on the traditional least-cost basis. This in turn requires the development of pricing policies designed to generate the demand level that will optimize an objective other than cost and more in accordance with the nature of inventory as an asset.

Mills (1957) explained the existence of inventories based on the buffer motive for holding inventories. This involves two essential considerations in which either is sufficient to explain the existence of inventories. On the one hand, the firm is uncertain about future demand, and since profit is lost if sales have to be missed or postponed, it is worthwhile for the firm to hold inventories. On the other hand, it is costly to change production rapidly, and therefore it is worthwhile to hold inventories in order to reduce fluctuations in production.

Carlton and Perloff (2000, p. 557-558) state that consumers judge a firm not only by its pricing policy but also by its inventory policy. Consumers care not only about the price but also about the probability that a good is available. According to them, inventory policies affect the probability that a firm has the good available. Some consumers prefer to shop at high-price stores that run out of goods infrequently, whereas others prefer to shop at stores that charge low prices but may run out of goods frequently. The variability of consumers' demand for a product affects a firm's costs because it must maintain a relatively large inventory to satisfy customers whose demand fluctuates a great deal. Furthermore, referring to Carlton (1977), the authors explain the following condition for the relationship between inventory and product price: the production of the goods must occur before demand is observed, and therefore there is some risk that the firm will run out of the good. The ratio of inventory to average demand depends on the ratio of price to cost. The reason is that the opportunity cost of lost sales rises with price, so that the incentive to hold inventories increases with price. In response to the riskiness of demand, firms increase their inventory holdings when price significantly exceeds marginal cost and decrease them when prices are close to marginal cost. The higher the price significantly above marginal cost, the more inventory will be maintained by a firm. The idea is similar to a risk-return relationship, in which a high return is required to assume more risk. Thus there is a positive relationship between inventory and expected sales value.

Maccini (1978) called models that presume prices are set as a markup over unit factor costs "markup models." According to Maccini, the influence of demand on markup is introduced by demand pressure factors, which include capacity utilization, unfilled order-shipment ratios, inventory sales ratios, unfilled order-capacity ratios, etc., that impinge on prices. In his model of firms that produce to stock, finished goods inventories enter the model in two ways. First, inventories appear in the firm's demand function, essentially to provide a motivation for the firm to hold inventories. Firms hold inventories primarily to protect themselves against stockouts. Maccini assumes that the larger the firm's stock of inventories relative to its estimate of expected demand, the smaller the possibility that the firm will be caught out of stock. Hence, the higher it can expect its inflow of new orders, shipments, and sales to be. Secondly, inventories also appear in the firm's cost function to take account of inventory holding costs in the form of storage costs, insurance costs, and the like.

2.4. Contribution of This Paper

This paper is intended to provide more evidence of a positive relationship between inventory and uncertainty in demand using a different set of data and analytical tools. This is motivated by a contradiction between what the stock-avoidance motive predicts and the study results, particularly by Lee and Koray, that find no significant relationship between the change in inventory and uncertainty of sales. Other studies, for example, Irvine (1984) and Hong Bo (2001), find a positive relationship between inventory and demand uncertainty. In particular, this paper examines the characteristics of inventories and sales in more specific retail industries, rather than in aggregate retail, which allows this study to conclude whether the characteristics of aggregate retail sales and inventory apply to its components. The ability to apply predictable inventory and sales volatility models is important for better inventory management and sales prediction. Using a more appropriate model, firms will reach a more accurate conclusion.

2.5. Previous Studies

Because this study uses models that require inventories and sales be cointegrated, and because the theoretical discussion in previous sections on the existence of an interrelationship between inventory and sales also implies the existence of cointegration, it will be relevant to present previous studies that examined the cointegration between sales and inventory. Studies that examined the cointegration of sales and inventory include Granger and Lee (1989), Callen, Hall and Henry (1990), and Lee and Koray (1994). Previous studies that examined the relationship between inventory and uncertainty of demand include Irvine (1984), who developed a model from price-cost margin equation. Hong Bo (2001) developed a model from an accelerator inventory equation. Also Lee and Koray (1994) and Granger and Lee (1989) developed a model using vector error correction.

Granger and Lee (1989) investigate the relationship between production, sales, and inventory for 27 U.S. industries and industrial aggregates. In this study, if the target level of inventory, X_t, is a fixed proportion λ of sales S_t. then $X_t - \lambda S_t = \mu$ is the control error and this should be expected to be $I(0)$, For each pair of sales (S_t) and inventory (X_t), the authors use the following steps: Step 1, form the production series using the formula: $P_t = S_t + \Delta X_t$ and define $Z_t = \Delta X_t$. Step 2, test if the series P_t, S_t and X_t are $I(1)$ using an ADF test using 12 lags. The authors find that each series is $I(1)$. Step 3, test if Z_t is $I(0)$ using the same procedure. Step 4, form two separate regressions of X_t on P_t and X_t on S_t ; that is, $X_t = a_1 + b_1 P_t + u_{1t}$, and $X_t = a_2 + b_2 S_t + u_{2t}$ and test if u 's are $I(0)$. The authors use an ADF test for this. The authors find that Z_t in Step 3 is $I(0)$ and u's are $I(0)$. Finally, the authors estimated using the following pair of error correction models (ECM), to see whether there is a multicointegration among production, sales, and inventory:

$$\begin{aligned} \Delta P_t &= \alpha_1 + \beta_1 Z_{t-1} + \beta_2 u_{2,t-1} + \gamma_1 \Delta P_{t-1} + \gamma_2 \Delta S_{t-1} + \varepsilon_{1t} \\ \Delta S_t &= \alpha_2 + \beta_3 Z_{t-1} + \beta_4 u_{2,t-1} + \gamma_3 \Delta P_{t-1} + \gamma_4 \Delta S_{t-1} + \varepsilon_{2t} \end{aligned} \qquad (2.1)$$

For ease of computing, the authors only use single lags. The results show that all the sales, production, and inventory series are cointegrated, they are all $I(1)$. According to these authors, evidence that indicates the presence of multicointegration includes the significant coefficients in the ECM and the significant ADF statistics for the u 's, among others. Particularly for the ECM results, the error corrections for ΔP_t has three significant variables while ΔS_t has only one significant variable so that the former is stronger than the latter. The authors conclude that sales series are more exogenously determined.

Cointegration between inventory and sales is also found by Callen, Hall, and Henry (1990), and Lee and Koray (1994).

Previous studies that relate inventory and uncertainty of demand use different analytical models. Irvine (1984) examined the factors that cause a department store to hold different amounts of inventory in individual departments of the store. In this work, the author includes a measure of demand uncertainty. The author found that inventory increases with uncertainty. In this study, the author defines the dependent variable to be the average monthly inventory held by the store in the i^{th} department each year, $\bar{y}_i(t)$. This dependent variable is assumed randomly distributed around the desired inventory, $y_i^d(t)$. As a measure of expected demand, the author uses $x(p)$ average real monthly sales, $SALESD_{i(t)}$. As a measure of the variance of each department's demand, the author uses the standard deviation of the twelve monthly sales values around the mean monthly sales level. The author realizes that this annual time series of standard deviation of sales, $SDMSD_{i(t)}$, is only a partial measure of the variance of demand, since it does not reflect the daily variance of sales. The author also realizes that because of the collection procedures utilized, it may also be biased downward as a measure of the month-to-month variance. In addition, since seasonal variance is somewhat predictable, it may be a poor measure of the uncertainty of demand. However, the author argues, it was the best and only measure of demand variance available. This explanation suggests that the author does not use seasonally adjusted data, and this might be the reason for the author to use the average monthly data. As a measure of profitability, the author uses a price-cost margin. Another variable included in the model is the inventory carrying cost. The per unit inventory carrying cost, $h_{i(t)}$ consists of several components. One, the financial carrying cost per unit of capital invested in inventory is the same for all the departments. Variation in this cost was measured by a time series on the average prime bank interest rate during each year, $PRIMER_{i(t)}$ .The prime rate was chosen over other interest rates available on a monthly basis, since small department stores generally use bank financing. The other components of per unit inventory carrying costs are good-specific. Since the author has no measure of each of these merchandise-specific per unit inventory carrying costs – physical deterioration costs, maintenance costs, physical storage costs, and style depreciation costs – their effect on $y^d(t)$, according to the author, must be inferred from their influence on the intercept.

Combining theoretical consideration with the data availability constraints and including a time trend, the author constructs a regression that shows variables that affect the average monthly inventory levels $IREAL_{i(t)}$.

$$\begin{aligned} IREAL_{i(t)} &= a + bSALES_{i(t)} + cSDMSD_{i(t)} + dGPROFIT_{i(t)} + ePRIMER_{i(t)} \\ &\quad + fTIME_{i(t)} + \varepsilon_{(t)} \end{aligned} \tag{2.2}$$

The author adds the time trend $TIME_{i(t)}$ to allow for the possibility that the inventory levels of these multi-product departments might also change owing to either an expansion of the variety of merchandise held or changes in inventory management technique.

Using pooling regression, the author obtains the following results: The positive coefficient of the average monthly sales $SALES_{i(t)}$ (the most important explanatory variable both statistically and economically) is as expected. The positive coefficient on $SDMSD_{i(t)}$, shows that the store definitely allocated more inventory capital to those departments with greater month-to-month demand fluctuations. The positive coefficient on the gross profit ratio $GPROFIT_{i(t)}$ confirms that the store allocated more inventory capital to the more profitable departments.

Hong Bo (2001), using a panel of 77 listed manufacturing firms, examines the effect of demand uncertainty, measured by the volatility of sales on inventory investment. The author puts forward the issue of the measurement of unobservable expectation errors made by the firm in forecasting future sales in the stock adjustment equation. This is the standard stock adjustment equation which states that the determinants of firm inventory investment are the last period stock of inventories, the level of current sales, and the level of unexpected sales. The author claims that the volatility of sales is a better proxy for the expectation errors than the level of unexpected sales embedded in the standard accelerator equation. Hong Bo refers to Lovell, M.C., "Manufacturers' Inventories, Sales Expectations, and Acceleration Principles", Econometrica Vol. 29, 1961, who states that the flexible accelerator buffer stock inventory model assumes that the actual stock of inventories (V) depends on the planned stock of inventories (V^p) and unanticipated changes in sales. That is

$$V_{it} = V_{it}^P + \left[E_{t-1}S_{it} - S_{it}\right] \qquad (2.3)$$

where $E_{t-1}S_{it}$ is the expected value of sales at the beginning of period t, S_{it} is the actual sales for firm i at time t. In this model, since the adjustment of the production plan takes time, the planned stock of inventories is partially adjusted towards the target (desired) stock of inventories, therefore

$$V_{it}^P = \lambda V_{it}^* + (1-\lambda)V_{i,t-1} \qquad (2.4)$$

where V_{it}^* is the target stock for firm i at time t, $V_{i,t-1}$ is the actual stock of inventories at the beginning of period t and λ is the adjustment speed parameter where $0 < \lambda < 1$. In line with the accelerator principle, the long-run equilibrium inventory stock is determined by the expected sales, that is, $V_{it}^* = \alpha + \beta E_{t-1} S_{it}$ where α is a constant, β is the accelerator coefficient that represents the long-run inventory-sales relationship. Substituting the last two equations into the first, the author obtains the stock adjustment equation and estimates the parameters as given by the following:

$$\Delta V_{it} = \lambda\alpha - \lambda V_{i,t-1} + \lambda\beta S_{it} - (1 + \lambda\beta)[S_{it} - E_{t-1} S_{it}] + \varepsilon_{it} \qquad (2.5)$$

This is the standard stock adjustment equation that states that the determinants of firm inventory investment are the last period stock of inventories, the level of current sales, and the level of unexpected sales. In this model ΔV_{it} is the change in inventory stock for firm i at time t, α is a constant, λ is the speed parameter of adjusting inventories, and β is the equilibrium coefficient of the inventory-sales relationship, which represents the accelerator effect of sales on inventory investment. In this model, sales are assumed to be exogenous. The author defines $[S_{it} - E_{t-1} S_{it}]$ as the expectation errors made by the firm in forecasting future sales. According to the author, the impact of this error term on inventory adjustment is negative, indicating that if actual sales exceed expected sales, the firm will reduce the stock of inventories to satisfy unexpected increases in sales.

The expectation error made by the firm in forecasting future sales $[S_{it} - E_{t-1} S_{it}]$ represents unexpected changes in sales and hence it is, in fact, a measure of demand uncertainty. However, the term $[S_{it} - E_{t-1} S_{it}]$ only represents the level of unexpected sales. It carries no information on the distribution of unexpected sales. If one uses

$[S_{it} - E_{t-1}S_{it}]$ as the proxy for the expectation errors, the firm is assumed to respond only to this error correction term $[S_{it} - E_{t-1}S_{it}]$ but not to the whole distribution of unexpected sales. Therefore, the dispersion of the forecast errors, or the volatility of sales, is not taken into account in the standard model.

Thus, in the standard stock adjustment model, the level of unexpected sales is used as the proxy for the expectation errors made by the firm in forecasting future sales. The author argues that the level of unexpected sales does not contain all information on the distribution of the movement of sales. Therefore, for empirical analysis, the author proposes to use the volatility of sales as the proxy for the expectation errors (demand uncertainty). This yields the following:

$$\Delta V_{it} = \lambda\alpha - \lambda V_{i,t-1} + \lambda\beta S_{it} - (1 + \lambda\beta)Volatility(S_{it}) + \varepsilon_{it} \qquad (2.6)$$

The author uses the following measures of volatility (the proxies for expectation errors). First, the residuals from estimating an AR(1) process of sales is used. This is based on the author's finding that the series of sample sales is stationary according to the ADF unit root test, therefore sales are assumed to follow AR(1). The author estimates the AR(1) process for sales for each firm separately and saves the residuals of the estimations. This series is used as a proxy for unexpected sales. This is the benchmark equation (the standard stock adjustment equation). Second, the 3-year moving variance of RESID is used. The author computes 3-year moving variances of the residuals to construct the volatility of sales. For example, to construct the volatility measure for the year 1987, the author computes the variance of the residuals of years 1987, 1986, and 1985. For the year 1988, the residuals in 1988, 1987, and 1986 are used and so on. The 3-year moving variance of the residuals is dated at the final year to serve as the volatility measure of sales for that year under the assumption that firms update their expectations based on past and available current information.

To check for robustness the author constructs an alternative volatility measure for sales to proxy for expected errors. This is done by calculating the 3-year moving variances of the annual growth rate of sales VAR(S_g). As a second robustness test, the author simply constructs the normal variance of sales. The author uses the 3-year moving variance of sales as the volatility measure for the third year. This volatility is named VAR(S). The author finds that all these measurements produce similar results with respect to the changes in the adjustment speed parameter and the impact of demand uncertainty on inventory investment. All measures of volatility produce significantly positive signs.

Lee and Koray (1994) empirically investigate the relationship between inventory behavior and volatility in sales in the U.S. wholesale and retail trades, measured as the conditional heteroscedasticity of sales, as well as the relationship between sales and volatility of inventories. Using a multivariate time-series model with time varying conditional variances, the authors empirically investigate how the change in inventories respond to uncertainty in sales and how the uncertainty in inventories may affect the change in sales. Data consist of monthly real inventory and sales series from 1967:01 to 1990:03 yielding a total of 279 observations. The presence of cointegration between monthly real inventory and sales series is tested using a residual test and a Johansen test. The residual tests involve the cointegrating regression $Inv_t = \hat{\alpha} + \hat{\beta} s_t + u_t$ and the unit root test for the OLS residual $\hat{u}_t$. The unit root hypothesis cannot be rejected for the inventory (Inv_t) and sales series (s_t) in both of the wholesale and retail sectors. The results show that inventory and sales are cointegrated. Using Phillips-Perron tests, the authors obtained the same result, that inventory and sales series are cointegrated. To analyze the relationship between sales and inventory, the authors use the following VEC model for both the wholesale and retail sectors.

$$\begin{aligned} \Delta Inv_t &= a_0 + a_1 u_{t-1} + \sum_{j=1}^{k} \left(a_{1+j} \Delta Inv_{t-j} + a_{1+k+j} \Delta s_{t-j} \right) + e_{it} \\ \Delta s_t &= b_0 + b_1 u_{t-1} + \sum_{j=1}^{k} \left(b_{1+j} \Delta Inv_{t-j} + b_{1+k+j} \Delta s_{t-j} \right) + e_{2t} \end{aligned} \tag{2.7}$$

The first equation shows the determinants of the adjustment of inventory while the second equation shows the determinants of the adjustment of sales, both in the long run. The symbol Δ represents first differencing. The variable u_t is taken from the cointegrating regression: $Inv_t = \alpha + \beta s_t + u_t$. Thus $u_t = Inv_t - \hat{\alpha} - \hat{\beta} s_t$ represent error correction term, and a_1 and b_1 measure the speed of adjustment.

Using a number of lags in the VECM selected, the authors find that the residuals are not serially correlated. The analysis focuses on the relationship between inventory behavior and uncertainty in sales, measured as conditional variance of sales, as well as the relationship between sales and volatility of inventories. For this purpose, a bivariate GARCH-M is specified in the VECM. The generalization of univariate GARCH models to multivariate GARCH models requires allowing the whole covariance matrix to change with time. All of the elements of the covariance matrix are allowed to be linear functions of lagged squares and cross products of the residuals and lagged variances and covariances. The authors use Bollerslev's (1990) model and assume the conditional correlations to be constant so that all the variation over time in conditional covariance are due to changes in the two conditional variances.

Instead of using the conditional variance, the authors use conditional standard-deviation, that is the squared-root of the variance, as the measure of uncertainty. The authors denote the variance $= h_t$, and standard deviation = $h_t^{1/2}$. Incorporating the uncertainty of sales and inventory into the previous system of equations, yields:

$$\begin{aligned}
&\Delta Inv_t = a_0 + a_1 u_{t-1} + \sum_{j=1}^{k} (a_{1+j}\Delta Inv_{t-j} + a_{1+k+j}\Delta s_{t-j}) + \delta_1 h_{11t}^{1/2} + \delta_2 h_{22t}^{1/2} + e_{1t} \\
&\Delta s_t = b_0 + b_1 u_{t-1} + \sum_{j=1}^{k} (b_{1+j}\Delta Inv_{t-j} + b_{1+k+j}\Delta s_{t-j}) + \delta_3 h_{11t}^{1/2} + \delta_4 h_{22t}^{1/2} + e_{2t} \qquad (2.8) \\
&h_{ii,t} = w_i + \alpha_i e_{i,t-1}^2 + \beta_i h_{ii,t-1} \qquad i = 1(Inventory), 2(Sales) \\
&\rho = h_{12,t}(h_{11,t}h_{22,t})^{-1/2}
\end{aligned}$$

According to the authors, to check if the error correction is non symmetric, that is whether positive u_t and negative u_t have different impacts on the dependent variables, the tests include new created variables to examine whether the coefficients of positive and negative u_t are significantly different. The authors do not use a dummy variable with a binary number as in a standard dummy variable analysis.The authors decompose the cointegrating residuals u_t into two variables, u_t^+ and u_t^-, instead. In this case the authors define u_t^+ = max (u_t,0) and u_t^- = min (u_t,0). If the error correction is not symmetric, then a significant difference exists between the coefficients of u_t^+ and u_t^-. The authors do not explain why they include u_t^+ and u_t^- in wholesale trade only and not in retail trade. The method used by the authors differs from asymmetric test in standard asymmetric GARCH models in which binary dummies are used. A list of models for testing the asymmetric GARCH, which examines whether different impacts of bad news or negative residuals from good news or positive residual on the magnitude of conditional variance, is presented by Engle and Ng (1993).

Lee and Koray's (1994) regression results show that the GARCH parameters are always highly significant in both the wholesale and retail sectors, and in general $\alpha_i + \beta_i$ is close to unity. The coefficients of the error correction term u_{t-1} are generally significant. However, none of the coefficients for the GARCH-M terms $h_{iit}^{1/2}$, $i = 1,2,$ is significant. The coefficients a_1 and b_1 are significant. The authors find that the behavior of inventories is explained by the stock adjustment for the cointegrated relationship between the stock and the flow series in the model as well as by the past changes in inventories and sales. The coefficients δ_1, δ_2, δ_3 and δ_4 are not significant. This evidence indicates, however, that uncertainty in sales does not have a significant effect on inventories in both of the U.S. wholesale and retail trade sectors. In other words, the change in inventories occurs as an adjustment process to the past changes in sales, but not much is due to volatility in sales. These results differ from the two studies discussed previously. These studies are: Irvin (1984) who uses inventory level data as a dependent variable with the volatility of sales as its regressor, and Hong Bo (2001) who uses the change in inventory or first differenced inventory series as a dependent variable with the volatility of sales as its regressor, which shows a positive relationship between demand uncertainty and inventories.

Including only the volatility of sales as the regressor in an inventory equation in isolation from volatility of inventory might avoid the impact of multicollinearity between these two volatility variables. In Lee and Koray's (1994) study, both the uncertainty of inventories and uncertainty of demand are included as regressors. In addition to using the VECM with the same specification as in Lee and Koray's study, this study also offers a

VECM with only the volatility of sales as a regressor in the inventory equation so that a comparison can be made. By using the identical model as Lee and Koray's study, this study shows the same results. That is no significant relationship exists between demand uncertainty and inventory in 6 retail series. Exhibit 1 might be useful to compare the behavior of the first differenced series of inventories and its corresponding conditional variance of demand in retail sectors generated from the same model specification as that in Lee and Koray's study, except for furniture which uses the model as reported in Table 4.7.

Exhibit 1
Comparison Between Growth in ln(Monthly Inventory Series) Defined as Δln(Inventory) and Mean Conditional Variance Sales generated by the same model as in Lee and Koray (1994) except Furniture by the VECM Model E (This specification of VECM models is discussed in Chapter 4 of this study)

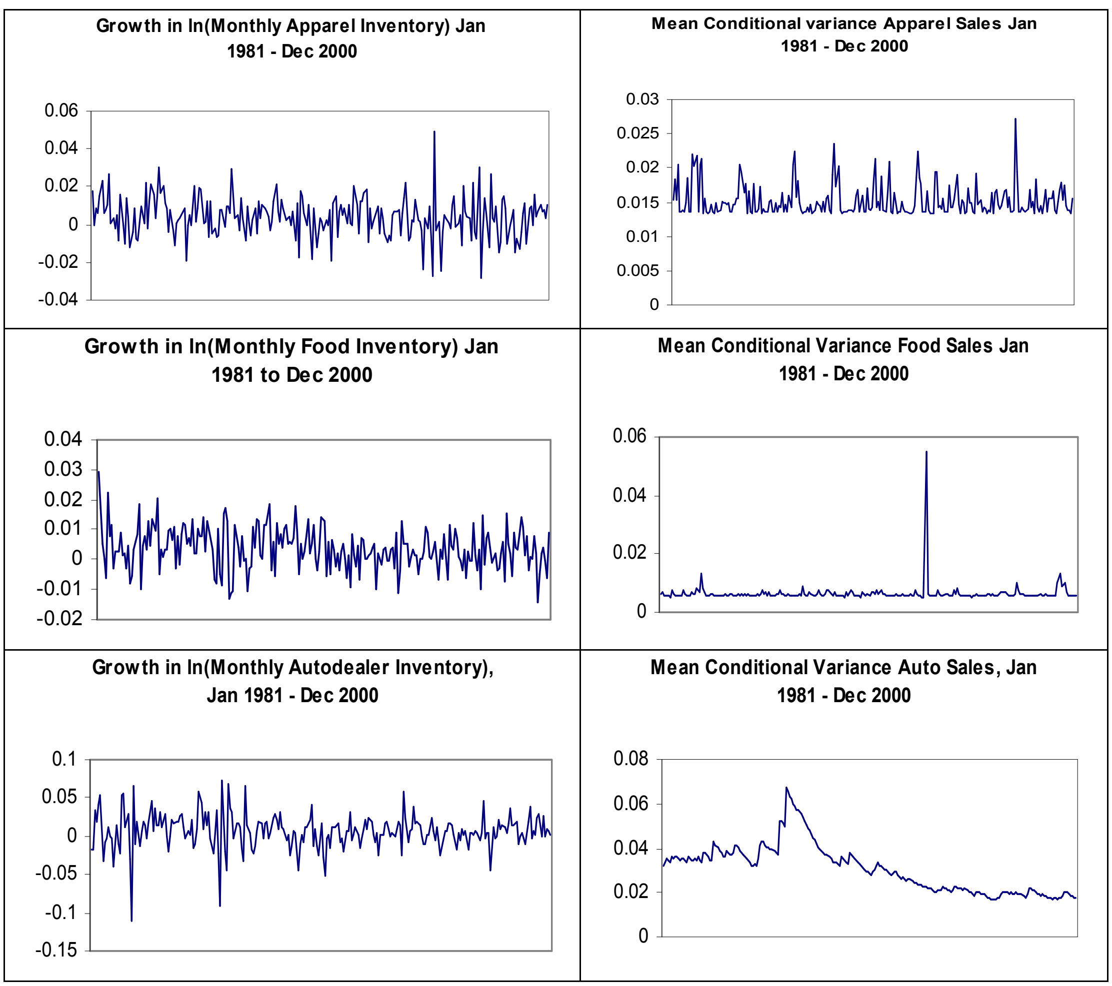
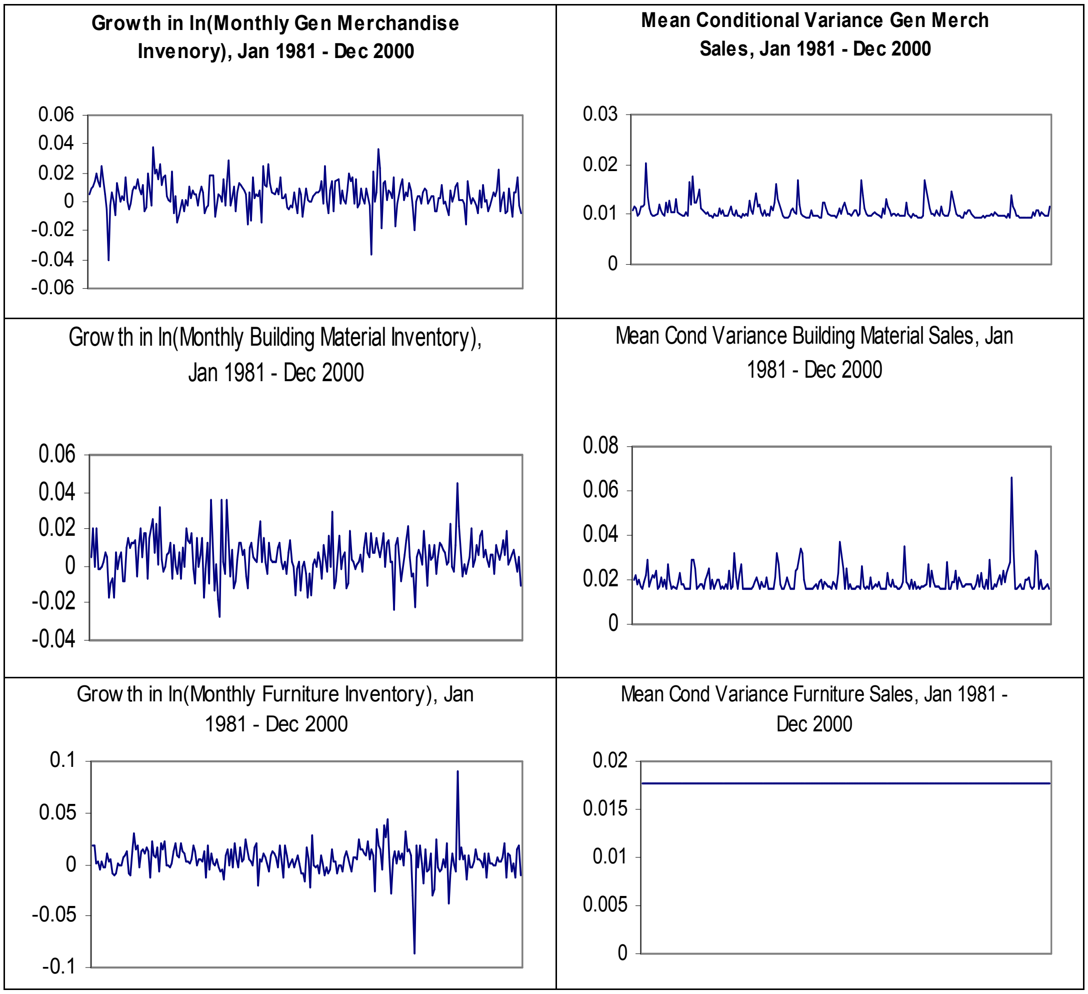


Exhibit 1 (Continued)



3. DATA AND ANALYTICAL TOOLS

3.1. Data

This study uses monthly retail sales and inventory data at a less aggregate level, that is, data from more specific retail groups which include apparel, building materials and hardware, food stores, furniture, general merchandise stores, and automotive dealers. The

Monthly Retail Survey Branch of the U.S. Census Bureau provides access for retail sales and inventory data for the aggregate level and for retail sales and inventory data for more specific retail groups. This study uses data from this source. Standard and Poor's Basic Statistics also publishes identical data. Unlike the aggregate data that have been available since January 1967, the less aggregate data have been available only since January 1981. This study uses seasonally adjusted monthly data from 1981:01 to 2000:12, yielding 240 observations. This is shorter than the previous study by Lee and Koray (1994) who investigate more aggregate data, also seasonally adjusted, from 1967:01 to 1990:03, consisting of 279 observations.

3.2. Models used: the VAR and VECM

Models that allow demand uncertainty to affect inventory include accelerator-based equations (Hong Bo, 2001), profitability or price-cost margin models (Irvine, 1984), and vector error correction models (Lee and Koray, 1994, Granger and Lee, 1989). These studies have been discussed in the previous section. The accelerator-based equation and profitability-based models are single equation models in which inventories are affected by sales and uncertainty. They do not show that sales are also affected by inventory. This paper will work with the same theme as Lee and Koray but uses a different data set for the same model and offers some alternative models. In Lee and Koray (1994) the data used are aggregate retail sales and retail inventory from 1967 to 1993, using an MGARCH-M with the VECM as the mean equation. This paper will use data with less aggregate retail sales and retail inventory from 1981 to 2000, using both the VECM and VAR model as the mean equations, which will be analyzed separately. In the VAR and

VECM, inventory and sales are allowed to influence each other. The VECM is a restricted form of the VAR model; that is, inventory and sales must be cointegrated.

This study follows the theoretical backgrounds previously discussed that sales and inventory affect each other, and will examine this interrelationship by applying both the VAR and VECM as the mean equations in the multivariate GARCH-M model. These two analytical tools will be applied separately. Because the volatility of sales or demand uncertainty is believed to affect inventory, uncertainty variables will be included in the mean equations. The use of the multivariate GARCH-M will also allow this study to examine the presence of time varying volatility of sales from the conditional variance equations of the multivariate GARCH model.

VAR, instead of simultaneous equations, is chosen with these considerations: (1) the only data available are sales and inventory, (2) the use of the VAR avoids the subjectivity in including exogenous variables, (3) based on the SIC and AIC, the number of lags of inventory and sales in the VAR is not great, only up to four, so that does not consume many degrees of freedom with 240 observations, and (4) only cointegrated sales and inventory are used in the model so that there is no mix between stationary and non-stationary series, and additionally the data in the form of logarithmic series are suitable. With the simultaneous equations, endogenous variables may appear on both the left and right hand sides of the system in addition to some other predetermined variables. In a VAR, only the lagged values of all of the endogenous variables in the system appear on the right-hand side of equations. Thus, there is no issue of simultaneity in the VAR. Using the VAR model, this study assumes that current inventory and sales are affected by both previous sales and previous inventories. This is not in contradiction with the common understanding that inventories are prepared to meet expected sales. The reason for this is that the expected normal sales are not observable. This paper adopts the approach of Maccini and Rosanna (1981). Even though these authors used a distributed lag model in empirical inventory analysis, their argument is still relevant to this paper for using lagged variables as independent variables. According to these authors, because the normal level of sales is unobservable and must be related to observable variables for estimation, the authors assume that expectations are formed autoregressively, that is, the variables are assumed to be a distributed lag function of past actual levels of itself.

Using a VAR model, one may also analyze the response of inventory or sales to shocks or changes in the error terms, ε_{1t} from the inventory equation and ε_{2t} from the sales equation. Changes in ε_{1t} will affect inventory in the current as well as future periods. The changes in ε_{1t} will also impact sales because inventory appears in the sales regression. Similarly, changes in ε_{2t}, in the sales equation, will affect inventory because sales appear in the inventory equation. However, the VAR models used in this study differ from the impulse response in that the impulse response function transforms the VAR into its MA form for analyzing the effect of current shock on future value of sales and inventory.

Even though in the VAR and in its derivative, the VECM, the inventory (sales) is expressed as a linear combination of lagged values of inventory (sales) and lagged values of sales (inventory), and in practice it may be expanded to include deterministic exogenous variables (Johnston and DiNardo 1997, 288). This study will include the demand uncertainty variable into the mean equations, VAR and VECM, in the multivariate GARCH-M system. Furthermore, the resulting error terms of conditional means as a measure of demand uncertainty are hypothesized to be time varying or heteroskedactic and assumed to follow the GARCH(1,1) process, and the VAR and VEC equation will have these heteroskedastic terms on its right-hand side.

3.3. Transforming the VAR Model to VECM

Since the notation I has been used for the term integration such as $I(0)$ or $I(1)$, for this theoretical discussion, the notation X is used for inventory. The notation Y is used to represent a vector whose elements are inventory X and sales S. The relationship at time t between Sales, S_t, and Inventory, X_t, could be $S_t = \beta X_t + \varepsilon_t$. If the sales series, S_t, and inventory series, X_t are $I(1)$, there may be a β such that the difference between these two series: $\varepsilon_t = S_t - \beta X_t$ is $I(0)$ or stationary with a zero mean. Thus, if the residual is stationary, these two series are cointegrated of degree one or $I(1)$. The vector of coefficients [1, - β] is called a cointegrating vector. The equation $S_t = \beta X_t + \varepsilon_t$ is called the cointegrating regression representing a long run equilibrium relation. The slope β is called the cointegrating parameter. In the short run S_t and X_t may deviate from each other. If there is a deviation from the long run equilibrium, a correction is needed. Because the term equilibrium has many meanings in economics, Cuthbertson, Hall, and Taylor (1992) define the term equilibrium as an observed relationship between variables which has been maintained for a long period

If current sales and inventory, S_t and X_t deviated from their previous figures, the current value $X_t - \beta S_t$, is non zero and each variable adjusts to restore to the equilibrium relationship. The deviation of S_t is $\Delta S_t = S_t - S_{t-1}$ and the deviation of X_t is $\Delta X_t = X_t - X_{t-1}$. The current equation of $X_t = \beta S_t$ should be adjusted by replacing X_t

and S_t by $X_{t-1} + \Delta X_t$ and $S_{t-1} + \Delta S_t$, respectively. The result shows that $X_{t-1} + \Delta X_t = \beta(S_{t-1} + \Delta S_t)$ or $\Delta X_t = \beta \Delta S_t - (X_{t-1} - \beta S_{t-1})$. This is a simple error correction model (ECM), in which the magnitude of current change in inventory responds proportionally to the current change in sales to correct for deviation from the equilibrium. There is a downward correction in the current period for a positive deviation and an upward correction for a negative error. A formal form of the equation is

$$\Delta X_t = \beta \Delta S_t - \gamma (X_{t-1} - \beta S_{t-1}) + \varepsilon_t \qquad (3.1)$$

where γ measures the speed of adjustment. For a bivariate VAR (1), the error correction form for X is $\Delta X_t = \delta_1 Z_{t-1} + \varepsilon_{1t}$ and for S is $\Delta S_t = \delta_2 Z_{t-1} + \varepsilon_{1t}$ where $Z_t = X_t - \beta S_t \sim I(0)$, or in the vector form:

$$\Delta Y_t = \Pi Y_{t-1} + \varepsilon_{1t} \qquad (3.2)$$

In the cointegration case, the matrix Π represents such a product of the speed of adjustment and the transposed cointegrating vector that can be written as $\Pi = BA'$. For a VAR(2), the vector error correction form is

$$\Delta Y_t = \Phi \Delta Y_{t-1} + \Pi Y_{t-1} + \varepsilon_{1t} \qquad (3.3)$$

A VECM is a model of the VAR that is designed for use with a nonstationary series that is known to be cointegrated, in which case a VEC model has built-in cointegration restriction. In other words, a VEC model is a VAR that includes the cointegration term in the equation. Thus, the existence of cointegration has been used to derive a VECM from the VAR model. The following transformation from a VAR to a VECM is based on Hamilton (1994). The resulting VECM is used for the Johansen's cointegration test. Transforming the VAR to VECM, the author starts from a VAR(k) process, that is,

$$Y_t = \alpha + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + ... + \Phi_k Y_{t-k} + \varepsilon_t \qquad (3.4)$$

Which can be written as:

$$Y_t - \Phi_1 Y_{t-1} - \Phi_2 Y_{t-2} - .... - \Phi_k Y_{t-k} = \alpha + \varepsilon_t \qquad (3.5)$$

Or $$(I - \Phi_1 L - \Phi_2 L^2 - ....\Phi_k L^k)Y_t = \alpha + \varepsilon_t \qquad (3.6)$$

If $\rho = \Phi_1 + \Phi_2 + ...\Phi_k$ and $\Gamma_s = -[\Phi_{s+1} + \Phi_{s+2} + ... + \Phi_k]$ $\quad for \quad s = 1,2,....,k-1$, the following polynomial is equivalent:

$$(I_n - \rho L) - (\Gamma_1 L + \Gamma_2 L^2 + ... + \Gamma_{k-1} L^{k-1})(1-L) = (I_n - \Phi_1 L - \Phi_2 L^2 - ..... - \Phi_k L^k) \qquad (3.7)$$

It follows that any VAR(k) process can be written in the form :

$$(I_n - \rho L)Y_t - (\Gamma_1 L + \Gamma_2 L^2 + ... + \Gamma_{k-1} L^{k-1})(1-L)Y_t = \alpha + \varepsilon_t \qquad (3.8)$$

or

$$Y_t = \Gamma_1 \Delta_1 Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + ... + \Gamma_{k-1} \Delta Y_{t-k+1} + \alpha + \rho Y_{t-1} + \varepsilon_t \qquad (3.9)$$

The following first difference of Y_t is obtained by subtracting Y_{t-1} from both sides the equation.

$$Y_t - Y_{t-1} = \Gamma_1 \Delta_1 Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + ... + \Gamma_{k-1} \Delta Y_{t-k+1} + \alpha + \rho Y_{t-1} + \varepsilon_t - Y_{t-1} \qquad (3.10)$$

This first difference will follow a VAR($k-1$) process if $\rho = I_n$ or $\rho Y_{t-1} = Y_{t-1}$; that is:

$$\Delta Y_t = \Gamma_1 \Delta_1 Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + ... + \Gamma_{k-1} Y_{t-k+1} + \alpha + \varepsilon_t \qquad (3.11)$$

If Y_t is $I(1)$, then the right-hand side is stationary. If $\rho \neq I_n$ or $\rho Y_{t-1} \neq Y_{t-1}$, the equation (3.11) becomes

$$\Delta Y_t = \Gamma_1 \Delta_1 Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + ... + \Gamma_{k-1} Y_{t-k+1} + \alpha + \Gamma_0 Y_{t-1} + \varepsilon_t \qquad (3.12)$$

In this equation, $\Gamma_0 = \rho - I_n = -(I_n - \Phi_1 - \Phi_2 - .... - \Phi_k)$. If Y_t has h cointegrating relations, the equation acts as the vector error correction in which the matrix Γ_0 represents a product of a speed of adjustment B and the cointegrating vector A. Thus,

$$\Delta Y_t = \Gamma_1 \Delta_1 Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + ... + \Gamma_{k-1} Y_{t-k+1} + \alpha - BA' Y_{t-1} + \varepsilon_t \qquad (3.13)$$

Defining $Z_t = A'Y_t$ where Z_t is a stationary $(hx1)$ vector, then (3.13) can be written as:

$$\Delta Y_t = \Gamma_1 \Delta_1 Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + ... + \Gamma_{k-1} Y_{t-k+1} + \alpha - BZ_{t-1} + \varepsilon_t \qquad (3.14)$$

The expression (3.14) is known as the error correction representation of the cointegrated system and is referred to as VECM. If there is only one cointegrating vector, each equation in the vector ΔY_t will have the following error correction form, for example for X_t:

$$\Delta X_t = \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \sum_{\psi=1}^{k-1} \psi_i \Delta S_{t-i} + A(X_{t-1} - \gamma_{12} S_{t-1}) + \varepsilon_t \qquad (3.15)$$

If the vector Y_t has more than two time series as its components, for example, if it has three time series, namely X_t, S_t and W_t, the number of cointegrating vectors could be 3 – 1, or 2. In this case, each equation of ΔY_t, for example X_t, will have these two error correction terms (Charemza and Deadman 1997, p.174), that is:

$$\begin{aligned}\Delta X_t = &\sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \sum_{i=1}^{k-1} \psi_i \Delta S_{t-i} + \sum_{i=1}^{k-1} \theta_i \Delta W_{t-1} + A_1 (X_{t-1} - \gamma_{12} S_{t-1} - \gamma_{13} W_{t-1}) \\ &+ A_2 (X_{t-1} - \gamma_{22} S_{t-1} - \gamma_{23} W_{t-1}) + \varepsilon_t\end{aligned} \qquad (3.16)$$

Other variables may also affect the amount of correction which may be represented by a constant or by a separate variable's name on the right-hand side of this error correction equation (Greene 1995, Johnston and DiNardo 1997). The bivariate VAR and VECM that will be used in this study include a constant as well as the heteroskedastic terms to represent demand uncertainty. The VAR model is presented in equation 3.42. The corresponding VECM model is presented in equation (4.1). Because we cannot regress a stationary series on a non-stationary series, we have to make sure that the series in the model are of the same degree of integration. Thus, this study has to perform a stationarity test. If the test shows that inventory or sales has a unit root or is not stationary, then a cointegration test must be performed to see whether the two series are cointegrated with the same order.

3.4. Unit Root Tests for Stationary Series

Because the existence of cointegration requires that the residual series ε_t be stationary, the cointegration test is identical to the stationary test. A simple method for a cointegration test is the ADF unit root test, that is, by testing whether the residual obtained from cointegrating regression is stationary. But this test cannot identify if more than one cointegrating equation exist. Another test, the Johansen cointegration test, based on a maximum likelihood approach, is used to identify if the cointegration exists and the number of cointegrating equations.

Because this study uses monthly data that has a small interval, there may be a very high serial correlation between adjacent values (Granger and Newbold 1974, p. 112). This may suggest that the coefficient from the regression of current series on the last period's series is close to one. In other words, the series has a unit root. Another reason is that inventory and sales increase over time so unit roots are likely to occur.

For a hypothetical series Y_t which has the equation $Y_t = pY_{t-1} + u_t$ if the coefficient of Y_{t-1} is equal to one, we face the unit root problem; that is, the series is not stationary. This equation may be manipulated by subtracting Y_{t-1} from both sides and defining $\Delta Y_t = Y_t - Y_{t-1}$, to have the expression:

$$\Delta Y_t = (p-1)Y_{t-1} + u_t \quad \text{or} \quad \Delta Y_t = \delta Y_{t-1} + u_t \qquad (3.17)$$

This expression will allow the unit root test to hypothesize the null by setting $\delta = 0$; that is , the series is not stationary or it has the unit root, because it implies that $p = 1$ as the alternative hypothesis is $\delta < 0$, that is, the unit root does not exist, or the series is stationary. This test is referred to as the Dickey Fuller test for unit root and is used for AR(1). A constant and time or trend may be added to the right-hand side of the equation that is in the form of $\Delta Y_t = \alpha + \delta Y_{t-1} + u_t$ or $\Delta Y_t = \alpha + \beta t + \delta Y_{t-1} + u_t$.

Further development of these models is in the form of:

$$\Delta Y_t = \alpha + \beta t + \delta Y_{t-1} + \gamma_i \sum_{i=1}^{m} \Delta Y_{t-i} + \varepsilon_t \qquad (3.18)$$

which is known as the augmented Dickey-Fuller (ADF) test. The Dickey Fuller or ADF test requires that ε_t has no serial correlation. In an ADF equation, a number of lagged ΔY is added to make the ε_t white noise. This ADF model is used for AR(k) series. The expression of the ADF is obtained from AR(k), that is, from an autoregressive process in levels,

$$Y_t = \lambda_1 Y_{t-1} + \lambda_2 Y_{t-2} + \dots\dots\dots\dots + \lambda_k Y_{t-k} + \alpha + \varepsilon_t \qquad (3.19)$$

The AR(k) process in differences is

$$\Delta Y_t = (1-\rho)Y_{t-1} + \gamma_1 \Delta Y_{t-1} + \gamma_2 \Delta Y_{t-2} + \dots\dots\dots + \gamma_{k-1} \Delta Y_{t-k+1} + \alpha + \varepsilon_t \qquad (3.20)$$

Where $\rho = \gamma_1 + \gamma_2 + \dots\dots\dots\dots + \gamma_p$. If a unit root exists, then $\gamma_1 + \gamma_2 + \dots\dots\dots\dots + \gamma_p = 1$ or $(1-\rho) = 0$ The null is $Ho: (1-\rho) = \delta = 0$, or the series has a unit root or is not stationary and alternatively $Ha: (1-\rho) = \delta < 0$. Thus, the ADF test is one sided. In the ADF test the Student's t is not used because the equation's parameters are obtained using OLS in which the variance of residuals is minimized. This may cause the test results to seem stationary even though the series, in fact, is not stationary (Cuthbertson, Hall and

Taylor 1992, p. 136). Engle and Granger (1987) and Mackinnon (1988) provide the alternative critical values to the Student's t statistics. The null of a unit root is not rejected when the ADF test statistic is greater than its critical value.

3.5. Testing for Cointegration

Two approaches are available to test whether a group of nonstationary series is cointegrated. The Engle and Granger method is based on assessing whether single equation estimates of equilibrium errors appear to be stationary. Johansen (1988) and Stock and Watson (1988) tests are based on a VAR approach. This section will discuss the Johansen test, which estimates the number of cointegrating relationships and provides a range of statistical tests. The method uses the following *N*-dimensional AR(k) as a starting point, that is:

$$Y_t = \alpha + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + ... + \Phi_k Y_{t-k} + \varepsilon_t \tag{3.21}$$

To implement the test, the model is transformed into the following error correction model:

$$\Delta Y_t = \Gamma_1 \Delta_1 Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + ... + \Gamma_{k-1} Y_{t-k+1} + \alpha + \Gamma_k Y_{t-k} + \varepsilon_t \tag{3.22}$$

Since Y_t is a vector of $I(1)$ variables, the left hand side of (3.22) is stationary and so are the first $(k-1)$ components of (3.22). Because the elements of the last term, that is, Y_{t-k} are not stationary, Γ_k must be a matrix of cointegrating parameters. An alternative interpretation of Γ_k is the correlation measure between ΔY_t and Y_{t-k}. The fact that both ΔY_t and Y_{t-k} represent a set of variables, the term canonical correlation is used in the Johansen methodology. The canonical correlation analysis seeks to identify and quantify the associations between two sets of variables. The first set of variables is represented by

ΔY_t and the second set of variables is represented by Y_{t-k}.The next step is to create an auxiliary regression by regressing ΔY_t and Y_{t-k}, both on the same set of explanatory variables and to obtain the corresponding residuals, that is:

$$\Delta Y_t = \hat{\pi}_0 + \hat{\Pi}_1 \Delta_1 Y_{t-1} + \hat{\Pi}_2 \Delta Y_{t-2} + \dots\dots\dots\dots + \hat{\Pi}_{k-1} Y_{t-k+1} + \hat{u}_t \qquad (3.23)$$
$$Y_{t-k} = \hat{\psi}_0 + \hat{\Psi}_1 \Delta y_{t-1} + \hat{\Psi}_2 \Delta y_{t-2} + \dots\dots\dots\dots + \hat{\Psi}_{k-1} \Delta_{t-k+1} + \hat{v}_t \qquad (3.24)$$

Charemza and Deadman (1997, p.171) suggest two ways to transform (3.21) into the error correction model, which yield the same results. The first is in the form of (3.25), which is the same as (3.22), and the second is in the form of (3.26):

$$\Delta Y_t = \Pi Y_{t-k} + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \varepsilon_t \qquad for \quad k \geq 2 \qquad (3.25)\ (3.22)$$

where: $\Gamma_i = -I + \Phi_1 + \dots\dots + \Phi_{k-1}$ and $\Pi = -(I - \Phi_1 - \dots\dots\Phi_k)$. Alternatively,

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i^* \Delta Y_{t-i} + \varepsilon_t \qquad (3.26)$$

where: $\Gamma_i^* = -(\Phi_{i+1} + \Phi_{i+2} \dots\dots + \Phi_k)$, $\quad i = 1,\dots\dots k-1$ and $\Pi = -(I - \Phi_1 - \dots\dots\Phi_k)$

According to the authors, the matrices Π are identical in both equations because it represents a constant dynamic adjustment of the first differences of variables respective to levels regardless of time difference. Because the left hand side of the equation is stationary, and $\sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i}$ is also stationary, the whole equation will also be stationary if ΠY_{t-1} or ΠY_{t-k} is stationary. Thus, the rank of matrix coefficients Π is to be examined to see whether there exist linear combinations between variables that are stationary. The equation (3.26) is also adopted by others such as Hamilton (1994) and the computer software EVIEWS. Hamilton (1994) notes that this second regression differs from the second regression used by Johansen (1991) who regresses Y_{t-k} instead of Y_{t-1}, on the same explanatory variables. According to the footnote made by this author, their residuals of the second regression are identical using either Y_{t-k} or Y_{t-1} in the second regression. In working with the Johansen test, Hamilton (1994) uses the following statistical equations:

$$Y_t = \Gamma_1 \Delta_1 Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + ... + \Gamma_{k-1} Y_{t-k+1} + \alpha + \rho Y_{t-1} + \varepsilon_t \qquad (3.27)$$

Where $\rho = \Phi_1 + \Phi_2 + ... + \Phi_k$ and $\Gamma_s = -[\Phi_{s+1} + \Phi_{s+2} + ... + \Phi_k]$ for $s = 1,2,...k-1$.

Subtracting both sides of (3.27) by Y_{t-1}, yields

$$\Delta Y_t = \Gamma_1 \Delta_1 Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + ... + \Gamma_{k-1} Y_{t-k+1} + \alpha + \Gamma_0 Y_{t-1} + \varepsilon_t \qquad (3.28)$$

Where $\Gamma_0 = \rho - I_n = -(I_n - \Phi_1 - \Phi_2 - .... - \Phi_k)$

To process the Johansen's algorithm, Hamilton (1994, p. 636) works with the following two auxiliary regressions. The first is for ΔY_t and the second is for Y_{t-1}. These two regressions have identical explanatory variables in the right-hand side.

$$\Delta Y_t = \hat{\pi}_0 + \hat{\Pi}_1 \Delta_1 Y_{t-1} + \hat{\Pi}_2 \Delta Y_{t-2} + ... + \hat{\Pi}_{k-1} Y_{t-k+1} + \hat{u}_t \qquad (3.29)$$
$$Y_{t-1} = \hat{\psi}_0 + \hat{\Psi}_1 \Delta Y_{t-1} + \hat{\Psi}_2 \Delta Y_{t-2} + ... + \hat{\Psi}_{k-1} \Delta Y_{t-k+1} + \hat{v}_t \qquad (3.30)$$

The Johansen method is directed to estimate the factorization of $\Gamma_0 Y_{t-1} = -BA' Y_{t-1}$ in equation (3.28), (3.12) and (3.31) so that $BA' Y_{t-1}$ is stationary. In this case, all possible cointegrating vectors, the A matrix, and the set of error-correction coefficients, the B matrix, will be estimated. Thus, considering all cointegrating vectors, the system will be:

$$\Delta Y_t = \Gamma_1 \Delta_1 Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + ... + \Gamma_{k-1} \Delta Y_{t-k+1} + \alpha - BA' Y_{t-1} + \varepsilon_t \qquad (3.31)$$

According to Cuthbertson, Hall and Taylor (1992, 136), if BA' were known, the maximum likelihood estimates of the Γ_i are obtained using OLS by first rearranging (3.31) as

$$\Delta Y_t + BA'Y_{t-1} = \Gamma_1 \Delta_1 Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + ... + \Gamma_{k-1} Y_{t-k+1} + \alpha + \varepsilon_t \tag{3.32}$$

The correlation between ΔY_t and Y_{t-1} is obtained by correcting the effect of ΔY_{t-j}, $j = 1,2,......k-1$ on ΔY_t and Y_{t-1}, that is taking out their effect and leaving ε_t. Correcting ΔY_t and Y_{t-1} for the effects of ΔY_{t-j}, the authors replace ΔY_t and Y_{t-1} with the residuals from (3.29) and (3.30), respectively. The equation (3.32) reduces to $\hat{\mu}_t + BA'\hat{v}_t = \varepsilon_t$. Hamilton (1994, 638) characterizes $\hat{\mu}_t + BA'\hat{v}_t$ as a vector, which has a sample mean zero and is orthogonal to ΔY_{t-j}, however, Hamilton (1994) uses the vector notation $\hat{\mu}_t - \xi_0 \hat{v}_t$, where $\xi_0 = -BA'$.

The Johansen's maximum likelihood method adopts the canonical correlation method to seek all the distinct combinations of the levels of Y_{t-1}, which provide high correlations with ΔY_t, the $I(0)$ element. The vectors $\hat{u}_t$ and $\hat{v}_t$ are the residuals from the regression with dependent variables ΔY_t and Y_{t-1}, respectively. These two sets of residuals are used to construct these covariance matrices:

$$\hat{\Sigma}vv = \frac{1}{T}\sum_{t=1}^{T} \hat{v}_t \hat{v}_t^{/}, \quad \hat{\Sigma}uu = \frac{1}{T}\sum_{t=1}^{T} \hat{u}_t \hat{u}_t^{/}, \quad \hat{\Sigma}uv = \frac{1}{T}\sum_{t=1}^{T} \hat{u}_t \hat{v}_t^{/}, \quad \text{and } \hat{\Sigma}vu = \hat{\Sigma}^{/}uv \tag{3.33}$$

The roots or eigenvalues λ of the matrix $(\hat{\Sigma}vv)^{-1}\hat{\Sigma}vu(\hat{\Sigma}uu)^{-1}\hat{\Sigma}uv$ can be interpreted as the proportion of variance accounted for by the correlation between the respective canonical variates, ΔY_t and Y_{t-1}. The eigenvalues are ordered from the highest to the lowest, such that if the square root of the eigenvalues $\hat{\lambda}$'s of this matrix is taken, the resulting number will be the correlation's coefficients. The canonical correlations measure the strength of association between the two sets of variables and the canonical correlation analysis searches for linear combinations of the original variables having maximal correlation. The maximum number of cointegrating relations = $N-1$ and $h < N$. The dimension of Γ_0 is $N\ x\ N$ and the dimensions of B and A' are $N\ x\ h$ and $h\ x\ N$, respectively. The restriction that $\Gamma_0 = BA'$ is required to test the null that the number of cointegration is h. Based on Hamilton (1994), with this restriction, the highest value of the log likelihood function is:

$$L_0 = -\frac{TN}{2}\log(2\pi) - \frac{TN}{2} - \frac{T}{2}\log\left|\hat{\Sigma}uu\right| - \frac{T}{2}\sum_{i=1}^{h}\log(1-\hat{\lambda}_i) \qquad (3.34)$$

The value of the log likelihood function for the number of N cointegration, or if no such restriction that $\Gamma_0 = BA'$ as the alternative hypothesis, is:

$$L_A = -\frac{TN}{2}\log(2\pi) - \frac{TN}{2} - \frac{T}{2}\log\left|\hat{\Sigma}uu\right| - \frac{T}{2}\sum_{i=1}^{N}\log(1-\hat{\lambda}_i) \qquad (3.35)$$

The Likelihood Ratio test statistic is then formed as $L_A - L_0 = -\frac{T}{2}\sum_{i=h+1}^{N}\log(1-\hat{\lambda}_i)$. For $I(0)$ series, the trace statistic is expected to be twice the log Likelihood Ratio (Hamilton 1994, p. 645). That is: $2(L_A - L_0) = -T\sum_{i=h+1}^{N}\log(1-\hat{\lambda}_i)$. In the Johansen test, the trace statistic test is $-T\sum_{i=h+1}^{h}\log(1-\hat{\lambda}_i)$. This is to be compared to its critical values to test the null that there are h or fewer cointegrating vectors. In the Johansen test, h is set equal to zero. Given eigenvalues data ordered from the largest to smallest $\lambda_1 > \lambda_2 > .... > \lambda_n$

and the number of cointegration equations h, the computation of trace statistics will be presented in table 3.1.

Table 3.1.
The Computations of Trace Statistics

Null Hypothesis	Eigenvalues	Trace Statistic
$h = 0$	λ_1	$-T[\log(1-\lambda_1) + \log(1-\lambda_2) + \log(1-\lambda_3) + \log(1-\lambda_4)]$
$h \leq 1$	λ_2	$-T[\log(1-\lambda_2) + \log(1-\lambda_3) + \log(1-\lambda_4)]$
$h \leq 2$	λ_3	$-T[\log(1-\lambda_3) + \log(1-\lambda_4)]$
$h \leq 3$	λ_4	$-T[\log(1-\lambda_4)]$
As an illustration, as presented by EVIEWS' manual (1997) for a four-variable system with 53 observations, the eigenvalues are ordered from the highest to the lowest:		
Ho: (# of Cointegrating Equations)	Eigenvalues	Computed Trace Statistic (likelihood ratio)
None	0.433165	-53[ln(1-0.433165)+ln(1-0.177584)+ln(1-0.112791)+ln(1-0.043411)] = 49.14436
At most 1	0.177584	-53[ln(1-0.177584)+ln(1-0.112791)+ln(1-0.043411)] = 19.05691
At most 2	0.112791	-53[ln(1-0.112791)+ln(1-0.043411)] = 8.694964
At most 3	0.043411	-53[ln(1-0.043411)] = 2.3522233

The computed trace statistics are to be compared to their critical values to determine the rejection or acceptance of the null hypothesis.

The columns of matrix A have an economic interpretation as cointegrating vectors after being normalized, that is, as long run parameters. The elements of matrix B measure the speed of adjustment as a result of a disturbance in the equilibrium relation. In practice, running the VECM requires two steps. First, obtain cointegrating residuals $A'Y_{t-1}$ and second, include these residuals as a regressor in the VECM.

3.6. Multivariate GARCH Models

Univariate ARCH or GARCH models involve two equations: a mean equation and a variance equation. The variance equation will indicate whether the resulting residuals from the mean equation significantly follow an ARCH or GARCH process. If so, the variance of residuals is not constant over time and the assumption of homoscedasticity is not realistic. A model with a time-varying variance, the autoregressive conditional heteroscedasticity (ARCH) was introduced by Engle(1982) to represent the variance process. In the ARCH model, the variance process, denoted by h_t, depends on q lagged values of the square of ε_t .

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_q \varepsilon_{t-q}^2 \qquad (3.36)$$

Another model of the time-varying variance process is the generalized autoregressive conditional heteroscedasticity (GARCH) introduced by Bollerslev (1986). This model assumes that h_t depends on p lagged values of itself or past conditional variances and q lagged values of the residuals. This is known as the GARCH(p,q) model, which is defined as

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_q \varepsilon_{t-q}^2 + \beta_1 h_{t-1} + ... + \beta_q h_{t-p} \qquad (3.37)$$

In the univariate ARCH or GARCH, the residuals are obtained from a single linear regression model, called mean equation. The term GARCH-in-Mean or GARCH-M is used when the variance of the model enters the mean equation as a regressor,

$$Y_t = f(X, h_t) \qquad (3.38)$$

where X are any regressors other than h_t. This GARCH-M model was introduced by Engle, Lilien, and Robins (1987).

In this study, the VAR with inventory and sales as its components will act as the mean equation, so that a multivariate GARCH or MGARCH modeling is used. In the multivariate case, the process Y_t is a vector with N time series. The basic framework for a multivariate GARCH or MGARCH model is introduced by Bollerslev, Engle, and Wooldridge (1988). The authors expand the univariate GARCH by vectorizing the conditional variance matrix. The matrix representation of a multivariate GARCH (p,q) or MGARCH(p,q) is given by:

$$vech(H_t) = C + \sum_{i=1}^{q} A_i vech(\varepsilon_{t-i}\varepsilon_{t-i}^{/}) + \sum_{j=1}^{p} B_j vech(H_{t-j}) \quad (3.39)$$

The authors denote $vech(.)$ as the column stacking operator of the lower portion of a symmetric matrix. For the number of time series N , C is $\frac{1}{2}(N(N+1)$ by 1 vector. A_i and B_j are coefficient matrices, each with $[\frac{1}{2}N(N+1) \quad x \quad \frac{1}{2}N(N+1)]/2$ dimension and ε_t is an $Nx1$ disturbance vector. This model, known as the VEC-BEW model, states that each element of H_t is a linear function of the lagged squared disturbances, cross products of disturbances, and lagged values of all elements of H_t . This VEC-BEW model is very general and requires many parameters to estimate. In addition, many parameters in this model cannot be easily interpreted. According to the authors, this GARCH specification does not arise out of any economic theory.

Denoting h_t and η_t for $vech(H_t)$ and $vech(\varepsilon_{t-i}\varepsilon_{t-i}^{/})$, respectively, we can express the multivariate GARCH(1,1) by $h_t = C + A\eta_{t-1} + Bh_{t-1}$. The matrix representation for MGARCH(1,1) for $N = 2$ requires 21 parameters.

$$\begin{bmatrix} h_{11,t} \\ h_{12,t} \\ h_{22,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} g_{11} & g_{12} & g_{13} \\ g_{21} & g_{22} & g_{23} \\ g_{31} & g_{32} & g_{33} \end{bmatrix} \begin{bmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \end{bmatrix} \quad (3.40)$$

For N = 2, 3, 4 the number of parameters is equal to 21, 78, and 210, respectively. Other variants of the VEC-BEW model reduce the number of parameters to be estimated. These models include a constant correlation (CC-MGARCH) model, Diagonal BEKK, BEKK model (Engle and Kroner, 1995), and Dynamic Conditional Correlation MGARCH (Engle 2001). For empirical purposes, this study will work with two simplified models: the MGARCH constant correlation model (3.42 and 3.43) and diagonal-BEKK model (3.42 and 3.47).

3.6.1. Multivariate GARCH-in-Mean: Constant Correlation Model

To reduce the number of parameters, Bollerslev (1990) proposed a constant correlation model called the CC-MGARCH with several characteristics. First, there is no cross equation dynamics as in the VEC-BEW model. The only dynamics are:

$$h_{ii,t} = c_{ii} + a_i \varepsilon_{i,t-1}^2 + g_i h_{ii,t-1} \qquad (3.41)$$

Second, to determine off-diagonal elements of Σ_t, Bollerslev uses a constant contemporaneous correlation: $h_{ij,t} = \rho_{ij} \sqrt{h_{ii,t} h_{jj,t}}$ where ρ_{ij} is the contemporaneous correlation of the two series, and $-1 \leq \rho_{ij,t} \leq +1$. It is assumed that the time varying conditional covariances are taken proportional or constant to the $\left(h_{ii,t} h_{jj,t}\right)^{1/2}$.

With the implementation of the CC-MGARCH to this study where $N = 2$, $p = 1$, and $q = 1$, the number of parameters is only 7. Suppose the multivariate GARCH-M means that the mean (VAR) equations with k lags are also a linear function of conditional variances, that is:

$$
\begin{aligned}
\log(Inv)_t &= \alpha + \sum_{i=1}^{k} \beta_i \log(Inv)_{t-i} + \sum_{i=1}^{k} \gamma_i \log(Sales)_{t-i} + \delta h_{11,t} + \varphi h_{22,t} + \varepsilon_{1,t} \\
\log(Sales)_t &= w + \sum_{i=1}^{k} \lambda_i \log(Inv)_{t-i} + \sum_{i=1}^{k} \theta_i \log(Sales)_{t-i} + \pi h_{11,t} + \psi h_{22,t} + \varepsilon_{2,t}
\end{aligned}
\tag{3.42}
$$

where the conditional variance and covariance equations are:

$$
\begin{aligned}
h_{11,t} &= a_0 + a_1 \varepsilon_{1,t-1}^2 + a_2 h_{11,t-1} \\
h_{22,t} &= b_0 + b_1 \varepsilon_{2,t-1}^2 + b_2 h_{22,t-1} \\
h_{12,t} &= \rho_{12} \sqrt{h_{11,t} h_{22,t}}
\end{aligned}
\tag{3.43}
$$

This constant correlation model assumes that the time-varying covariances are proportional to the square root of the product of the two corresponding conditional variance. This allows the conditional correlations to be constant over time. Even though the conditional correlation is constant, the conditional covariance is still time varying because it is determined by the dynamics of both $h_{11,t}$ and $h_{22,t}$.

The interpretation of the parameters in the conditional variance equations shows the existence of a time-varying variance if a_1, a_2, b_1 and b_2 are significantly different from zero. If $a_1 = a_2 = 0$ and $b_1 = b_2 = 0$, ε_t is simply a white noise series which means that ε_t and ε_{t-k} are independent. The spillover of volatility of inventory and volatility of sales exists if ρ_{12} is significant. Uncertainty of sales has an impact on inventories if φ is significant. Using the GARCH-in-mean allows us to test the effect of uncertainty, which is measured by the time-varying variance. The parameter values are obtained from the maximum likelihood estimates that provide a maximum value of the likelihood function.

3.6.2. Multivariate GARCH-in-Mean: the BEKK Diagonal Model

In order to reduce the number of parameters and guarantee positive definiteness, Engle and Kroner (1995) introduce a multivariate GARCH named the BEKK (named after Baba, Engle, Kraft, and Kroner) model. The feature of the BEKK model is that it does not require estimates of many parameters and guarantees that the variance covariance matrices are positive definite. The general form of the BEKK model for N series is:

$$H_t = C_0^{/}C_0 + \sum_{k=1}^{K}\sum_{i=1}^{q} A_{ik}^{/}\varepsilon_{t-i}\varepsilon_{t-i}^{/}A_{ik} + \sum_{k=1}^{K}\sum_{i=1}^{p} G_{ik}^{/}H_{t-i}G_{ik} \qquad (3.44)$$

where C_0, A_{ik} and G_{ik} are (NxN) matrices and C_0 is triangular. To reduce the number of parameters in the BEKK model, literature discussions often assume the summation limit K is reduced to 1, which makes the model become:

$$H_t = C_0^{/}C_0 + \sum_{i=1}^{q} A_i^{/}\varepsilon_{t-i}\varepsilon_{t-i}^{/}A_i + \sum_{j=1}^{q} G_j^{/}H_{t-j}G_j \qquad (3.45)$$

Illustrating this model, Engle and Kroner use a simple GARCH(1,1) with $K = 1$, that is:

$$H_t = C^{/}C + A^{/}\varepsilon_{t-1}\varepsilon_{t-1}^{/}A + G^{/}H_{t-1}G \qquad (3.46)$$

For a BEKK model with $N = 2$ and $p = q = 1$, there are 11 parameters including a constant. Its matrix form is:

$$H_t = C_0^{/}C_0 + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}^{/} \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}^{/} H_{t-1} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \qquad (3.47)$$

If A and G are diagonal, the BEKK is simply the vector diagonal model

4. EMPIRICAL RESULTS

4.1. Empirical Models Used in This Study

This section reports the empirical results from applying the constant correlation and diagonal-BEKK models of a multivariate GARCH-in-Mean with the VECM and VAR as the mean equations [1].

For the purpose of examining the relationship between inventory and demand uncertainty, the interrelationship between inventory and sales and the time varying variance of sales, this study will work with the relevant VAR and VECM specifications. The first is Model A. In this model, the conditional volatility terms included in the mean equation are the conditional standard deviation of all residuals and do not include the conditional covariance terms. The reason for applying this model is to compare the results to the previous study by Lee and Koray (1994) who use an identical model. Model A is a bivariate constant correlation GARCH-M with a VECM as the mean equation with the following structure:

$$\begin{aligned}
\Delta \ln(Inv)_t &= \alpha_0 + \alpha_1 u_{t-1} + \sum_{i=1}^{k} \alpha_{1+i} \Delta \ln(Inv)_{t-i} + \sum_{i=1}^{k} \alpha_{1+k+i} \Delta \ln(Sales)_{t-i} + \delta h_{11,t}^{1/2} + \varphi h_{22,t}^{1/2} + \varepsilon_{1,t} \\
\Delta \ln(Sales)_t &= \beta_0 + \beta_1 u_{t-1} + \sum_{i=1}^{k} \beta_{1+i} \Delta \ln(Inv)_{t-i} + \sum_{i=1}^{k} \beta_{1+k+i} \Delta \ln(Sales)_{t-i} + \pi h_{11,t}^{1/2} + \psi h_{22,t}^{1/2} + \varepsilon_{2,t}
\end{aligned} \qquad (4.1)$$

where the functional form of the conditional variances and covariances is:

$$\begin{aligned}
h_{11,t} &= a_0 + a_1 \varepsilon_{1,t-1}^2 + a_2 h_{11,t-1} \\
h_{22,t} &= b_0 + b_1 \varepsilon_{2,t-1}^2 + b_2 h_{22,t-1} \\
h_{12,t} &= \rho_{12} \sqrt{h_{11,t} h_{22,t}}
\end{aligned} \qquad (4.2)$$

[1] The results are obtained using MATLAB with multivariate GARCH-in-mean programs written by Aaron Smallwood, Department of Economics, University of Oklahoma.

To enrich the analysis, this study will also present the results of Model B in which the conditional variance of residuals $h_{11,t}$ and $h_{22,t}$ are used instead of the conditional standard deviations $h_{11,t}^{1/2}$ and $h_{22,t}^{1/2}$ as the measures of uncertainty. Because the VECM and VAR models both are categorized as seemingly unrelated regressions, there is a possibility of a linear relationship between the component residuals. To isolate the effect of multicollinearity between the conditional standard deviation (variance) of sales and the conditional standard deviation (variance) of inventory, this study will work with Model C and Model D. Model C, only includes the conditional standard deviation of sales in the inventory equation. Model D, only includes the conditional variance of sales in the inventory equation. In Model C and D, there are no volatility terms in the sales equation. Models E and F are also surveyed. Model E includes both the conditional standard deviations of sales and of inventory in the inventory equation. Model F includes both the conditional variances of sales and of inventory. Models E and F differ from Models A and B in that in Models E and F the conditional variance and standard deviation terms are only included in the inventory equations, not in the sales equation.

For the purpose of analyzing the VAR model, the VECM structure is changed by replacing Δln(Inv) and Δln(Sales) with ln(Inv) and ln(Sales), respectively. In addition, the cointegrating residuals μ_{t-1} are not included in the VAR.

4.2. The Results of Unit Root Tests

This study uses both the augmented Dickey-Fuller (ADF) tests and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests with constant and trend to test if inventory and sales are stationary. The ADF tests are based on a maximum of 14 lags with the ultimate selection based on the AIC. The results using EVIEWS are reported in table 4.1.

Table 4.1
ADF's Unit Root Tests
Log (Monthly Sales) and Log(Monthly Inventory) Series

Series	Augmented Dickey Fuller (ADF) Tests with Constant and Trend, Based on AIC Ho: The series has a unit root (or not stationary)	
	Test Statistic (t)	Lag
Log(Furniture Sales)	-1.689349	1
Log(Furniture Inventory)	-1.706129	0
Log(Food Sales)	-1.542319	1
Log(Food Inventory)	-1.743147	0
Log(General Merchandise Sales)	-2.303926	4
Log(General Merchandise Inventory)	-0.799526	10
Log(Auto Sales)	-2.297362	2
Log(Auto Inventory)	-2.185293	14
Log(Apparel Sales)	-1.592871	4
Log(Apparel Inventory)	-2.257359	3
Log(Bld Mat & Hardware Sales)	-2.599089	12
Log(Bld Mat & Hardware Inventory)	-1.678016	5
Critical values at 1 %	Range: -3.999465	to -3.992500
Critical values at 5 %	-3.4299923	to -3.428819
Critical values at 10 %	-3.138502	to -3.137851

Note: The range of critical values is reported because the ADF tests provide slightly different critical values for each test statistic. All augmented Dickey Fuller (ADF) test statistics fail to reject the null that the series has a unit root or is non stationary.

Table 4.1 lists the ADF unit root tests for sales and inventories for the six retail trade sectors and the number of lags in the ADF at which the minimum AIC is observed. The ADF tests show that all of the Dickey Fuller's t-statistics for the six series are greater than the critical values as shown on the bottom panel of the table. In other words, the ADF test statistics fail to reject the null at 1% confidence level that sales and inventory series have a unit root or are non stationary. Using a more aggregate sales and inventory level data for different periods, Lee and Koray (1994) using Phillips and Perron tests, found similar results.

Table 4.2
KPPS's Unit Root Tests
Log (Monthly Sales) and Log(Monthly Inventory) Series

Series	Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Tests with Constant and Trend. Ho: The series is stationary	
	Test Statistic (t)	Lag
Log(Furniture Sales)	0.190242*	11
Log(Furniture Inventory)	0.256962**	11
Log(Food Sales)	0.418451**	12
Log(Food Inventory)	0.478259**	11
Log(General Merchandise Sales)	0.224466**	11
Log(General Merchandise Inventory)	0.339336**	11
Log(Auto Sales)	0.190900*	11
Log(Auto Inventory)	0.309773**	11
Log(Apparel Sales)	0.435321**	11
Log(Apparel Inventory)	0.474377**	11
Log(Bld Mat & Hardware Sales)	0.167957*	11
Log(Bld Mat & Hardware Inventory)	0.212079*	11
Critical values at 1 %	0.216	
Critical values at 5 %	0.146	
Critical values at 10 %	0.119	

Note : The KPPS test statistics with * and ** are greater than the critical values at 5% and 1% confidence level, respectively. Therefore reject the null that the series are stationary.

Table 4.2 reports the KPPS tests for unit roots. These tests also provide evidence that the series are non-stationary. Unlike the ADF test in which the null is that the series have a unit root or are non stationary, the KPSS tests have the null that the series is stationary. The table shows that the KPSS test statistics are greater than the critical values at 5% or 1% confidence level, which means that the test rejects the null that the series are stationary.

4.3. The Results of Cointegration Tests

This section investigates the long-term relationship between inventory and sales in each retail sector by employing cointegration tests. The purpose of a cointegration test is to determine whether the non-stationary sales and inventory series are cointegrated. If two series are cointegrated, there is a linear combination or cointegrating equation that can be interpreted as a long-run equilibrium relationship between sales and inventory. Because this study will use both the VEC and VAR models, inventory and sales series should be integrated of the same order.

Table 4.3
The Johansen's Cointegration Tests
With no Deterministic Trend (Restricted Constant)
Using EVIEWS Based on Trace Statistics

Series: log(Inv) and log(Sales)	Hypothesized Number of Coint. Equations	Eigenvalue	Trace Statistic	Critical Values	
				5%	1%
Furniture T=238	None At most 1	0.127166 0.027006	38.88629 6.515873	19.96 9.24	24.60 12.97
Food T=237	None At most 1	0.224142 0.019191	64.73956 4.592418	19.96 9.24	24.60 12.97
General Merch T=236	None At most 1	0.228522 0.027604	67.83572 6.606232	19.96 9.24	24.60 12.97
Auto T=236	None At most 1	0.186363 0.029273	55.68444 7.011681	19.96 9.24	24.60 12.97
Apparel T=237	None At most 1	0.173178 0.046503	56.35497 11.28560	19.96 9.24	24.60 12.97
Building Mat T=238	None At most 1	0.179392 0.053791	60.21432 13.15944	19.96 9.24	24.60 12.97

Table 4.3 reports the results of the Johansen cointegration tests using EVIEWS. Except for building material, the trace statistics reject the null that there is no cointegration at the 1% significance level. The trace statistics fail to reject the null that

there is at most 1 cointegration equation. These results mean that sales and inventory series in furniture, food, general merchandise, autos, and apparel are integrated of the same order. Thus there exists a long run linear relationship between inventory and sales in the 5 retail sectors under this study.

The first column of Table 4.3 lists the retail sectors, and the second column is the number of cointegrating relations under the null. The first figure of the trace statistic in column 4 is the test statistic of the null of zero cointegrating relations against N cointegrating relations, where N is the number of endogenous variables. The second trace statistic tests the null of one cointegrating relation against N cointegrating relations. Because the maximum number of cointegrating relations is (N-1) and N = 2, the maximum number of cointegrating relations is one. In a VAR model explaining N = 2 variables, there can be at most h = 2-1 = 1 cointegrating vectors (Charemza and Deadman 1997, p. 176). The table shows that the tests reject the null that there is no cointegrating relation and they fail to reject the null of one cointegration relation at 1% confidence level except for building and material retail sales and inventory which reject both the zero and one cointegration relations. Because the number of cointegrating vectors is no more than one, this study will consider the number of cointegration in building materials series as only one. EVIEWS provides one cointegration equation result for each pair of series. Similar results are reported in Table 4.4 using Max-eigen statistics. The tests reject the null that there is no cointegration between inventory and sales in furniture, food, general merchandise, autos, and apparel retails indicated by the Max-eigen statistics that are greater than their critical values. The tests fails to reject the null that there is at most 1 cointegrating relation. For building material, the tests reject the null that there is no cointegration as well as the null that there is at most 1 cointegration. These results imply that there is more than one cointegration in the building material retail.

Table 4.4
The Johansen's Cointegration Tests
With no Deterministic Trend (Restricted Constant)
Using EVIEWS Based on Max-eigen Statistics

Series: log(Inv) and log(Sales)	Hypothesized Number of Coint. Equations	Eigenvalue	Max-Eigen Statistic	Critical Values	
				5%	1%
Furniture T=238	None At most 1	0.127166 0.027006	32.37042 6.515873	15.67 9.24	20.20 12.97
Food T=237	None At most 1	0.224142 0.019191	60.14715 4.592418	15.67 9.24	20.20 12.97
General Merch T=236	None At most 1	0.228522 0.027604	61.22949 6.606232	15.67 9.24	20.20 12.97
Auto T=236	None At most 1	0.186363 0.029273	48.67276 7.011681	15.67 9.24	20.20 12.97
Apparel T=237	None At most 1	0.173178 0.046503	45.06937 11.28560	15.67 9.24	20.20 12.97
Building Mat T=238	None At most 1	0.179392 0.053791	47.05488 13.15944	15.67 9.24	20.20 12.97

The normalized cointegrating equation for each retail sector's inventory and sales are reported as follows: (numbers in parentheses are standard errors of the coefficients).

$$\ln(\text{Furniture Inventory})_{t-1} = -\underset{(0.42015)}{3.059030} - \underset{(0.04683)}{0.757657} \ln(\text{Furniture Sales})_{t-1}$$

$$\ln(\text{Food Inventory})_{t-1} = \underset{(0.19999)}{0.159064} - \underset{(0.05840)}{1.013701} \ln(\text{Food Sales})_{t-1}$$

$$\ln(\text{Gen. Merch. Inventory})_{t-1} = \underset{(1.33497)}{-4.075183} - \underset{(0.44068)}{0.518736} \ln(\text{Gen. Merch. Sales})_{t-1}$$

$$\ln(\text{Auto Inventory})_{t-1} = \underset{(0.11139)}{-0.753187} - \underset{(0.03126)}{0.972063} \ln(\text{Auto Sales})_{t-1}$$

$$\ln(\text{Apparel Inventory})_{t-1} = -2.918081 - 0.787176 \ln(\text{Apparel Sales})_{t-1}$$
$$(0.39890) \quad (0.04447)$$

$$\ln(\text{Bldg Material Inventory})_{t-1} = -2.141123 - 0.871162 \ln(\text{Bldg Material Sales})_{t-1}$$
$$(0.35169) \quad (0.03975)$$

4.4. The Number of Lags in the VAR and VECM

The evidence of cointegration between sales and inventories in all of the six retail sectors provides support for the hypothesis that these two series may be interrelated so that the vector error correction model (VECM) and the vector autoregression (VAR) may be used for analyzing the impact of random disturbances on the system of two variables: sales and inventories.

Table 4.5
Number of Lags p in Vector Autoregressive (VAR) for Log(Series)

$$\log(Inv)_t = \alpha_{10} + \sum_{i=1}^{p} \delta_{1i} \log(Inv)_{t-i} + \sum_{i=1}^{p} \beta_{1i} \log(Sales)_{t-i} + \varepsilon_{1i}$$

$$\log(Sales)_t = \alpha_{20} + \sum_{i=1}^{p} \delta_{2i} \log(Inv)_{t-1} + \sum_{i=1}^{p} \beta_{2i} \log(Sales)_{t-i} + \varepsilon_{2t}$$

Series	Based on Max Lag = 15		Based on Max Lag = 15	
	p	Min SIC	p	Min AIC
Log(Furniture Inventory) and Log(Furniture Sales)	1	-10.78858	1	-10.87585
Log(Food Inventory) and Log(Food Sales)	2	-14.25797	2	-14.40386
Log(Gen Merchandise Inv) and Log(Gen Merchandise Sales)	2	-12.15077	3	-12.30533
Log(Auto Inventory) and Log(Auto Sales)	3	-8.459918	3	-8.664782
Log(Apparel Inventory) and Log(Apparel Sales)	1	-11.54323	2	-11.64911
Log(Bld Mat&Hardware Inv) and Log(Bld Mat&Hardware Sales)	1	-11.00287	1	-11.09015

Table 4.5 reports the number of lags in each VAR equation using level series at which the minimum SIC and AIC for each retail sector are observed. Table 4.6 reports the number of lags in each VAR equation using the first differenced series at which the minimum SIC and AIC for each retail sector are observed. This number of lags will be used for empirical VECM.

Table 4.6
Number of Lags q in Vector Autoregressive (VAR)
for First Differenced Log(Series)

$$\Delta \log(Inv)_t = \lambda_{10} + \sum_{i=1}^{q} \gamma_{1i} \Delta \log(Inv)_{t-i} + \sum_{i=1}^{q} \theta_{1i} \Delta \log(Sales)_{t-i} + \upsilon_{1i}$$

$$\Delta \log(Sales)_t = \lambda_{20} + \sum_{i=1}^{q} \gamma_{2i} \Delta \log(Inv)_{t-1} + \sum_{i=1}^{q} \theta_{2i} \Delta \log(Sales)_{t-i} + \upsilon_{2t}$$

Series	Based on Max Lag = 15		Based on Max Lag = 15	
	q	Min SIC	q	Min AIC
Log(Furniture Inventory) and Log(Furniture Sales)	1	-10.75096	2	-10.84184
Log(Food Inventory) and Log(Food Sales)	1	-14.30673	1	-14.39427
Log(Gen Merchandise Inv) and Log(Gen Merchandise Sales)	1	-12.21895	4	-12.32662
Log(Auto Inventory) and Log(Auto Sales)	2	-8.460325	2	-8.60657
Log(Apparel Inventory) and Log(Apparel Sales)	1	-11.51668	1	-11.60422
Log(Bld Mat&Hardware Inv) and Log(Bld Mat&Hardware Sales)	1	-10.92753	3	-11.01696

The minima of the SIC and AIC were found from running a VAR with up to 15 lags and a constant. In general, the number of lags are small ranging only from 1 to 3 for the VAR and from 1 to 4 for the VECM, thus, avoiding consuming a large number of degrees of freedom.

4.5. VECM Results: Constant Correlation Models

The results for the multivariate constant correlation GARCH-in-Mean with the VECM as the mean equation for the six retail series are reported in Table 1 through Table 6 in the Appendix 1. The results for apparel, auto dealers and food are reported using 6 models from Model A to Model F for each. Since the data for building material, general merchandise and furniture are not suitable for particular models using MATLAB, only 5, 5, and 3 models are reported for these sectors, respectively.

Tables 1 through 6 report the following results of the effects of sales volatility on inventory. In apparel, auto dealer, and building material retail sectors, none of the coefficients of the conditional variance of sales nor conditional standard deviation of sales in the inventory equation is significant across models reported. This means that volatility of sales as a measure of demand uncertainty does not affect growth of inventory in these three retail sectors. From 5 models reported for general merchandise, only one model shows a significant coefficient of conditional standard deviation of sales in the inventory equation. With 6 models reported for food retail series, the sales volatility measure using conditional variance of sales is negatively significant in inventory equations as shown in 3 models, but the coefficients are not significant if the sales volatility measure is replaced by the conditional standard deviation of sales, as shown in 3 other models. For furniture series, 3 models are reported. The results show significantly negative coefficients of sales volatility in the inventory equation either using conditional variance or using standard deviation of sales as a measure of sales volatility. The results are observed from 2 models in which only sales volatility is alone in the inventory equations. The results turn out to be insignificant when both sales volatility and inventory volatility enter the inventory equation as reported in the third model. This may be due to the existence of multicollinearity between two volatility measures. The same situation is also observed in the general merchandise sector. In the models where the multicollinearity is high, the corresponding t-ratios of constant correlation are extremely high.

The tables also report the spillover volatility and the existence of time varying volatility of sales. The spillover volatility between inventory and sales is represented by the constant correlation coefficients. These constant correlations are significant in auto dealers (all models), furniture (all models), food (5 out of 6 models), apparel (2 out of 6 models) and general merchandise (2 out of 5 models), but no models in building material and hardware. Time-varying volatility (variance) of sales is represented by the coefficients of ARCH and/or GARCH from the conditional variance equations. The significances of the parameters of the ARCH or GARCH in the conditional variance equation for sales are found in auto dealers (5 models), in furniture (all models), in food (4 out of 6 models), in general merchandise (2 out of six models), and none in apparel or in building material retails.

4.6. Comparison of Current VECM Results to Previous Study

Table 4.7a and 4.7b compare the current results to the study by Lee and Koray (1994) using aggregate retail series and the current study using six retail sectors. Both are using models with identical variables, except for furniture. In this study, Model A is identical to the model used by Lee and Koray. The first figure in the tables is the coefficient of the parameter and the second figure inside brackets is the t-statistic. Table 4.7a reports the results of the current study for food, auto, and furniture retail sectors compared to the previous study which is reported in the first two columns of the table. Table 4.7b reports the results of the current study for apparel, building materials, and general merchandise retail sectors, compared to the previous study reported in the first two columns of the table.

Table 4.7a
Previous Study Based on Aggregate Retails and Current Study Based on Less Aggregate Retail Data. t-ratios are reported in brackets [ ]

	Previous Study (Lee & Koray's Aggregate Retail Trade)		Food Retails (Model A)		Auto Retails (Model A)		Furniture Retails (Model E)	
	Mean Equation		Mean Equation		Mean Equation		Mean equation	
	ΔInv_t	ΔSls_t	$\Delta \ln(Inv)_t$	$\Delta \ln(Sls)_t$	$\Delta \ln(Inv)_t$	$\Delta \ln(Sls)_t$	$\Delta \ln(Inv)_t$	$\Delta \ln(Sls)_t$
Constant	0.189 [0.32]	0.229 [0.29]	-0.008823 [-0.0710]	-0.001889 [-0.0455]	-0.017851 [-0.6271]	0.141174 [2.2518]	372.3697 [0.4954]	0.2594 [3.0450]
CointRes	-0.083 [-5.49]	0.006 [0.37]	-0.020676 [-0.0867]	-0.047669 [-2.8642]	0.037219 [0.8337]	-0.204011 [-2.5503]	-0.0161 [0.0467]	-0.0955 [-3.0527]
$CondStd_{In}$	-0.123 [-0.64]	-0.780 [-0.78]	1.1300422 [0.2330]	-1.64047 [-0.2501]	-0.612660 [-0.4309]	0.152941 [0.3599]	0.0496 [0.0064]	NA
$CondStd_{Sls}$	0.141 [0.32]	0.090 [0.183]	-0.507518 [-0.6477]	-0.317691 [-0.5607]	0.405001 [0.2273]	-0.22223 [-0.3851]	-20989.0 [-0.4953]	NA
	Cond. Var. Inventory	Cond. Var. Sales	Cond. Var. Inventory	Cond. Var. Sales	Cond. Var. Inventory	Cond. Var. Sales	Cond. Var. Inventory	Cond. Var. Sales
Constant	0.036 [0.88]	0.552 [3.54]	0.0000361 [12.8550]	0.0000187 [9.2146]	0.000250 [1.1076]	0.000083 [0.3279]	0.0000121 [0.1432]	0.0002681 [61385.0]
ARCH	0.132 [1.98]	0.573 [2.21]	0.141307 [0.3456]	0.271614 [0.7195]	0.452271 [0.8711]	0.246283 [0.3641]	0.2251 [0.3799]	0.0000002 [0.0461]
GARCH	0.832 [7.93]	0.129 [0.89]	0.007616 [0.0053]	0.248004 [1.1113]	0.000000 [0.00000]	0.695062 [1.4224]	0.7498 [1.9221]	0.1482 [74.8702]
ConsCorr	-0.100 [-1.556]		0.185145 [1.9351]		-0.348722 [-4.3328]		0.2923 [9.8170]	

Source: Tables 1 through 6 in the Appendix 1.

Three statistics from the previous study are compared to this study, including the conditional standard deviation of sales, the constant correlation figures, and the time varying volatility. The conditional standard deviation of sales has insignificant coefficients in all six inventory equations, which means that uncertainty of demand, represented by conditional standard deviation of sales, does not affect inventory in these six retails: food, auto, furniture, apparel, building material, and general merchandise. These are the same as in the previous study for aggregate retail. The constant correlation coefficients are reported on the bottom of each table. Unlike the previous study, constant correlation coefficients in the current study for food, auto, furniture and apparel, are significantly different from zero. These indicate a spillover volatility between inventory and sales in food, auto, furniture and apparel retails. The remaining correlation coefficients are not significant.

Table 4.7b
Previous Study Based on Aggregate Retails and Current Study Based on Less Aggregate Retail Data. t-ratios are reported in brackets [ ]

	Previous Study (Lee & Koray's Aggregate Retail Trade)		Apparel Retails (Model A)		Building Material Retails (Model A)		Gen. Merchandise Retails (Model A)	
	Mean Equation		Mean Equation		Mean Equation		Mean equation	
	ΔInv_t	ΔSls_t	$\Delta ln(Inv)_t$	$\Delta ln(Sls)_t$	$\Delta ln(Inv)_t$	$\Delta ln(Sls)_t$	$\Delta ln(Inv)_t$	$\Delta ln(Sls)_t$
Constant	0.189 [0.32]	0.229 [0.29]	0.533845 [0.0036]	0.998082 [0.0149]	-0.022188 [-0.1909]	0.486020 [0.8478]	-0.444917 [-46.2246]	-0.238891 [-6.6579]
CointRes	-0.083 [-5.49]	0.006 [0.37]	-0.258335 [-.0.0041]	-0.435572 [-0.0150]	0.012986 [0.2052]	-0.237466 [-0.8934]	0.010258 [6.4603]	-0.055943 [-6.5028]
$CondStd_{In}$	-0.123 [-0.64]	-0.780 [-0.78]	0.529431 [0.0579]	1.286759 [0.1583]	-0.241088 [-0.1009]	1.623092 [1.4432]	44.038461 [40.6415]	32.569976 [11.8354]
$CondStd_{Sls}$	0.141 [0.32]	0.090 [0.183]	4.579478 [1.0319]	0.430465 [0.0198]	0.026250 [0.1149]	0.123993 [0.3139]	-0.066205 [-0.7195]	-0.323923 [-0.8285]
	Cond. Vari. Inventory	Cond. Var. Sales	Cond. Var. Inventory	Cond. Var. Sales	Cond. Variance Inventory	Cond. Var. Sales	Cond. Var. Inventory	Cond. Var. Sales
Constant	0.036 [0.88]	0.552 [3.538]	0.0000 [0.0000]	0.000113 [0.0006]	0.0000894 [4.2658]	0.000235 [0.3191]	0.0000952 [6309.50]	0.0000574 [2.7568]
ARCH	0.132 [1.98]	0.573 [2.211]	1.00000 [0.1404]	0.441097 [0.0925]	0.132354 [1.6114]	0.415214 [0.7168]	0.004620 [1.9461]	0.285821 [1.9575]
GARCH	0.832 [7.93]	0.129 [0.898]	0.0000 [0.00000]	0.476827 [0.0007]	0.000000 [0.00000]	0.000000 [0.00000]	0.016734 [1.2368]	0.248398 [2.8952]
ConsCorr	-0.100 [-1.556]		1.00000 [3.6392]		0.063367 [0.6115]		0.040902 [0.4819]	

Source: Tables 1 through 6 in the Appendix 1.

The existence of a time varying volatility of sales is suggested from the significance of either the ARCH or GARCH coefficients, or both, in the conditional variance equations of sales. The previous study shows that there was a time-varying volatility of sales in the aggregate retail series. The ARCH coefficient is significant. In the current study, from the six retail sectors, significant GARCH effects are observed in furniture and general merchandise series. A significant ARCH effect is only observed in general merchandise retail. The different results in time varying volatility between the aggregate and less aggregate retails suggest that the characteristics of aggregate series do not fully represent the characteristics of the less aggregate markets.

4.7. VECM Results: Diagonal-BEKK Models

The main purpose of presenting the diagonal models is to see whether the different processes of GARCH affect the volatility influence on inventory. The results from using the diagonal model for the multivariate GARCH-in-Mean with the VECM as the mean equation are reported in Table 7 through Table 12 in the Appendix 2. The results for apparel, auto, furniture, building material, and general merchandise retails are reported using 2 models for each. The results for food retail use 3 models.

The effects of sales volatility on growth of inventory and the existence of time-varying volatility are reported from the diagonal-BEKK models. A significantly positive relation between sales volatility and inventory levels is observed in apparel (1 out of 2 models), furniture (1 out of 2 models) and food (1 out of 3 models). In apparel, the result is not significant if the conditional variance of sales as a measure of sales volatility is used. In furniture, the result turns out to be negative upon inclusion of inventory volatility into the equation indicating a multicollinearity between the two volatilities. In food, the result becomes negative if the conditional variance deviation of sales is replaced by the conditional standard deviation of sales. Also in food, the coefficients of both volatility of sales and inventory are not significant if they both enter the inventory equation. The volatility of sales does not affect the growth of inventory in auto dealers. In building material and general merchandise retails, the volatility of sales significantly affects the growth of inventory with negative signs. The time-varying volatilities of sales are observed in apparel, auto dealers, furniture, and food, across the models reported. In building material and general merchandise retails, the time varying variance of sales are only observed in one of two models reported, indicated by the significant coefficient of ARCH or GARCH in the conditional variance equations for sales.

4.8. VAR Results: Constant Correlation Models

The results of constant correlation multivariate GARCH-in-Mean using VAR as the mean equation are reported in Tables 13-18 in the Appendix 3. The results for furniture, building materials, apparel, and auto dealers are reported using 4 models. The results for food and general merchandise are reported using 3 models.

The tables report the effects of sales volatility on inventory, spillover volatility, and the time varying variance of sales in each retail sector. In furniture, building materials, and general merchandise, the coefficients of the conditional variance of sales or conditional standard deviation of sales in the inventory equations are significantly positive across models reported. This means that volatility of sales as a measure of demand uncertainty positively affects the level of inventory in these retail sectors. The coefficients of conditional standard deviation of sales or conditional variance of sales as a measure of demand uncertainty are also significantly positive in auto dealers (2 out of 4 models). For food, the coefficient of standard deviation of sales in its inventory equation is significantly negative (1 out of 3 models). For apparel, the coefficients are not significant across 4 models reported. For auto series, 4 models are reported. The results show significantly positive coefficients of sales volatility alone in the inventory equation either using conditional variance or using standard deviation of sales as a measure of sales volatility. The results turn out to be insignificant when both sales volatility and inventory volatility enter the inventory equation as reported in the other model. This may be due to the existence of multicollinearity between two volatility measures. All of the models in which inventories are significantly affected by volatility of sales show positive signs in the coefficients.

Spillover volatility, shown by significant constant correlation coefficients, can be observed in building material (2 out of 4 models), furniture (2 out of 4 models), food (2 out of 3 models), general merchandise (1 out of 3 models), and auto dealers (2 out of 4 models). Time-varying volatility of sales indicated by the significance of ARCH or GARCH effects, or both, in the conditional variance equation of sales, are observed in furniture (2 out of 4 models), building material (3 out of 4 models), food (1 out of 3 models), general merchandise (all 3 models reported), and auto dealers (2 out of 4 models), and none in apparel retails.

4.9. VAR Results: Diagonal-BEKK Models

The results from using the diagonal model for the multivariate GARCH-in-Mean with the VAR as the mean equation are reported in Table 19 through Table 24 in the Appendix 4. The purpose of presenting the diagonal models is to see whether the different process of GARCH affect the volatility influence on inventory. The results for food, auto dealers, and general merchandise are reported using 4 models. The results for apparel and furniture use 3 models and building material uses 2 models.

The effects of sales volatility on inventory using the diagonal-BEKK models show various results. A significantly positive relation between sales volatility and inventory levels is observed in auto dealer retail across 4 models and in furniture across 3 models. In apparel, the results are mixed with a significantly positive relation if the conditional standard deviation of sales is used as the measure of volatility, but with an insignificant relation if the conditional variance is used. The result is significantly negative when both the volatilities of sales and of inventory are included. In food, there is a significantly positive relation between level of inventory and volatility of sales in 3 out of 4 models reported. There seems a multicollinearity between the conditional variance of sales and inventory since the coefficient of the conditional variance of sales changes from insignificant to significant upon the inclusion of the conditional variance of inventory. In general merchandise retail, a negative relation between sales volatility and the level of inventory is observed in the models in which the volatility of sales alone is in the inventory equation. The signs change from a significantly negative to a significantly positive relation upon the inclusion of the conditional volatility of inventory, an indication of a multicollinearity problem. In building material, a significant relation between the volatility of sales is observed in the model in which the conditional standard deviation of sales is used. The relation is not significant if the conditional variance of sales is used as the measure of sales volatility. Surprisingly, the time-varying volatilities of sales are observed in all retail series across models reported, as indicated by the significant coefficient of ARCH or GARCH in the conditional variance equations for sales.

4.10. Summary of the Results

Table 4.8 summarizes the significance of the interrelationships between inventory and sales and Table 4.9 summarizes the significance of the effects of demand uncertainty on inventory as well as the significance of the time varying volatility of sales. Table 4.8 summarizes the significant interrelationships between inventory and sales which is observed in at least 1 model. The significant interrelationships between inventory and sales are observed in the six retail sectors in any one or in a combination of the following forms: (1) The levels of inventory are significantly influenced by levels of sales and the levels of sales are significantly influenced by levels of inventory, (2) Inventories are influenced by the volatility of sales and sales are influenced by volatility of inventory, and (3) Spill-over volatilities between inventory and sales are indicated by the significance of constant correlation coefficients.

Table 4.8 shows the existence of the interrelationship between inventory and sales in all 6 retail sectors. Apparel sales and inventories are interrelated, as indicated by the significant coefficients of sales in inventory equations and vise versa. These are observed in both the VAR and VECM using diagonal-BEKK models. Another indication is the dependency of inventory to sales volatility and the dependency of sales to inventory volatility as reported in the VAR with diagonal-BEKK models, as well as significant correlation between inventory and sales in the VECM with constant correlation. Building material sales and inventories are also interrelated as indicated by the significant coefficients of sales in inventory equations and vise versa. These are observed in both the

VAR and VECM with constant correlation, and in the VAR with diagonal models but not in the VECM with diagonal models. Another indication is the significant correlation coefficient between inventory and sales in the VAR model.

Table 4.8
The Summary Results: Significant Interrelationships Between Inventory and Sales Observed in at Least 1 Model From Multivariate GARCH-in-Mean Using VAR or VECM as the Mean Equation

Retail Sectors	Constant Correlation Model				Diagonal Model			
	Inventory depends on Sales		Sales depends on inventory		Inventory depend on Sales		Sales depends on inventory	
	VAR	VECM	VAR	VECM	VAR	VECM	VAR	VECM
Apparel	No	No	No	Yes	Yes	Yes	Yes	Yes
Building Material	Yes	Yes	Yes	Yes	Yes	No	Yes	No
Food	Yes	Yes	Yes	Yes	Yes	No	Yes	No
Furniture	Yes	No	No	Yes	Yes	Yes	Yes	No
Auto dealers	No	No	Yes	Yes	Yes	No	Yes	Yes
Gen Merchandise	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Retail Sectors	Inventory depends on Sales Volatility		Sales depends on inventory Volatility		Inventory depend on Sales Volatility		Sales depends on inventory volatility	
	VAR	VECM	VAR	VECM	VAR	VECM	VAR	VECM
Apparel	No	No	No	No	Yes **	Yes	Yes	NA
Building material	Yes	No	No	No	Yes	Yes*)	NA	NA
Food	Yes*	Yes*)	Yes	No	Yes	Yes**)	Yes	Yes
Furniture	Yes	Yes*)	Yes	NA	Yes	Yes**)	NA	NA
Auto dealers	Yes	No	No	No	Yes	No	Yes	NA
Gen Merchandise	Yes	Yes	Yes	No	Yes **	Yes*)	Yes	NA

Retail Sectors	Significant Correlation Coefficients (Spillover of Volatility)	
	VAR with Constant Correlation	VECM with Constant Correlation
Apparel	No	Yes
Building Material	Yes	No
Food	Yes	Yes
Furniture	Yes	Yes
Auto dealers	Yes	Yes
Gen Merchandise	Yes	Yes

Note: *) Negative signs.
**) Negative and positive signs are observed in apparel with positive a sign and in GM with negative sign if sales volatility alone in the equation, in furniture with a positive sign if sales volatility alone in the equation, and in food the results differ in between std deviation and variance of sales alone in the equation.

In the building material, the volatility of sales (inventory) does not affect inventory (sales) suggesting no interdependence of sales and inventory. Food sales and inventory are interrelated as suggested by the significant coefficients of sales in inventory equations and vise versa. These are observed in both the VAR and VECM with constant correlation, as well as in the VAR, but not in the VECM with diagonal models. The correlation coefficient between inventory and sales is also significant in both the VAR and VECM model. The volatility of sales (inventory) affects inventory (sales) suggesting interdependence of sales and inventory. These are observed in the VAR with constant correlation and in both the VAR and VECM with diagonal models. Furniture sales and inventory are interrelated as observed by the significant coefficients of sales in inventory equations and vise versa in the VAR with diagonal model only. Another indication is observed from the significant correlation coefficient between inventory and sales in both the VAR and VECM models. Also the volatility of sales (inventory) affects inventory (sales) as observed from the VAR with constant correlation, suggesting the interdependence of sales and inventory. Auto dealers' sales and inventory are interrelated as observed by the significant coefficients of sales in inventory equations and vise versa in the VAR with diagonal only. Another indication is observed from the significant correlation coefficient between inventory and sales in both the VAR and VECM models. The dependence of inventory on sales volatility and the dependency of sales on inventory volatility is observed in the VAR with diagonal model. General Merchandise sales and inventory are interrelated as observed by the significant coefficients of sales in inventory equations and vise versa in the VAR and VECM with constant correlation and with diagonal models as well. The correlation coefficient between inventory and sales is also significant in both the VAR and VECM models. Another indication is the dependence of inventory on sales volatility and the dependence of sales on inventory volatility as observed in both the VAR, with constant correlation diagonal models.

The summary of the effects of demand uncertainty on inventory are reported in the upper panel of Table 4.9. The results are mixed across the four columns in the upper part of the table. In general, as shown in the table, the positive effects of demand uncertainty on inventory holdings are observed in the VAR models but not in the VECM models. Significant positive effects of demand uncertainty on inventory are observed in building material, furniture, auto dealers, and general merchandise retails using the VAR with GARCH constant correlation models. The effects remain positive in the VAR diagonal-BEKK models for building material, furniture, and auto dealers. There is a mixed, or positive and negative, sign in the building material using different scenarios within the VAR diagonal model. The positive signs are observed when only the volatility of sales is included in the inventory equation and the negative sign is observed when both the volatility of sales and inventory are included. This may indicate the existence of multicollinearity. In the VAR section, no consistent effects of demand uncertainty on inventory are observed in apparel and food retails. For apparel, there is not a significant effect in the VAR constant correlation to a mixed result in the VAR diagonal-BEKK models. The food inventory has a negative sign in the VAR constant correlation and a positive sign in the VAR diagonal-BEKK models.

The summary of the time varying sales volatility is reported in the lower panel of Table 4.9. The time varying volatility of sales is observed across the 6 retail sectors and across models except apparel in the VAR and VECM constant correlation and building material in the VECM constant correlation. The significance of time varying volatility of sales is suggested by the significance of the ARCH or the GARCH coefficients or both, in the equations of the conditional variance of sales.

Table 4.9
The Summary Results of the Significant Relation Between Inventory and Demand Uncertainty and Time Varying Volatility of Sales Observed at Least in 1 Model

Significant Relation Between Inventory and Demand Uncertainty

Retail Sectors	VAR		VECM	
	Constant Correlation	Diagonal-BEKK Model	Constant Correlation	Diagonal-BEKK Model
Apparel	No	Mixed*)	No	Positive
Building Material	Positive	Positive	No	Negative
Food	Negative	Positive	Negative	Mixed*)
Furniture	Positive	Positive	Negative	Mixed**)
Auto dealers	Positive	Positive	No	No
Gen Merchandise	Positive	Mixed**)	Positive	Negative

Note: *) Signs differ between two models. **) Possible multicollinearity

Time Varying Volatility of Sales

Retail Sectors	VAR		VECM	
	Constant Correlation	Diagonal-BEKK Model	Constant Correlation	Diagonal-BEKK Model
Apparel	No	ARCH, GARCH	No	ARCH, GARCH
Building Material	GARCH, ARCH	ARCH, GARCH	No	GARCH
Food	GARCH	ARCH, GARCH	ARCH, GARH	ARCH, GARCH
Furniture	GARCH	ARCH, GARCH	GARCH	ARCH, GARCH
Auto dealers	ARCH	ARCH, GARCH	ARCH, GARCH	ARCH, GARCH
Gen Merchandise	ARCH, GARCH	ARCH, GARCH	ARCH, GARCH	GARCH

5. CONCLUSIONS

The long-term relationships between inventory and demand exist in six retail sectors as found in this study as well as in the aggregate retail as found in Lee and Koray (1994). Statistically, in these six retail sectors, inventory and demand are cointegrated of degree one, the same as in the aggregate retail found by the previous study.

Various relationships between demand uncertainty and inventory are observed from the constant correlation and diagonal-BEKK bivariate GARCH-M models with VECM, and the constant correlation and the diagonal-BEKK bivariate GARCH-M models with VAR as the form of mean equations. First, using the constant correlation MGARCH-M with various VECM specifications to represent the mean equation, this study finds that there are only a few cases in which the effects of sales volatility on inventory are significant. In particular, using the same VECM specification as in Lee and Koray (1994), this study finds no significant effects of sales volatility on inventory. This means that no effects of demand uncertainty are observed on inventory both in the aggregate retail as shown by Lee and Koray and in the less aggregate retail shown in this study. Second, using the diagonal BEKK GARCH-M with VECM specification, the results are mixed. The results depend on the model specification used and the choice between conditional standard deviation and variance of sales. Third, using the constant correlation GARCH-M with vector autoregressive (VAR) to represent the mean equation, only in apparel retail does this study find no significantly positive relationships between inventory and uncertainty of demand. In 5 other retail sectors, as observed in most cases, the relations are significant with a positive sign, as expected. Fourth, using the diagonal-BEKK with vector autoregressive (VAR) to represent the mean equation, only in general merchandise does this study observe significantly negative relationships between inventory and uncertainty of demand. In 5 other retail sectors, the relations are significant with a positive sign as observed in most cases.

The insignificant effects of demand uncertainty on inventory are observed, in most cases, from the use of the constant correlation GARCH-M with VECM as the mean equation. Because these insignificant effects are consistent either for the aggregate series as in Lee and Koray or for most cases in six less aggregate series as found in the current study, this may raise the question of whether different characteristics of demand uncertainty among the six retail sectors really does not affect inventory decisions. We might be suspicious that the VECM itself may not allow the regression coefficients of the residual-based uncertainty measure to be significant. This may need further study.

The positive relationships between inventory and demand uncertainty, as observed in the VAR models, follow the stock avoidance motive of holding inventory. The firm's purpose of maintaining inventory is to avoid loss of goodwill and potential sales from inability to satisfy the unanticipated demand. The fact that there are also negative relationships between demand uncertainty and inventory suggest that the stock avoidance motive does not hold for particular retails. The condition for a positive relationship is that the price is high enough to cover the cost of inventory holdings as hypothesized by Carlton (1977) so that a negative or an insignificant relationship is possible when the price cannot cover the cost. This condition may be overlooked by the stock avoidance motive.

This study finds significant interrelationships between inventory and sales as observed in the six retail sectors in the form of one or a combination of the following: (1) The levels of inventory are significantly influenced by levels of sales and the levels of sales are significantly influenced by levels of inventory, (2) Inventories are influenced by the volatility of sales and sales are influenced by volatility of inventory, and (3) Spill-over volatilities between inventory and sales are indicated by the significance of constant correlation coefficients.

In general, demand volatilities in the 6 retail sectors are not constant across models. They are time-varying or changing with time. A few exceptions are observed, including the demand volatilities, in apparel in the constant correlation VAR and diagonal-BEKK VECM only, and in building material in the diagonal-BEKK VECM.

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APPENDIX 1
VECM Results for ln(Retail Series), Constant Correlation Models

Table 1
VECM Results: Constant Correlation
Multivariate GARCH-in-Mean ln(Apparel Series)
Mean Equation: VECM. (Robust Standard Errors are Reported in Parentheses)

	Model A		Model B		Model C	
	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$
Constant	0.533845 (147.9025) 0.0036	0.998082 67.1587 0.0149	-0.014188 (0.3331) -0.0426	0.357102 (0.8161) 0.4375	0.5588 (0.4839) 1.1549	1.3455 (0.1641) 8.1979
$\Delta\ln(Inv)_{t-1}$	0.523828 (768.4658) 0.0007	1.544725 (233.8715) 0.0066	0.017245 (0.0963) 0.1791	0.171996 (0.5125) 0.3356	0.3392 (6.0900) 0.0557	2.2909 (9.0158) 0.2541
$\Delta\ln(Sales)_{t-1}$	0.043086 (11.2323) 0.0038	0.550523 (149.5914) 0.0037	0.062659 (0.0675) 0.9288	-0.348259 (0.0638) -5.4616	-0.0671 (1.9515) -0.0344	0.3099 (3.6939) 0.0839
CointRes	-0.258335 (63.6908) -.0.0041	-0.435572 (29.0245) -0.0150	0.006622 (0.1263) 0.0524	-0.152028 (0.3483) -0.4363	-0.2676 (0.2725) -0.9819	-0.5786 (0.0836) -6.9226
CondVarInv			12.403798 (62.2493) 0.1993	23.869562 (37.8246) 0.6311		
CondVarSls			3.900824 (198.7750) 0.0196	1.833633 (34.9348) 0.0525		
CondStdInv	0.529431 (9.1507) 0.0579	1.286759 (8.1266) 0.1583				
CondStdSls	4.579478 (4.4377) 1.0319	0.430465 (21.7482) 0.0198			4.4258 (12.9818) 0.3409	
	CondVarInv	CondVarSls	CondVarInv	CondVarSls	CondVarInv	CondVarSls
Constant	0.0000 (0.3303) 0.0000	0.000113 (0.1960) 0.0006	0.0000819 (0.0000109) 7.4765	0.000155 (0.000893) 0.1731	0.0000614 (0.0032) 0.0195	0.00000 (0.0038) 0.0000
ARCH	1.00000 (7.1219) 0.1404	0.441097 (4.7670) 0.0925	0.254432 (0.1655) 1.5371	0.244598 (1.0109) 0.2420	1.0000 (11.6120) 0.0861	0.3358 (2.2747) 0.1476
GARCH	0.0000 (684.1958) 0.00000	0.476827 (675.5070) 0.0007	0.0000 (0.1603) 0.0000	0.093865 (2.3249) 0.0404	0.0000 (0.0744) 0.0000	0.2701 (0.6252) 0.4319
ConsCorr	1.00000 (0.2748) 3.6392		-0.017373 0.0718 -0.2421		1.000 (0.1428) 7.0052	

Table 1 (Continued)
VECM Results: Constant Correlation
Multivariate GARCH-in-Mean ln(Apparel Series)
Mean Equation: VECM. (Robust Standard Errors are Reported in Parentheses)

	Model D		Model E		Model F	
	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$
Constant	-0.0269 (2.0362) -0.0132	0.3518 (1.2728) 0.2764	-0.0313 (1.7136) -0.0183	0.3515 (1.9708) 0.1784	-0.0289 (0.1450) -0.1991	0.3518 (2.6522) 0.1326
$\Delta\ln(Inv)_{t-1}$	0.0044 (2.1249) 0.0021	0.1864 (1.22474) 0.1494	0.000424 (2.9902) 0.0001	0.1811 (2.3259) 0.0779	-0.0012 (0.9840) -0.0012	0.1840 (1.1455) 0.1607
$\Delta\ln(Sales)_{t-1}$	0.0599 (0.3977) 0.1507	-3.463 (0.9648) -0.3589	0.0607 (1.0575) 0.0574	-0.3473 (1.6238) -0.2139	0.0607 (0.2965) 0.2047	-0.3467 (0.4379) -0.7916
CointRes	0.0127 (0.9194) 0.0138	-0.1485 (0.5360) -0.2771	0.0128 (0.5135) 0.0249	-0.1484 (0.8295) -0.1789	0.0130 (0.1105) 0.1177	-0.1485 (1.1306) -0.1313
CondVarInv					13.5205 (110.00) 0.1229	
CondVarSls	3.5369 365.27 0.0097				2.8714 (446.49) 0.0064	
CondStdInv			0.3994 (15.3961) 0.0259			
CondStdSls			0.0638 (23.3154) 0.0027			
	CondVarInv	CondVarSls	CondVarInv	CondVarSls	CondVarInv	CondVarSls
Constant	0.0000814 (0.0028) 0.0287	0.000165 (0.0001849) 0.8927	0.0000817 (0.000549) 0.1487	0.0001678 (0.000741) 0.2263	0.0000821 (0.000345) 0.2378	0.000166 (0.0023) 0.0708
ARCH	0.2638 (9.7602) 0.0270	0.2396 (0.9485) 0.2526	0.2506 (9.2594) 0.0271	0.2395 (1.9798) 0.1210	0.2480 (2.3037) 0.1076	0.2394 (1.3616) 0.1758
GARCH	0.0000 (6.5770) 0.0000	0.0559 (0.4705) 0.1273	0.000 (11.6577) 0.000	0.0483 (1.3938) 0.0347	0.0000 (2.5790) 0.0000	0.0551 (5.7674) 0.0095
ConsCorr	-0.0163 (0.5859) -0.0278		-0.0176 (0.6403) -0.274		-0.0190 (0.1984) -0.0956	

Table 2
Constant Correlation
Multivariate GARCH-in-Mean ln(Auto Dealers Series)
Mean Equation: VECM. (Robust Standard Errors are Reported in Parentheses)

	Model A		Model B		Model C	
	Δln(Inv)$_t$	Δln(Sales)$_t$	Δln(Inv)$_t$	Δln(Sales)$_t$	Δln(Inv)$_t$	Δln(Sales)$_t$
Constant	-0.017851 (0.0285) -0.6271	0.141174 (0.0627) 2.2518	-0.017305 (0.0273) -0.6339	0.134682 (0.0309) 4.3591	-0.0175 (0.0280) -0.6246	0.1317 (0.0328) 4.0105
Δln(Inv)$_{t-1}$	0.214805 (0.1088) 1.9741	0.092723 (0.1569) 0.5909	0.212977 (0.0915) 2.3267	0.181327 (0.1432) 1.2665	0.2245 (0.1232) 1.8220	0.1232 (0.1017) 1.2112
Δln(Inv)$_{t-2}$	-0.075041 (0.2598) -0.2889	0.370891 (0.1249) 2.9696	-0.013859 (0.2218) -0.0625	0.309603 (0.1222) 2.5342	-0.0195 (0.1648) -0.1183	0.3234 (0.1217) 2.6581
Δln(Sales)$_{t-1}$	0.057539 (0.1045) 0.5506	-0.392759 (0.2748) -1.429	0.042608 (0.1211) 0.3519	-0.290381 (0.1008) -2.8820	0.0293 (0.0915) 0.3198	-0.3895 (0.1123) -3.4681
Δln(Sales)$_{t-2}$	0.012116 (0.0818) 0.1482	-0.233829 (0.1053) -2.2204	-0.009436 (0.0490) -0.1925	-0.092307 (0.0621) -1.4875	0.0079 (0.0468) 0.1691	-0.2571 (0.0605) -4.2503
CointRes	0.037219 (0.0446) 0.8337	-0.204011 (0.0800) -2.5503	0.035946 (0.0494) 0.7277	-0.198169 (0.0419) -4.7335	0.0288 (0.0501) 0.5737	-0.1943 (0.0484) -4.0139
CondVarInv			-5.509993 (14.7005) -0.3748	-2.02915 (10.9410) -0.1855		
CondVarSls			1.914242 (2.2516) 0.8502	-0.662369 (3.7053) -0.1788		
CondStdInv	-0.612660 (1.4220) -0.4309	0.152941 (0.6729) 0.3599				
CondStdSls	0.405001 (1.1253) 0.2273	-0.222226 (0.5771) -0.3851			0.1561 (0.5304) 0.2942	
	CondVarInv	CondVarSls	CondVarInv	CondVarSls	CondVarInv	CondVarSls
Constant	0.000250 (0.000226) 1.1076	0.000083 (0.000252) 0.3279	0.000262 (0.0004) 0.5817	0.000517 (0.0010) 0.5082	0.000261 (0.0003) 0.8403	0.0000126 (0.0002) 0.0753
ARCH	0.452271 (0.5192) 0.8711	0.246283 (0.6765) 0.3641	0.416728 (0.4135) 1.0078	0.696855 (0.4501) 1.5484	0.4301 (0.5111) 0.8415	0.0917 (0.0573) 1.6001
GARCH	0.000000 (0.5943) 0.00000	0.695062 (0.4887) 1.4224	0.000000 (0.7473) 0.00000	0.00000 (0.5094) 0.00000	0.000 (0.7972) 0.0000	0.8953 (0.0492) 18.1846
ConsCorr	-0.348722 (0.0805) -4.3328		-0.366888 (0.0899) -4.0830		-0.3281 (0.1204) -2.7256	

Table 2 (Continued)
Constant Correlation
Multivariate GARCH-in-Mean ln(Auto Dealers Series)
Mean Equation: VECM. (Robust Standard Errors are Reported in Parentheses)

	Model D		Model E		Model F	
	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$
Constant	-0.0149 (0.0321) -0.4630	0.1320 (0.0336) 3.9231	-0.0130 (0.0157) -0.8259	0.1331 (0.0346) 3.8435	-0.0150 (0.0309) -0.4839	0.1319 (0.0353) 3.7322
$\Delta\ln(Inv)_{t-1}$	0.2252 (0.1381) 1.6309	0.1230 (0.1008) 1.2201	0.2117 (0.0982) 2.1559	0.1258 (0.0970) 1.2970	0.2251 (0.1388) 1.6220	0.1230 (0.1004) 1.2259
$\Delta\ln(Inv)_{t-2}$	-0.0196 (0.1587) -0.1236	0.3245 (0.1224) 2.6512	-0.0347 (0.2148) -0.1617	0.3285 (0.1218) 2.6962	-0.0190 (0.1815) -0.1047	0.3244 (0.1246) 2.6028
$\Delta\ln(Sales)_{t-1}$	0.0299 (0.0942) 0.3179	-0.3918 (0.1109) -3.5330	0.0345 (0.0997) 0.3463	-0.3956 (0.1154) -3.4272	0.0300 (0.0972) 0.3086	-0.3914 (0.1154) -3.3923
$\Delta\ln(Sales)_{t-2}$	0.0076 (0.0480) 0.1574	-0.2570 (0.0605) -4.2478	0.0268 (0.0602) 0.4448	-0.2643 (0.0614) -4.3017	0.0072 (0.0631) 0.1143	-0.2571 (0.0624) -4.1238
CointRes	0.0294 (0.0526) 0.5581	-0.1950 (0.0497) -3.9244	0.0300 (0.0424) 0.7093	-0.1963 (0.0507) -3.8744	0.0294 (0.0537) 0.5479	-0.1948 (0.0522) -3.7344
CVInv					0.2096 (14.0318) 0.0149	
CVSls	1.6090 (3.1605) 0.5091				1.5702 (3.5563) 0.4415	
CondStdInv			-0.3400 (1.0094) -0.3368			
CondStdSls			0.2019 (0.2033) 0.9927			
	CondVarInv	CondVarSls	CondVarInv	CondVarSls	CondVarInv	CondVarSls
Constant	0.0002638 (0.0003) 0.9447	0.00001191 (0.0000856) 0.1390	0.000259 (0.000273) 0.9529	0.0000139 (0.000037) 0.3734	0.000264 (0.000276) 0.9557	0.0000118 (0.000085) 0.1378
ARCH	0.4239 (0.4667) 0.9082	0.0871 (0.0298) 2.9213	0.4371 (0.4447) 0.9829	0.0944 (0.0221) 4.2721	0.4238 (0.4599) 0.9215	0.0869 (0.0294) 2.9562
GARCH	0.0000 (0.7583) 0.0000	0.9000 (0.0261) 34.4458	0.0000 (0.6622) 0.0000	0.8913 (0.0135) 66.1311	0.0000 (0.7606) 0.0000	0.9003 (0.0255) 35.2790
ConsCorr	-0.3297 (0.0901) -3.6578		-0.3333 (0.0816) -4.0829		-0.3297 (0.0972) -3.3926	

Table 3
Constant Correlation
Multivariate GARCH-in-Mean ln(Furniture Series)
Mean Equation: VECM. (Robust Standard Errors are Reported in Parentheses)

	Model C		Model D		Model E	
	$\Delta\ln(Inv)_t$	$\Delta\ln(Sls)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sls)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sls)_t$
Constant	382.6241 (87.3518) 4.3803	0.2648 (0.1359) 1.9483	191.7743 (30.6474) 6.2574	0.2651 (0.0911) 2.9120	372.3697 (751.59) 0.4954	0.2594 (0.0852) 3.0450
$\Delta\ln(Inv)_{t-1}$	-0.0396 (1.2101) -0.0328	0.1225 (0.2691) 0.4552	-0.0589 (0.0924) -0.6378	0.1248 (0.0694) 1.7991	-0.000676 (0.2971) -0.0023	0.1208 (0.0743) 1.6258
$\Delta\ln(Sls)_{t-1}$	0.0318 (0.0743) 0.4279	-0.1662 (0.0729) -2.2799	0.0401 (0.0410) 0.9778	-0.1652 (0.0715) -2.3111	0.0252 (0.0872) 0.2884	-0.1685 (0.1083) -1.5563
CointRes	-0.0237 (0.0031) -7.5277	-0.0975 (0.0487) -2.0012	-0.0211 (0.000556) -38.0028	-0.0976 (0.0344) -2.8403	-0.0161 (0.0350) 0.0467	-0.0955 (0.0313) -3.0527
CondVarInv						
CondVarSls			-609220.0 (97426.0) -6.2531			
CondStdInv					0.0496 (7.7217) 0.0064	
CondStdSls	-21565.00 (4924.90) -4.3789				-20989.0 (42378.0) -0.4953	
	CondVarInv	CondVarSls	CondVarInv	CondVarSls	CondVarInv	CondVarSls
Constant	0.0000959 (0.0026) 0.0363	0.000268 (3.9053e-09) 68639.0	0.00009176 (0.000298) 0.3075	0.000268 (3.1585e-10) 848660.0	0.00001207 (0.0000843) 0.1432	0.0002681 (4.3667e-09) 61385.0
ARCH	0.6472 (1.7734) 0.3650	0.0000 (4.0076e-08) 0.0000	0.5700 (0.7657) 0.7444	0.0000 (8.6022e-08) 0.0000	0.2251 (0.5924) 0.3799	0.000000183 (0.00000398) 0.0461
GARCH	0.0814 (4.5103) 0.0181	0.1482 (0.0019) 78.8121	0.1569 (0.7516) 2.087	0.1482 (0.000185) 799.33	0.7498 (0.3901) 1.9221	0.1482 (0.0020) 74.8702
ConsCorr	0.3014 (0.0047) 63.6074		0.3073 (0.0017) 182.69		0.2923 (0.0298) 9.8170	

Table 4
Constant Correlation
Multivariate GARCH-in-Mean ln(Food Retail Series)
Mean Equation: VECM. (Robust Standard Errors are Reported in Parentheses)

	Model A		Model B		Model C	
	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$
Constant	-0.008823 (0.1244) -0.0710	-0.001889 (0.0415) -0.0455	-0.006529 (0.0344) -0.1895	-0.009984 (0.0058) -1.7355	-0.0058 (0.0310) -0.1879	-0.0130 (0.0087) -1.4916
$\Delta\ln(Inv)_{t-1}$	0.058602 (0.3279) 0.1787	0.159639 (0.1644) 0.9710	0.055342 (0.1082) 0.5114	0.155729 (0.0741) 2.1014	0.0582 (0.0849) 0.6858	0.1466 (0.0714) 2.0537
$\Delta\ln(Sls)_{t-1}$	-0.025313 (0.0637) -0.3974	-0.497534 (0.0676) -7.3616	-0.026967 (0.0544) -0.4960	-0.491251 (0.0653) -7.5286	-0.0105 (0.0546) -0.1924	-0.4615 (0.0629) -7.3390
CointRes	-0.020676 (0.2384) -0.0867	-0.047669 (0.0166) -2.8642	-0.021424 (0.0828) -0.2587	-0.047747 (0.0165) -2.8957	-0.0257 (0.0768) -0.3344	-0.0439 (0.0223) -1.9728
CondVarInv			60.015825 (87.2464) 0.6879	-90.950563 (60.8873) -1.4938		
CondVarSls			-24.119925 (11.7076) -2.0602	-17.325787 (27.5067) -0.6299		
CondStdInv	1.1300422 (4.8522) 0.2330	-1.64047 (6.5595) -0.2501				
CondStdSls	-0.507518 (0.7836) -0.6477	-0.317691 (0.5666) -0.5607			-0.1383 (0.2008) -0.6889	
	CondVarInv	CondVarSls	CondVarInv	CondVarSls	CondVarInv	CondVarSls
Constant	0.0000361 (0.0000028) 12.8550	0.0000187 (0.00000203) 9.2146	0.0000359 (0.000000078) 459.27	0.0000188 (0.00000075) 25.0248	0.0000373 (0.0000256) 1.4544	0.0000206 (0.0000053) 3.9117
ARCH	0.141307 (0.4089) 0.3456	0.271614 (0.3775) 0.7195	0.148705 (0.1085) 1.3701	0.261710 (0.1667) 1.5695	0.1592 (0.1474) 1.0798	0.2144 (0.1606) 1.3347
GARCH	0.007616 (1.4250) 0.0053	0.248004 0.2232 1.1113	0.000000 (0.4123) 0.00000	0.25218 (0.1085) 2.3250	0.0000 (0.3673) 0.0000	0.2552 (0.1354) 1.8844
Const Corr	0.185145 (0.0957) 1.9351		0.181409 (0.0707) 2.5658		0.1723 (0.0743) 2.3178	

Table 4 (Continued)
Constant Correlation
Multivariate GARCH-in-Mean ln(Food Retail Series)
Mean Equation: VECM. (Robust Standard Errors are Reported in Parentheses)

	Model D		Model E		Model F	
	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$
Constant	-0.0059 (0.0277) -0.2121	-0.0132 (0.0094) -1.4055	-0.0119 (0.5413) -0.0220	-0.0131 (0.1299) -0.1012	0.1528 (0.0507) 3.0135	-0.1869 (0.0396) -4.7182
$\Delta\ln(Inv)_{t-1}$	0.0589 (0.0806) 0.7311	0.1463 (0.0711) 2.0564	0.0646 (1.8416) 0.0351	0.1479 (0.2079) 0.7112	1.3177 (0.8057) 1.6355	-1.0333 (3.6588) -0.2824
$\Delta\ln(Sls)_{t-1}$	-0.0190 (0.0553) -0.3443	-0.4653 (0.0621) -7.4901	-0.0151 (0.2317) -0.0651	-0.4673 (0.3539) -1.3206	-3.7486 (1.7268) -2.1708	-1.0422 (1.8052) -0.5774
CointRes	-0.0257 (0.07000) -0.3678	-0.0444 (0.0240) -1.8514	-0.0228 (1.4051) -0.0162	-0.0444 (0.3286) -0.1351	0.3581 (0.0663) 5.4037	-0.5099 (0.0683) -7.4638
CondVarInv					16.99215 (958.48) 0.0177	
CondVarSls	-20.5179 (8.5892) -2.3888				-20.7054 (10.8738) -1.9042	
CondStdInv			1.2275 (0.3992) 3.0747			
CondStdSls			-0.2560 (2.8462) -0.0899			
	CondVarInv	CondVarSls	CondVarInv	CondVarSls	CondVarInv	CondVarSls
Constant	0.0000375 (0.0000254) 1.4761	0.0000204 (8.0176e-07) 25.4343	0.000036 (0.0000717) 0.5015	0.0000205 (0.000053) 0.3866	0.0000292 (0.0000546) 0.5353	0.0000478 (0.000606) 0.0789
ARCH	0.1543 (0.1281) 1.2042	0.1994 (0.1299) 1.5356	0.1661 (3.1426) 0.0529	0.2086 (1.5532) 0.1343	8.3267e-17 (0.0022) 3.8061e-14	1.0000 (0.1584) 6.3140
GARCH	0.0000 (0.3291) 0.0000	0.2717 (0.1171) 2.3197	0.0000 (7.9156) 0.0000	0.2634 (2.3818) 0.1106	0.0000 (0.3732) 0.0000	0.0000 (0.5145) 0.0000
Const Corr	0.1716 (0.0742) 2.3122		0.1837 (0.3566) 0.5151		1.0000 (0.0097) 103.06	

Table 5
Constant Correlation
Multivariate GARCH-in-Mean ln(Building Material and Hardware Retail Series)
Mean Equation: VECM, (Robust Standard Errors are Reported in Parentheses)

	Model A		Model B		Model C	
	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$
Constant	-0.022188 (0.1162) -0.1909	0.486020 (0.5733) 0.8478	-0.022478 (0.0713) -0.3154	0.503584 (0.3784) 1.3307	-0.0245 (0.0599) -0.4095	0.5244 (0.3193) 1.6421
$\Delta\ln(Inv)_{t-1}$	-0.014678 0.0867 -0.1693	0.055236 (0.1085) 0.5093	-0.007205 (0.0784) -0.0920	0.060625 (0.1367) 0.4434	0.0424 (0.0725) 0.5843	0.0846 (0.1844) 0.4586
$\Delta\ln(Inv)_{t-2}$	-0.018086 (0.0784) -0.2306	0.043217 (0.1695) 0.2550	-0.020418 (0.0687) -0.2972	0.036032 (0.1912) 0.1885	-0.0027 (0.0659) -0.0409	0.0380 (0.1973) 0.1925
$\Delta\ln(Inv)_{t-3}$	0.143268 (0.0742) 1.9299	0.297496 (0.1181) 2.5189	0.14275 (0.0747) 1.9115	0.298649 (0.1529) 1.9537	0.1431 (0.0702) 2.0397	0.2687 (0.2074) 1.2954
$\Delta\ln(Sales)_{t-1}$	0.073254 (0.0439) 1.6704	-0.328896 (0.1233) -2.6677	0.07251 (0.0355) 2.0434	-0.334124 (0.1368) -2.4432	0.0787 (0.0360) 2.1840	-0.3565 (0.1476) -2.4161
$\Delta\ln(Sales)_{t-2}$	0.058144 (0.0392) 1.4816	-0.208187 (0.1592) -1.3074	0.058409 (0.0320) 1.8279	-0.208937 (0.0997) -2.0954	0.0595 (0.0296) 2.0066	-0.2194 (0.0972) -2.2588
$\Delta\ln(Sales)_{t-3}$	0.110988 (0.0343) 3.2314	-0.096999 (0.1446) -0.6710	0.111231 (0.0320) 3.4774	-0.094768 (0.0899) -1.054	0.0998 (0.0321) 3.1072	-0.0919 (0.1554) -0.5914
CointRes	0.012986 (0.0633) 0.2052	-0.237466 (0.2658) -0.8934	0.012625 (0.0349) 0.3616	-0.240742 (0.1809) -1.3307	0.0132 (0.0292) 0.4534	-0.2468 (0.1500) -1.6461
CondVarInv			-10.986782 (54.0204) -0.2034	56.700265 (31.9457) 1.7749		
CondVarSls			0.554614 (2.5699) 0.2158	5.867776 (10.9710) 0.5348		
CondStdInv	-0.241088 (2.3901) -0.1009	1.623092 (1.1246) 1.4432				
CondStdSls	0.026250 (0.2284) 0.1149	0.123993 (0.3951) 0.3139			-0.0295 (0.1473) -0.2000	
	CondVarInv	CondVarSls	CondVarInv	CondVarSls	CondVarInv	CondVarSls
Constant	0.0000894 (0.0000209) 4.2658	0.000235 (0.000736) 0.3191	0.0000897 (0.00000997) 8.9942	0.000234 (0.000497) 0.4710	0.0000202 (0.0000158) 1.2782	0.000234 (0.0006604) 0.3543
ARCH	0.132354 (0.0821) 1.6114	0.415214 (0.5793) 0.7168	0.12961 (0.0513) 2.5283	0.421765 (0.7655) 0.5509	0.0907 (0.0397) 2.2843	0.4288 (0.6421) 0.6677
GARCH	0.000000 (0.3967) 0.00000	0.000000 (1.3403) 0.00000	0.000000 (0.2019) 0.0000	0.00000 (1.2465) 0.0000	0.7118 (0.0339) 20.9831	0.0000 (1.4357) 0.0000
ConsCorr	0.063367 (0.1036) 0.6115		0.06111351 (0.0955) 0.6424		0.0700 (0.1041) 0.6720	

Table 5 (Continued)
Constant Correlation
Multivariate GARCH-in-Mean ln(Building Material and Hardware Retail Series)
Mean Equation: VECM, (Robust Standard Errors are Reported in Parentheses)

	Model E		Model F	
	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$
Constant	-0.0206	0.5230	-0.7355	0.5758
	(0.1920)	(0.3036)	(471.5141)	(38.9129)
	-0.1072	1.7225	-0.0016	0.0148
$\Delta\ln(Inv)_{t-1}$	0.0127	0.0816	0.0060	0.0091
	(0.1198)	(0.1829)	(19.6802)	(18.4269)
	0.1061	0.4464	0.000305	0.000492
$\Delta\ln(Inv)_{t-2}$	-0.0236	0.0362	-0.0346	0.0587
	(0.0667)	(0.1961)	(7.6885)	(15.7896)
	-0.3543	0.1845	-0.0045	0.0037
$\Delta\ln(Inv)_{t-3}$	0.1458	0.2705	0.0145	0.2498
	(0.0746)	(0.1981)	(23.6627)	(14.7513)
	1.9555	1.3656	0.0006	0.0169
$\Delta\ln(Sales)_{t-1}$	0.0739	-0.3550	0.0488	-0.2140
	(0.0421)	(0.1600)	(81.2844)	(25.3995)
	1.7553	-2.2181	0.0006	-0.0084
$\Delta\ln(Sales)_{t-2}$	0.0615	-0.2176	0.1096	-0.1617
	(0.0423)	(0.0936)	(291.8540)	(43.7103)
	1.4527	-2.3250	0.0004	0.0037
$\Delta\ln(Sales)_{t-3}$	0.1131	-0.0905	3.7719	-0.0521
	(0.0389)	(0.1496)	(32.0049)	(79.7264)
	2.9068	-0.6050	0.1179	-0.0007
CointRes	0.0129	-0.2462	-0.2424	0.1432
	(0.0959)	(0.1427)	(230.3763)	(11.3539)
	0.1344	-1.7258	-0.0011	0.0126
CVln(Inv)			0.1083	
			(1.2441)	
			0.0871	
CVln(Sls)			0.1851	
			(4.0989)	
			0.0452	
CondStdInv	-0.3149			
	(1.1043)			
	-0.2852			
CondStdSls	-0.0161			
	(0.1992)			
	-0.0808			
	CondVarInv	CondVarSls	CondVarInv	CondVarSls
Constant	0.0000896	0.000234	1.1948	1.0869
	(0.000045)	(0.000666)	(44.1949)	(23.0220)
	1.9898	0.3514	0.0270	0.0472
ARCH	0.1293	0.4293	0.1194	0.3720
	(0.0913)	(0.6504)	(56.8736)	(15.1563)
	1.4161	0.6601	0.0021	0.0245
GARCH	0.0000	0.0000	-3.1483e-18	0.0000
	(0.3812)	(1.4332)	(72.5893)	(28.6338)
	0.0000	0.0000	-4.3372e-20	0.0000
ConsCorr	0.0629		0.0719	
	(0.1075)		(6.2939)	
	0.5854		0.0114	

Table 6
Constant Correlation
Multivariate GARCH-in-Mean ln(General Merchandise Retail Series)
Mean Equation: VECM. (Robust Standard Errors are Reported in Parentheses)

	Model A		Model B		Model C	
	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$
Constant	-0.444917	-0.238891	-0.013265	0.076596	1.1928	0.1203
	(0.0096)	(0.0359)	(0.0412)	(0.0373)	(0.8938)	(0.0352)
	-46.2246	-6.6579	-0.3219	2.0544	1.3345	3.4196
$\Delta\ln(Inv)_{t-1}$	0.104217	0.092228	0.106683	0.079665	-0.8397	0.0505
	(0.0606)	(0.0626)	(0.0717)	(0.1014)	(7.4085)	(0.2712)
	1.7207	1.4722	1.4870	0.7855	-0.1133	0.1862
$\Delta\ln(Inv)_{t-2}$	0.003254	0.033277	0.009194	0.03908	-0.5934	0.0203
	(0.0691)	(0.0577)	(0.0699)	(0.0619)	(2.3947)	(0.1109)
	0.0471	0.5768	0.1315	0.6309	-0.2478	0.1832
$\Delta\ln(Inv)_{t-3}$	0.087934	-0.014309	0.118406	-0.007878	2.0323	0.0221
	(0.0620)	(0.0566)	(0.0979)	(0.0761)	(11.5473)	(0.4336)
	1.4177	-0.2527	1.2091	-0.1035	0.1760	0.0509
$\Delta\ln(Inv)_{t-4}$	-0.048289	0.199579	-0.03585	0.205392	0.4887	0.1865
	(0.0806)	(0.0597)	(0.0870)	(0.0615)	(3.7595)	(0.1426)
	-0.5990	3.3407	-0.4123	3.3397	0.1300	1.3077
$\Delta\ln(Sales)_{t-1}$	0.111087	-0.468857	0.084569	-0.478395	0.5554	-0.4634
	(0.0548)	(0.0694)	(0.0771)	(0.1391)	(3.4279)	(0.1415)
	2.0277	-6.7584	1.0968	-3.4398	0.1620	-3.2748
$\Delta\ln(Sales)_{t-2}$	0.171045	-0.396211	0.154402	-0.40024	-1.2152	-0.4264
	(0.0568)	(0.0804)	(0.0785)	(0.1314)	(7.2456)	(0.2441)
	3.0097	-4.9260	1.9663	-3.0457	-0.1677	-1.7470
$\Delta\ln(Sales)_{t-3}$	0.167514	-0.238113	0.151083	-0.243237	0.3288	-0.2241
	(0.0648)	(0.0736)	(0.0827)	(0.1067)	(5.3118)	(0.1645)
	2.5838	-3.2368	1.8259	-2.2792	0.0619	-1.3621
$\Delta\ln(Sales)_{t-4}$	0.075117	-0.204185	0.057481	-0.209104	-0.6296	-0.2135
	(0.0550)	(0.0594)	(0.0601)	(0.0772)	(2.3463)	(0.0887)
	1.3650	-3.4387	0.9571	-2.7075	-0.2684	-2.4070
CointRes	0.010258	-0.055943	0.004568	-0.056687	-1.1643	-0.0888
	(0.0016)	(0.0086)	(0.0134)	(0.0259)	(0.7943)	(0.0273)
	6.4603	-6.5028	0.3405	-2.1916	-1.4658	-3.2561
CondVarInv			90.810008	50.082833		
			(335.7061)	(61.1721)		
			0.2705	0.8187		
CondVarSls			-0.699839	-15.256021		
			(17.2799)	(16.4526)		
			-0.0405	-0.9273		
CondStdInv	44.038461	32.569976				
	(1.0836)	(2.7519)				
	40.6415	11.8354				
CondStdSls	-0.066205	-0.323923			5.6367	
	(0.0920)	(0.3910)			(2.7385)	
	-0.7195	-0.8285			2.0583	
	CondVarInv	CondVarSls	CondVarInv	CondVarSls	CondVarInv	CondVarSls
Constant	0.0000952	0.0000574	0.0000869	0.0000556	2.3113	0.0019
	(1.5083e-08)	(0.0000208)	(0.000000623)	(0.0000259)	(0.1873)	(0.000304)
	6309.50	2.7568	139.66	2.1427	12.3375	6.1125
ARCH	0.004620	0.285821	0.090284	0.262251	1.000	0.8118
	(0.0024)	(0.1460)	(0.2178)	(0.1544)	(2.6110)	(1.9039)
	1.9461	1.9575	0.4144	1.6983	0.3830	0.4264
GARCH	0.016734	0.248398	0.044332	0.282516	0.0000	0.1882
	(0.0135)	(0.0858)	(0.1303)	(0.0918)	(0.0785)	(0.2219)
	1.2368	2.8952	0.3402	3.0760	0.0000	0.8481
ConsCorr	0.040902		0.047534		0.9765	
	(0.0849)		(0.0901)		(0.00000923)	
	0.4819		0.5276		105860.00000	

Table 6 (Continued)
Constant Correlation
Multivariate GARCH-in-Mean ln(General Merchandise Retail Series)
Mean Equation: VECM. (Robust Standard Errors are Reported in Parentheses)

	Model D		Model E	
	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$
Constant	0.0028	0.0772	5.0329	0.0838
	(0.0229)	(0.1704)	(539.05)	(0.5072)
	0.1219	0.4533	0.0093	0.1651
$\Delta\ln(Inv)_{t-1}$	0.1032	0.0605	2.8652	0.0696
	(0.0985)	(0.0774)	(322.50)	(0.2144)
	1.0481	0.7811	0.0089	0.3248
$\Delta\ln(Inv)_{t-2}$	0.0281	0.0451	-6.9846	0.0368
	(0.0692)	(0.0664)	(2601.8)	(2.5588)
	0.4052	0.6788	-0.0027	0.0144
$\Delta\ln(Inv)_{t-3}$	0.1635	-0.0023	46.2368	0.0227
	(0.1243)	(0.1079)	(1786.8)	(2.0396)
	1.3154	-0.0212	0.0259	0.0111
$\Delta\ln(Inv)_{t-4}$	-0.0236	0.2171	20.7318	0.2247
	(0.0953)	(0.0847)	(218.81)	(0.2777)
	-0.2479	2.5645	0.0947	0.8091
$\Delta\ln(Sales)_{t-1}$	0.0462	-0.4777	9.8625	-0.4729
	(0.0689)	(0.5827)	(3096.00)	(3.0207)
	0.6698	-0.8198	0.0032	-0.1565
$\Delta\ln(Sales)_{t-2}$	0.1222	-0.3983	-34.6775	-0.4167
	(0.0789)	(0.4099)	(1903.8)	(1.0740)
	1.5479	-0.9717	-0.0182	-0.3880
$\Delta\ln(Sales)_{t-3}$	0.1128	-0.2460	2.0566	-0.2445
	(0.0745)	(0.3656)	(2274.4)	(1.4578)
	1.5130	-0.6729	0.000904	-0.1678
$\Delta\ln(Sales)_{t-4}$	0.0318	-0.2079	-10.1802	-0.2131
	(0.0701)	(0.2261)	(1585.3)	(1.1163)
	0.4536	-0.9192	-0.0064	-0.1909
CointRes	-0.000877	-0.0545	-4.7809	-0.0592
	(0.0178)	(0.1318)	(491.78)	(0.4437)
	-0.0492	-0.4131	-0.0097	-0.1333
CVln(Inv)				
CVln(Sls)	-1.1748			
	(52.2042)			
	-0.0225			
CondStdInv			0.0895	
			(4.0311)	
			0.0222	
CondStdSls			-0.5077	
			(5098.1)	
			-0.0000996	
	CondVarInv	CondVarSls	CondVarInv	CondVarSls
Constant	0.000083	0.0000614	601.1004	0.000198
	(0.0000467)	(0.000042)	(41.7555)	(0.0095)
	1.7855	1.4616	14.3957	0.0208
ARCH	0.1444	0.2834	0.0000	0.7830
	(0.3593)	(0.5911)	(16.1266)	(24.9840)
	0.4020	0.4794	0.0000	0.0313
GARCH	0.0422	0.2242	0.0000	0.2170
	(0.2056)	(0.6252)	(0.1142)	(16.6215)
	0.2052	0.3586	0.0000	0.0131
ConsCorr	0.0552		0.8260	
	(0.0878)		(0.000527)	
	0.6284		1566.8	

Comparison Current VECM Results to Previous Study

Table 7-a
Previous Study Based on Aggregate Retails and Current Study Based on Less Aggregate Retail Data. t-ratios are reported in brackets [ ]

	Previous Study (Lee & Koray's Aggregate Retail Trade)		Food Retails (Model A)		Auto Retails (Model A)		Furniture Retails (Model E)	
	Mean Equation		Mean Equation		Mean Equation		Mean equation	
	ΔInv_t	ΔSls_t	$\Delta ln(Inv)_t$	$\Delta ln(Sls)_t$	$\Delta ln(Inv)_t$	$\Delta ln(Sls)_t$	$\Delta ln(Inv)_t$	$\Delta ln(Sls)_t$
Constant	0.189 [0.32]	0.229 [0.29]	-0.008823 [-0.0710]	-0.001889 [-0.0455]	-0.017851 [-0.6271]	0.141174 [2.2518]	372.3697 [0.4954]	0.2594 [3.0450]
CointRes	-0.083 [-5.49]	0.006 [0.37]	-0.020676 [-0.0867]	-0.047669 [-2.8642]	0.037219 [0.8337]	-0.204011 [-2.5503]	-0.0161 [0.0467]	-0.0955 [-3.0527]
$CondStd_{In}$	-0.123 [-0.64]	-0.780 [-0.78]	1.1300422 [0.2330]	-1.64047 [-0.2501]	-0.612660 [-0.4309]	0.152941 [0.3599]	0.0496 [0.0064]	NA
$CondStd_{Sls}$	0.141 [0.32]	0.090 [0.183]	-0.507518 [-0.6477]	-0.317691 [-0.5607]	0.405001 [0.2273]	-0.22223 [-0.3851]	-20989.0 [-0.4953]	NA
	Cond. Var. Inventory	Cond. Var. Sales	Cond. Var. Inventory	Cond. Var. Sales	Cond. Var. Inventory	Cond. Var. Sales	Cond. Var. Inventory	Cond. Var. Sales
Constant	0.036 [0.88]	0.552 [3.54]	0.0000361 [12.8550]	0.0000187 [9.2146]	0.000250 [1.1076]	0.000083 [0.3279]	0.0000121 [0.1432]	0.0002681 [61385.0]
ARCH	0.132 [1.98]	0.573 [2.21]	0.141307 [0.3456]	0.271614 [0.7195]	0.452271 [0.8711]	0.246283 [0.3641]	0.2251 [0.3799]	0.0000002 [0.0461]
GARCH	0.832 [7.93]	0.129 [0.89]	0.007616 [0.0053]	0.248004 [1.1113]	0.000000 [0.00000]	0.695062 [1.4224]	0.7498 [1.9221]	0.1482 [74.8702]
ConsCorr	-0.100 [-1.556]		0.185145 [1.9351]		-0.348722 [-4.3328]		0.2923 [9.8170]	

Table 7-b
Previous Study Based on Aggregate Retails and Current Study Based on Less Aggregate Retail Data. t-ratios are reported in brackets [ ]

	Previous Study (Lee & Koray's Aggregate Retail Trade)		Apparel Retails (Model A)		Building Material Retails (Model A)		Gen. Merchandise Retails (Model A)	
	Mean Equation		Mean Equation		Mean Equation		Mean equation	
	ΔInv_t	ΔSls_t	$\Delta ln(Inv)_t$	$\Delta ln(Sls)_t$	$\Delta ln(Inv)_t$	$\Delta ln(Sls)_t$	$\Delta ln(Inv)_t$	$\Delta ln(Sls)_t$
Constant	0.189 [0.32]	0.229 [0.29]	0.533845 [0.0036]	0.998082 [0.0149]	-0.022188 [-0.1909]	0.486020 [0.8478]	-0.444917 [-46.2246]	-0.238891 [-6.6579]
CointRes	-0.083 [-5.49]	0.006 [0.37]	-0.258335 [-.0.0041]	-0.435572 [-0.0150]	0.012986 [0.2052]	-0.237466 [-0.8934]	0.010258 [6.4603]	-0.055943 [-6.5028]
$CondStd_{In}$	-0.123 [-0.64]	-0.780 [-0.78]	0.529431 [0.0579]	1.286759 [0.1583]	-0.241088 [-0.1009]	1.623092 [1.4432]	44.038461 [40.6415]	32.569976 [11.8354]
$CondStd_{Sls}$	0.141 [0.32]	0.090 [0.183]	4.579478 [1.0319]	0.430465 [0.0198]	0.026250 [0.1149]	0.123993 [0.3139]	-0.066205 [-0.7195]	-0.323923 [-0.8285]
	Cond. Vari. Inventory	Cond. Var. Sales	Cond. Var. Inventory	Cond. Var. Sales	Cond. Variance Inventory	Cond. Var. Sales	Cond. Var. Inventory	Cond. Var. Sales
Constant	0.036 [0.88]	0.552 [3.538]	0.0000 [0.0000]	0.000113 [0.0006]	0.0000894 [4.2658]	0.000235 [0.3191]	0.0000952 [6309.50]	0.0000574 [2.7568]
ARCH	0.132 [1.98]	0.573 [2.211]	1.00000 [0.1404]	0.441097 [0.0925]	0.132354 [1.6114]	0.415214 [0.7168]	0.004620 [1.9461]	0.285821 [1.9575]
GARCH	0.832 [7.93]	0.129 [0.898]	0.0000 [0.00000]	0.476827 [0.0007]	0.000000 [0.00000]	0.000000 [0.00000]	0.016734 [1.2368]	0.248398 [2.8952]
ConsCorr	-0.100 [-1.556]		1.00000 [3.6392]		0.063367 [0.6115]		0.040902 [0.4819]	

APPENDIX 2
VECM Results for ln(Retail Series), Diagonal Models

Table 1
VECM Results: Diagonal Model
Multivariate GARCH-in-Mean ln(Apparel Series)
Mean Equation: VECM. (Robust Standard Errors are Reported in Parentheses)
Models A,B,E and F are not reported, data are not suitable.

	Model C		Model D	
	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$
Constant	0.8240 (0.0444) 18.5555	0.0187 (0.0024) 7.7265	-2.3818 (44119.0) -0.0000539	0.4177 (19.4734) 0.0214
$\Delta\ln(Inv)_{t-1}$	-0.0892 (0.0040) -22.2333	0.2121 (0.0144) 14.7382	-0.0451 (569.0319) -0.0000793	0.1477 (2164.9) 0.0000682
$\Delta\ln(Inv)_{t-2}$	-0.2776 (0.0257) -10.8188	-0.0508 (0.0025) -20.3643	0.0074 (71.9206) 0.0001029	-0.0070 (23.5793) -0.000296
$\Delta\ln(Sales)_{t-1}$	-0.0129 (0.0011) -11.5663	-0.3703 (0.0314) -11.7814	0.0670 (394.5812) 0.0001698	-0.3835 (2894.9) -0.000132
$\Delta\ln(Sales)_{t-2}$	-0.0101 (0.0000366) -277.3802	-0.1145 (0.0337) -3.3952	0.0189 (14.5904) 0.0013	-0.1901 (159.3855) -0.0012
CointRes	-0.3467 (0.0191) -18.1680	-0.0043 (0.0009444) -4.5024	1.0585 (19136.0) 0.0000553	-0.1168 (1.3801) -0.0846
CondVarInv				
CondVarSls			-3.8152e-09 (2.9873e-08) -0.1277	
CondStdInv				
CondStdSls	3.8649e-09 (9.7287e-013) 3972.7			
	CondVarInv	CondVarSls	CondVarInv	CondVarSls
Constant	4716200.0 (319000.0) 14.7844	2612900.0 (176730.0) 14.7847	4716200.0 (650570.0) 7.2493	2612900.0 (169220.0) 15.4404
ARCH	326.8065 (0.6908) 473.0739	-353.6047 (20.1015) -17.5910	325.8071 (42.2112) 7.7185	-353.6047 (2601.4) -0.1359
GARCH	-0.00000095 (1.2948e-07) -7.3273	0.00000082 (2.1058e-08) 38.9390	0.0005103 (0.000118) 4.3417	0.0015 (0.000145) 10.4806

Table 2
Diagonal Models
Multivariate GARCH-in-Mean ln(Auto Dealers Series)
Mean Equation: VECM. (Robust Standard Errors are Reported in Parentheses)
Models A,B,E and F are not reported, data are not suitable.

	Model C		Model D	
	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$
Constant	-0.0095 (0.0163) -0.5847	0.1268 (0.0328) 3.8679	-0.0055 (0.0159) -0.3439	0.1268 (0.0334) 3.7930
$\Delta\ln(Inv)_{t-1}$	0.2005 (0.0724) 2.7689	0.1626 (0.0953) 1.7070	0.2021 (0.0739) 2.7343	0.1587 (0.0961) 1.6525
$\Delta\ln(Inv)_{t-2}$	-0.0453 (0.0753) -0.6014	0.3209 (0.1176) 2.7297	-0.0454 (0.0760) -0.5978	0.3217 (0.1180) 2.7255
$\Delta\ln(Sales)_{t-1}$	0.0113 (0.0501) 0.2262	-0.3905 (0.1010) -3.8655	0.0120 (0.0521) 0.2297	-0.3911 (0.1046) -3.7381
$\Delta\ln(Sales)_{t-2}$	0.0021 (0.0386) 0.0542	-0.2349 (0.0623) -3.7696	0.000629 (0.0388) 0.0162	-0.2358 (0.0625) -3.7733
CointRes	0.0159 (0.0225) 0.7058	-0.1881 (0.0484) -3.8842	0.0157 (0.0234) 0.6727	-0.1881 (0.0494) -3.8108
CVInv				
CVSls			1.9528 (1.5884) 1.2295	
CondStdInv				
CondStdSls	0.1992 (0.1254) 1.5890			
	CondVarInv	CondVarSls	CondVarInv	CondVarSls
Constant	-0.0163 (0.0011) -14.6287	0.00000375 (0.000457) 0.0082	0.0164 (0.0014) 12.1510	0.00000466 (0.00047) 0.0099
ARCH	-0.6210 (0.0923) -6.7266	-0.3448 (0.0484) -7.1194	-0.6174 (0.0945) -6.5350	-0.3413 (0.0629) -5.4250
GARCH	-0.0626 (0.1232) -0.5082	0.9225 (0.0026) 351.9215	0.0599 (0.1373) 0.4365	-0.9233 (0.0079) -116.8436

Table 3
Diagonal Model
Multivariate GARCH-in-Mean Furniture Series
Mean Equation: VECM. (Robust Standard Errors are Reported in Parentheses)
Models A, B, D and F are not reported, data are not suitable.

	Model C		Model E	
	$\Delta\ln(Inv)_t$	$\Delta\ln(Sls)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sls)_t$
Constant	-9.9722 (132.6801) 0.0752	0.5340 (4742.00) 0.0001126	0.0632 (0.0063) 9.9512	0.2688 (2.1834) 0.1231
$\Delta\ln(Inv)_{t-1}$	-0.0151 (2590.3) -0.00000584	-0.1334 (19928.0) -0.00000669	0.0109 (0.0737) 0.1483	0.1476 (0.7183) 0.2055
$\Delta\ln(Inv)_{t-2}$	-0.2840 (22843.0) -0.00001143	-0.3246 (42315.0) -0.00000767	-0.0482 (0.0684) -0.7056	-0.0493 (0.7397) -0.0667
$\Delta\ln(Sls)_{t-1}$	0.6276 (19945.0) 0.0000315	-0.1335 (15728.0) -0.00000849	0.1203 (0.0486) 2.4745	-0.1875 (1.6566) -0.1132
$\Delta\ln(Sls)_{t-2}$	-0.0952 (3386.10) -0.0000281	-0.1657 (21948.0) -0.00000755	0.1568 (0.0771) 2.0335	-0.0597 (0.7966) -0.0749
CointRes	3.7055 (51.6889) 0.0717	-0.1712 (1862.9) -0.00009192	-0.0147 (0.0029) -5.0428	-0.1043 (0.8336) -0.1251
CVInv				
CVSls				
CondStdInv			-0.2162 (0.1601) -1.3508	
CondStdSls	0.0079 (0.00064161) 12.2623		-0.00000064 (1.4199e-08) -45.0134	
	CondVarInv	CondVarSls	CondVarInv	CondVarSls
Constant	-1.5228 (1.8753) -0.8120	28597.0 (2501.1) 11.4336	0.0081 (0.000746) 10.8779	28595.0 (2408.80) 11.2349
ARCH	1.4244 (1.7991) 0.7917	-8.1278 (4542.4) -0.0018	1.2769 (0.1832) 11.8710	-8.0896 (11.8846) 6.9708
GARCH	-0.8524 (0.0624) -13.6492	0.2504 (0.0143) 17.5412	0.0054 (0.0108) -0.6807	0.0027 (0.000444) 0.4956

Table 4
Diagonal Model
Multivariate GARCH-in-Mean ln(Food Retail Series)
Mean Equation: VECM. (Robust Standard Errors are Reported in Parentheses)
Models B, E and F are not reported, data are not suitable.

	Model A		Model C		Model D	
	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$
Constant	1.13771 (4.4927) 0.2532	-0.0606 (0.4432) -0.1367	0.1343 (0.1803) 0.7448	-0.0104 (0.0140) -0.7465	-0.0900 (0.2186) -0.4119	-0.0369 (0.0116) -3.1838
$\Delta\ln(Inv)_{t-1}$	0.12258 (2.4253) 0.0505	0.82508 (3.2811) 0.2515	-2.8284 (5.6034) -0.5048	0.3162 (0.5151) 0.6138	1.6175 (1.2985) 1.2457	-0.000758 (0.1400) -0.0054
$\Delta\ln(Sls)_{t-1}$	0.32963 (72.8030) 0.0045	-0.30739 (12.9863) -0.0237	0.4230 (4.9548) 0.0854	-0.5671 (0.4967) -1.1417	-0.3270 (8.6576) -0.0378	-0.4336 (0.8755) -0.4952
CointRes	2.20863 (9.5382) 0.2316	-0.1830 (1.1504) -0.1591	0.2026 (0.4413) 0.4592	-0.0405 (0.0337) -1.2025	-0.2281 (0.4234) -0.5387	-0.0698 (0.0132) -5.2843
CVInv						
CVSls					0.000002421 (0.000000215) 11.2404	
CondStdInv	-0.1588 (0.3925) -0.4046	0.13469 (0.0647) 2.0812				
CondStdSls	1.7212 (3.9550) 0.4352	-1.46022 (0.7050) -2.0713	-0.000231 (0.0000362) -6.3727			
	CondVarInv	CondVarSls	CondVarInv	CondVarSls	CondVarInv	CondVarSls
Constant	2735.002 (815.5177) 3.3537	-0.006622 (0.0626) -0.1059	2734.00 (288.1164) 9.4892	-0.0052 (0.000478) -10.8633	2734.8 (303.7381) 9.0038	0.0049 (0.0005) 8.9941
ARCH	1.2746 (4.0158) 0.3174	1.03704 (1.2819) 0.8090	0.8028 (0.6351) 1.2641	0.4204 (0.1448) 2.9038	0.6688 (0.2897) 2.3085	0.3917 (0.1736) 2.2560
GARCH	-0.04496 (0.0024) -19.0440	-0.04497 (0.0024) -18.4357	-0.0966 (0.00000734) -13162.0	-0.0966 (0.00000727) -13287.0	-0.0676 (0.0000255) -2643.8	-0.0675 (0.0000256) -2638.20

Table 5
Diagonal Model
Multivariate GARCH-in-Mean ln(Building Material and Hardware Retail Series)
Mean Equation: VECM, (Robust Standard Errors are Reported in Parentheses)
Models A, B, E and F are not reported, data are not suitable.

	Model C		Model D	
	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$
Constant	-16.0643 (2.4962) -6.4355	0.4185 (2.9481) 0.1420	-23.9691 (4095.90) -0.0059	0.4221 (0.9958) 0.4239
$\Delta\ln(Inv)_{t-1}$	0.0310 (0.2034) 0.1525	0.0078 (0.1365) 0.0569	0.0399 (2.3578) 0.0169	0.0072 (0.9112) 0.0079
$\Delta\ln(Inv)_{t-2}$	-0.0116 (0.0502) -0.2307	0.0595 (0.6414) 0.0927	-0.0022 (2.6331) -0.0008	0.0591 (0.6674) 0.0885
$\Delta\ln(Inv)_{t-3}$	0.1317 (0.8462) 0.1557	0.2494 (1.4816) 0.1683	0.1399 (31.5671) 0.0044	0.2488 (16.1101) 0.0154
$\Delta\ln(Sales)_{t-1}$	0.0754 (0.3342) 0.2258	-0.2097 (0.6282) -0.3338	0.0854 (29.1003) 0.0029	-0.2094 (9.2470) -0.0226
$\Delta\ln(Sales)_{t-2}$	0.1612 (0.2151) 0.7496	-0.1617 (0.6219) -0.2600	0.1711 (15.6184) 0.0110	-0.1616 (13.3492) -0.0121
$\Delta\ln(Sales)_{t-3}$	0.0390 (0.1244) 0.3136	-0.0519 (0.0082) -6.3495	0.0490 (4.3222) 0.0113	-0.0518 (15.9746) -0.0032
CointRes	7.8416 (1.2176) 6.4405	-0.1942 (1.4341) -0.1354	11.7006 (1999.30) 0.0059	-0.1860 (0.4422) -0.4208
CVln(Inv)				
CVln(Sls)			-8.4912e-10 (3.1513e-07) -0.0027	
CondStdInv				
CondStdSls	-5.2996e-07 8.4604e-10 -626.4059			
	CondVarInv	CondVarSls	CondVarInv	CondVarSls
Constant	6337500.0 (428660.0) 14.7844	783530.0 (52997.00) 14.7844	6327100.0 (451010.0) 14.0287	785060.0 (45927.0) 17.0936
ARCH	708.2384 (7.3649) 96.1646	-218.5853 (1564.7) -0.1397	708.9864 (126.7588) 5.5932	-219.0131 (550.7018) -0.3977
GARCH	0.000000304 (0.00000131) 0.2326	0.00000058 (0.00000127) 0.4553	0.00084445 (0.0000518) 16.3099	0.0021 (0.000133) 15.4790

Table 6
Diagonal Model
Multivariate GARCH-in-Mean ln(General Merchandise Retail Series)
Mean Equation: VECM. (Robust Standard Errors are Reported in Parentheses)
Models A, B, E and F are not reported, data are not suitable.

	Model C		Model D	
	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$	$\Delta\ln(Inv)_t$	$\Delta\ln(Sales)_t$
Constant	0.0111	0.0808	-0.1883	0.0675
	(0.0179)	(0.5904)	(0.0225)	(0.0147)
	0.6186	0.1368	-8.3743	4.5883
$\Delta\ln(Inv)_{t-1}$	0.1377	0.0636	-0.7773	0.0906
	(1.1065)	(0.0917)	(0.2913)	(0.0783)
	0.1245	0.6941	-2.6682	1.1569
$\Delta\ln(Inv)_{t-2}$	0.0034	0.0419	-0.1155	0.1051
	(0.4902)	(0.1648)	(0.1798)	(0.0630)
	0.0069	0.2545	-0.6422	1.6676
$\Delta\ln(Inv)_{t-3}$	0.2029	-0.0222	0.4574	-0.0372
	(0.0732)	(0.1064)	(0.3175)	(0.0476)
	2.7733	-0.2085	1.4409	-0.7803
$\Delta\ln(Inv)_{t-4}$	0.0104	0.2475	0.2526	0.1434
	(0.1312)	(0.3279)	(0.1686)	(0.0646)
	0.0795	0.7548	1.4983	2.2185
$\Delta\ln(Sales)_{t-1}$	0.0159	-0.4605	-0.2883	-0.4021
	(0.0539)	(2.0477)	(0.3232)	(0.0707)
	0.2942	-0.2249	-0.8920	-5.6840
$\Delta\ln(Sales)_{t-2}$	0.0796	-0.3915	-0.6411	-0.3320
	(0.1558)	(1.7396)	(0.2475)	(0.0880)
	0.5105	-0.2251	-2.5907	-3.7732
$\Delta\ln(Sales)_{t-3}$	0.0870	-0.2697	-0.5807	-0.1718
	(0.2453)	(1.3709)	(0.2347)	(0.0749)
	0.3545	-0.1967	-2.4744	-2.2943
$\Delta\ln(Sales)_{t-4}$	0.0042	-0.2090	-0.5395	-0.1911
	(0.0791)	(0.8194)	(0.1692)	(0.0685)
	0.0528	-0.2551	-3.1880	-2.7902
CointRes	-0.0072	-0.0574	-0.1939	-0.0476
	(0.0255)	(0.4545)	(0.0177)	(0.0116)
	-0.2834	-0.1262	10.9244	-4.0901
CVln(Inv)				
CVln(Sls)			-0.0000398	
			(0.00000842)	
			-4.7270	
CondStdInv				
CondStdSls	-0.0123			
	1.6023			
	-0.0077			
	CondVar ln(Inv)	CondVar ln(Sls)	CondVar ln(Inv)	CondVar ln(Sls)
Constant	-0.0084	0.0078	1831.00	-0.0062
	(0.0025)	(0.0106)	(122.6940)	(0.0012)
	-3.4393	0.7379	14.9232	-5.3805
ARCH	-0.5513	-0.5354	28.8293	-0.5952
	(0.5374)	(1.0587)	(4.7261)	(0.0888)
	-1.0259	-0.5057	6.1000	-6.7017
GARCH	-0.2121	0.4623	-0.0057	-0.0055
	(0.1503)	(0.3981)	(0.000134)	(0.000112)
	-1.4108	1.1614	-42.3876	-49.5004

APPENDIX 3
VAR Results for ln(Retail Series), Constant Correlation Models

Table 1
Constant Correlation
Multivariate GARCH-in-Mean: ln(Furniture) Retail Series
Mean Equation : VAR, (Robust Standard errors are reported in parentheses)
Models B and F are not reported, data are not suitable

	Model A		Model C		Model D	
	ln(Inv)t	ln(Sales)t	ln(Inv)t	ln(Sales)t	ln(Inv)t	ln(Sales)t
Constant	-3.093198 (0.1600) -19.3285	-3.873274 (0.1540) -25.1557	-4.4302 (0.1084) -40.8618	-0.0060 (0.0773) -0.0782	-0.5357 (2.2579) -0.2373	0.0080 (6.7787) 0.0012
$\ln(\text{Inventory})_{t-1}$	0.897638 (0.0008) 1131.5	0.003072 (0.0028) 1.0788	0.9347 (0.0067) 138.67	0.0143 (0.0080) 1.7776	0.9243 (0.3128) 2.9546	0.0084 (0.6869) 0.0122
$\ln(\text{Sales})_{t-1}$	0.080901 (0.0005) 150.09	0.992538 (0.0027) 366.44	0.0512 (0.0063) 8.1011	0.9853 (0.000285) 3461.5	0.0586 (0.2529) 0.2316	0.9899 (0.0034) 295.16
Cond.Var.Inv						
Cond Var.Sls					1030.6 (65.2580) 15.7930	
Cond.Std.Inv	-0.006637 (0.0667) -0.0994	0.215696 (0.0208) 10.372				
Cond Std.Sls	151.294918 (8.2673) 18.3004	175.647471 (5.0255) 34.9509	229.5415 (1.8478) 124.23			
	Cond.Var of Inventry	Cond.Var of Sales	Cond.Var of Inventory	Cond. Var of Sales	Cond.Var of Inventory	Cond.Var of Sales
Constant	0.00000818 (1.9938e-05) 0.4103	0.0004961 (3.3933e-08) 14620.0	3.143e-007 (0.0001969) 0.0016	0.0003695 (1.0013e-06) 369.07	0.00009225 (0.0009) 0.1040	0.00072891 (0.0028) 0.2628
ARCH	0.19606 (0.0529) 3.706	0.00000 (6.400e-07) 0.0000	0.00000 (1.4003e-05) 0.000	0.00001739 (5.9700e-05) 0.2914	0.8782 (5.5155) 0.1592	0.00001668 (0.0291) 0.0005739
GARCH	0.787319 (0.0259) 30.456	0.0000 (0.0006) 0.0000	1.00000 (0.0241) 41.5199	0.0844 (0.0259) 3.2550	0.0019 (0.2247) 0.0086	0.00000 (0.0738) 0.0000
Const.Corr.	0.344659 (0.0019) 177.33		0.3967 (0.0609) 6.5119		0.3965 (5.6564) 0.0701	

Table 1 (Continued)
Constant Correlation
Multivariate GARCH-in-Mean: ln(Furniture) Retail Series
Mean Equation : VAR,
(Robust Standard errors are reported in parentheses)

	Model E	
	ln(Inv)t	ln(Sales)t
Constant	-1.6036 (0.2908) -5.5146	-0.0036 (0.6699) -0.0054
$\ln(\text{Inventory})_{t-1}$	0.9466 (0.0081) 117.41	0.0116 (0.0712) 0.1629
$\ln(\text{Sales})_{t-1}$	0.0388 (0.0214) 1.8141	0.9879 (0.0001928) 5124.9
Cond.Var.Inv		
Cond Var.Sls		
Cond.Std.Inv	-41.5911 (20.3310) -2.0457	
Cond Std.Sls	107.3603 (3.7306) 28.7780	
	Cond.Var of Inventory	Cond.Var of Sales
Constant	0.0001749 (0.0000136) 12.8686	0.00005007 (7.3293e-08) 683.12
ARCH	0.0000 (3.9031e-06) 0.0000	0.0002892 (0.000162) 1.7847
GARCH	0.0990 (0.5779) 0.1712	0.8961 (0.0010) 939.78
Constant Corr.	0.4154 (0.6583) 0.6311	

Table 2
Constant Correlation
Multivariate GARCH-in-Mean: ln(Building Material) Retail Series
Mean Equation : VAR, (Robust Standard errors are reported in parentheses)

	Model A		Model C		Model D	
	ln(Inv)t	ln(Sales)t	ln(Inv)t	ln(Sales)t	ln(Inv)t	ln(Sales)t
Constant	-2.553749 (0.0000118) -216920.0	-1.859106 (23.4419) -0.0793	-2.2482 (0.0049) -462.45	-0.1720 (0.0569) -3.0224	-1.0774 (0.0126) -85.4247	-0.1627 (0.0510) -3.1895
$\ln(Inve)_{t-1}$	0.933217 (0.0125) 74.3676	0.076814 (0.3179) 0.2416	0.9374 (2.7092e-04) 3459.9	0.0786 (0.0065) 12.1152	0.9118 (0.001) 903.06	0.0754 (0.0057) 13.2121
$\ln(Sales)_{t-1}$	0.057635 (0.0450) 1.2815	0.934861 (0.1940) 4.8197	0.0542 (9.775e-05) 554.63	0.9331 (8.670e-04) 1076.2	0.0749 (0.0013) 59.3327	0.9355 (5.890e-04) 1588.3
Cond.Var.Inv						
Cond Var.Sls					1627.7 (7.4919) 217.26	
Cond.Std.Inv	112.94390 (0.0001188) 950600.00	189.760896 (276.3617) 0.6866				
Cond Std.Sls	45.465551 (2.5702) 17.6893	-40.709746 (771.2828) -0.0528	87.5344 (0.1490) 587.53			
	Cond.Varof Inventory	Cond.Var of Sales	Cond.Varof Inventory	Cond. Var of Sales	Cond.Varof Inventory	Cond.Var of Sales
Constant	0.000199 (0.0002279) 0.8752	0.000583 (0.0003657) 1.5947	0.000104 (8.6896e-06) 11.9898	0.000635 (1.725e-06) 368.14	0.000065027 (6.7086e-05) 0.9693	0.00073287 (1.3704e-06) 534.79
ARCH	0.000950 (0.0148) 0.0640	0.000360 (0.0163 0.0221	0.0067 (1.558e-04) 42.6937	0.000111 (7.401e-06) 15.0050	0.8322 (0.6600) 1.2608	0.000067232 (7.1063e-05) 0.9461
GARCH	0.00000 (0.9512) 0.00000	0.009374 (1.4568) 0.0064	0.0318 (0.0258) 1.2327	0.1429 (0.000507) 281.92	0.0000 (0.0155) 0.0000	0.0667 (0.0016) 41.2422
Const.Corr.	0.174874 (6.2426) 0.0280		1.924 (0.0198) 9.7078		0.1098 (0.0197) 5.5817	

Table 2 (Continued)
Constant Correlation
Multivariate GARCH-in-Mean: ln(Building Material) Retail Series
Mean Equation : VAR,
(Robust Standard errors are reported in parentheses)

	Model E	
	ln(Inv)t	ln(Sales)t
Constant	-1.8788 (0.1043) -18.0121	-0.1707 (0.0674) -2.5339
$\ln(\text{Inve})_{t-1}$	0.9381 (0.0023) 403.10	0.0780 (0.0065) 12.068
$\ln(\text{Sales})_{t-1}$	0.0537 (0.0107) 5.0395	0.9336 (0.0012) 749.47
Cond.Var.Inv		
Cond Var.Sls		
Cond.Std.Inv	-104.1009 (4.0674) -25.5940	
Cond Std.Sls	119.0936 (0.4092) 291.03	
	Cond.Varof Inventory	Cond. Var of Sales
Constant	0.0001084 (3.117e-08) 3478.3	0.0006 (1.5405e-06) 369.19
ARCH	0.0000 (1.105e-05) 0.0000	9.4923e-005 (5.1687e-05) 1.8365
GARCH	0.00000 (0.0064) 0.0000	0.1580 (0.0143) 11.0366
Constant Corr.	0.0860 (0.1346) 0.6395	

Table 3
Constant Correlation
Multivariate GARCH-in-Mean: ln(Food) Retail Series
Mean Equation : VAR, (Robust Standard Errors are Reported in Parentheses)

	Model A		Model C		Model E	
	ln(Inv)t	ln(Sales)t	ln(Inv)t	ln(Sales)t	ln(Inv)t	ln(Sales)t
Constant	-0.589906 (0.0278) -21.2239	-0.977335 (0.0205) -47.6452	-0.0095 (6.3783) -0.0015	0.0028 (19.7239) 0.00014	-0.0142 (3.7660) -0.0038	0.0033 (5.9965) 0.000554
$\ln(\text{Inve})_{t-1}$	0.949115 (0.0029) 327.35	0.263552 (0.0123) 21.5084	1.0656 (1.3443) 0.7927	0.1046 (12.5333) 0.0083	1.0549 (1.2222) 0.8631	0.1064 4.0195 0.0265
$\ln(\text{Inve})_{t-2}$	0.005138 (0.0213) 0.2409	-0.243593 (0.0264) -9.218	0.1071 (6.2429) 0.0172	-0.1745 (12.6149) -0.0138	0.1458 5.3734 0.0271	-0.1728 4.2427 -0.0407
$\ln(\text{Sales})_{t-1}$	-0.048404 (0.0078) -6.2145	0.645506 (0.0038) 171.28	0.0020 (2.4218) 0.000812	0.5031 (14.9512) 0.0337	-0.0094 (1.5107) -0.0062	0.5050 5.1328 0.0984
$\ln(\text{Sales})_{t-2}$	0.094483 (0.0254) 3.7138	0.330024 (0.0266) 12.3971	-0.2876 (6.64440 -0.0433	0.4160 (20.8404) 0.0200	-0.3109 5.9061 -0.0526	0.4179 7.0684 0.0591
Cond.Var.Inv						
Cond Var.Sls						
Cond.Std.Inv	218.95671 (1.3679) 160.06	33.614099 (5.9844) 5.6170			-0.0976 0.2653 -0.3681	
Cond Std.Sls	-216.66977 (3.6270) -59.7373	57.790098 (8.8434) 6.5348	-0.0968 (0.2557) -0.3787		0.0822 0.1137 0.7233	
	CondVarInv	CondVarSls	CondVarInv	CondVarSls	CondVarInv	CondVarSls
Constant	0.000154 (1.7588e-139) 1.637e+121	0.00009993 (4.3225e-010) 2.3119e+005	0.0299 (0.0184) 1.6313	0.0857 (0.2273) 0.3769	0.0427 (0.0152) 2.8003	0.0887 (0.1119) 0.7925
ARCH	0.00000 (4.6118e-131) 0.00000	0.00000 (1.0583e-07) 0.00000	0.1656 (0.0436) 3.7999	0.2401 (0.9514) 0.2524	0.1674 (0.0254) 6.5989	0.2401 (0.5214) 0.4606
GARCH	0.022593 (0.000603) 37.4666	0.002947 (0.0004778) 6.1674	-2.7901e-019 (0.1765) -1.5805e-018	0.2083 (2.3465) 0.0888	-3.5132e-019 (0.1948) -1.8037e-018	0.2083 (1.2968) 0.1607
Constant Corr.	0.656026 (0.000251) 2617.00		0.1906 (0.11440 1.6661		0.1906 (0.0890) 2.1421	

Table 4
Constant Correlation
Multivariate GARCH-in-Mean: ln(Apparel Retail Series)
Mean Equation : VAR, (Robust Standard errors are reported in parentheses)

	Model A		Model C		Model D	
	ln(Inv)t	ln(Sales)t	ln(Inv)t	ln(Sales)t	ln(Inv)t	ln(Sales)t
Constant	-7.560614 (241534.24) -0.0000313	0.055659 (850365.18) 0.0000000655	0.2055 (17.7858) 0.0116	-0.0931 (0.1656) -0.5622	0.1874 (132.6582) 0.0014	-0.0945 (0.6589) -0.1433
$\ln(\text{Inve})_{t-1}$	1.017155 (188.8326) 0.0054	0.146749 (193441.94) 0.000000759	0.8738 (0.0220) 39.7336	0.1883 (0.3458) 0.5446	0.6958 (19.5178) 0.0356	0.1750 (1.9473) 0.0899
$\ln(\text{Inve})_{t-2}$	-0.091294 (67761.676) -0.00000135	-0.091285 (27716.286) -0.00000329	0.0115 (9.4809) 0.0012	-0.1267 (0.1306) -0.9703	-0.1668 (31.2210) -0.0053	-0.1400 (1.6256) -0.0861
$\ln(\text{Sales})_{t-1}$	0.102408 (101561.29) 0.000001008	0.68627 (54847.21) 0.00001251	0.0602 (2.3020) 0.0262	0.6881 (0.0246) 27.9425	-0.1013 (7.9151) -0.0128	0.6760 (0.3784) 1.7864
$\ln(\text{Sales})_{t-2}$	-0.040352 (36313.536) -0.000001111	0.261509 (90503.596) 0.000002889	-0.0058 (10.6931) -0.0005	0.2537 (0.2662) 0.9532	0.2524 (33.6738) 0.0075	0.2416 (0.3382) 0.7144
Cond.Var.Inv						
Cond Var.Sls					0.0454 (212.8857) 0.0002132	
Cond.Std.Inv	-128.8938 (16788199.96) -0.00000768	126.1758 (22986105.004) 0.00000549				
Cond Std.Sls	525.357143 (788003.22) 0.000667	-120.07751 (8754401.86) -0.0000137	0.0457 (3.9541) 0.0116			
	CndVarInv	CndVarSls	CndVarInv	CndVarSls	CndVarInv	CndVarSls
Constant	0.000253 (6.05e-07) 418.4844	0.000357 (6.5e-08) 5487.4	0.0097 (0.0212) 0.4586	0.0007 (0.0016) 0.4376	0.0003 (0.0347) 0.0078	0.0007 (0.0062) 0.1215
ARCH	0.000622 (0.4582) 0.0014	0.000031 (0.0003) 0.1044	0.1561 (0.1579) 0.9882	0.2302 (0.8247) 0.2791	0.1569 (0.0292) 5.3756	0.2302 (0.6202) 0.3712
GARCH	0.117683 (71555.2621) 0.0000016446	0.000000 (15312.3798) 0.00000	-1.0594e-020 (0.1377) -7.6914e-020	0.000 (0.1036) 0.000	-6.6174e-024 (0.2544) -2.6008e-023	0.0000 (3.0311) 0.0000
Constant Corr.	-0.192795 (5624.4162) -0.0000343		-0.0135 (1.1824) -0.0114		-0.0135 (0.1511) -0.0892	

Table 4 (Continued)
Constant Correlation
Multivariate GARCH-in-Mean: ln(Apparel Retail Series)
Mean Equation : VAR,
(Robust Standard errors are reported in parentheses)

	Model E	
	ln(Inv)t	ln(Sales)t
Constant	0.1820 (66.6489) 0.0027	-0.0945 (0.5633) -0.1677
$\ln(\text{Inve})_{t-1}$	0.6497 (10.8875) 0.0597	0.1746 (1.9476) 0.0896
$\ln(\text{Inve})_{t-2}$	0.2618 (15.5733) 0.0168	-0.1404 (0.9201) -0.1526
$\ln(\text{Sales})_{t-1}$	-0.1374 (4.3138) -0.0318	0.6756 (0.1024) 6.6004
$\ln(\text{Sales})_{t-2}$	-0.2008 (17.5538) -0.0114	0.2413 (1.2263) 0.1968
Cond.Var.Inv		
Cond Var.Sls		
Cond.Std.Inv	0.0487 (0.7367) 0.0661	
Cond Std.Sls	0.0086 (40.1830) 0.0002	
	CndVarInv	CndVarSls
Constant	0.000205 (0.1194) 0.0017	0.0012 (0.0021) 0.5489
ARCH	0.1518 (0.0154) 9.8570	0.2302 (0.2185) 1.0536
GARCH	-1.5469e-021 (0.1804) -8.5734e-21	0.0000 (0.6656) 0.000
Constant Corr.	-0.0135 (0.0800) -0.1684	

Table 5
Constant Correlation
Multivariate GARCH-in-Mean: ln(General Merchandise) Retail Series
Mean Equation : VAR, (Robust standard errors are reported in parentheses)

	Model A		Model C		Model E	
	Ln(Inv)t	Ln(Sls)t	Ln(Inv)t	Ln(Inv)t	Ln(Inv)t	Ln(Sls)t
Constant	0.115504 (3.4210) 0.0338	-0.343870 (0.000205) -1677.20	-6.7866 (0.1471) -46.1432	-6.7485 (0.1348) -50.0536	2.3760 (0.3566) 6.6636	2.3594 (0.0124) 189.85
$\ln(Inv)_{t-1}$	0.747207 (0.0350) 21.346	0.099238 (0.000059) 1688.5	1.2217 (1.36050 0.8980	0.8016 (0.0069) 116.74	1.0594 (0.1025) 10.3383	0.3723 (0.1091) 3.4130
$\ln(Inv)_{t-2}$	0.070916 (3.5062) 0.0202	-0.821401 (0.000239) -3435.8	0.5948 (0.3438) 1.7302	1.4705 (0.0012) 1271.9	0.2137 (0.2232) 0.9575	-0.3412 (0.1961) -1.7398
$\ln(Inv)_{t-3}$	0.035066 (4.7897) 0.0073	0.462282 (0.0024) 189.36	1.5169 (1.0638) 1.4260	0.0697 (0.0267) 2.6069	-0.2785 (0.1479) -1.8822	-0.0051 (0.0537) -0.0943
$\ln(Sales)_{t-1}$	0.077593 (1.4565) 0.0533	0.890212 (0.0034) 265.72	-0.9371 (0.8335) -1.1242	-0.1439 (0.0186) -7.7172	-0.9604 (0.2087) -4.6020	-0.3407 (0.1154) -2.9517
$\ln(Sales)_{t-2}$	-0.019387 (2.4531) -0.0079	0.670523 (0.0020) 329.18	-0.1616 (0.0109) -14.8504	0.4865 (0.0064) 76.1731	-0.2879 (0.3651) -0.7886	0.3149 (0.0104) 30.3136
$\ln(Sales)_{t-3}$	0.038331 (4.7261) 0.115504	-0.379603 (0.000066) -0.343870	0.4134 (0.0587) 7.0389	-0.0458 (0.0098) -4.6524	0.2251 (0.1026) 2.1936	-0.0295 (0.0478) -0.6171
CondStdInv	-58.03632 (203.2119) -0.2856	1.804726 (0.0018) 1020.3			-0.1702 (0.5417) -0.3142	
CondStdSls	5.499382 (0.2553) 21.5389	6.139145 (0.0057) 1073.6	1.0113 (0.0369) 27.4197		0.9940 (0.1702) 5.8388	
	CondVarInv	CondVarSls	CondVarInv	CondVarSls	CondVarInv	CondVarSls
Constant	0.00000184 (3.4491e-06) 0.5338	0.011789 (6.8298e-06) 1726.10	0.0000226 (0.0006485) 0.0349	0.0001214 (0.0010) 0.1165	0.000029482 (2.1094e-05) 1.3977	0.000029775 (0.0026) 0.0116
ARCH	-0.000014 (1.1469e-05) -1.2294	0.209352 (0.000162) 1289.0	0.0375 (0.0433) 0.8656	1.0000 (0.0744) 13.4333	0.1311 (0.9378) 0.1398	1.0000 (0.0216) 46.2757
GARCH	0.975908 (0.000211) 4626.1	0.122419 (0.000898) 136.32	0.8615 (0.6374) 1.3516	0.00000 (0.1017) 0.000	0.7163 (0.2986) 2.3991	0.0000 (0.0609) 0.000
Constant Corr	0.175734 (0.0810) 2.1705		0.7020 (0.5595) 1.2546		0.7049 (1.0142) 0.6950	

Table 6
Constant Correlation
Multivariate GARCH-in-Mean: ln(Auto) Retail Series
Mean Equation : VAR, (Robust standard errors are reported in parentheses)

	Model A		Model C		Model D	
	Ln(Inv)t	Ln(Sls)t	Ln(Inv)t	Ln(Sls)t	Ln(Inv)t	Ln(Sls)t
Constant	0.033191	0.005603	-5.1338	-0.0186	-1.3581	-0.0182
	(0.0434)	(0.0460)	(0.9064)	(0.9541)	(0.0172)	(0.0407)
	0.7645	0.1217	-5.6639	-0.0195	-79.1124	-0.4467
$\ln(Inv)_{t-1}$	1.228492	0.18035	1.1524	0.3257	1.1251	0.2885
	(0.0068)	(0.0286)	(0.0708)	(0.3705)	(0.0012)	(0.0619)
	180.2519	6.3035	16.2667	0.8791	901.8714	4.6620
$\ln(Inv)_{t-2}$	-0.194909	0.155612	-0.1662	-0.0047	-0.1868	0.0503
	(0.0483)	(0.0387)	(0.4167)	(0.4193)	(0.0204)	(0.1377)
	-4.0355	4.0248	-0.3990	-0.0113	-9.1738	0.3650
$\ln(Inv)_{t-3}$	-0.099639	-0.289916	-0.0599	-0.2733	-0.0091	-0.3191
	(0.0363)	(0.0022)	(0.2353)	(0.1841)	(0.0288)	(0.1052)
	-2.7474	-131.5254	-0.2544	-1.4847	-0.3159	-3.0343
$\ln(Sales)_{t-1}$	0.065958	0.983228	0.0186	0.6134	0.0323	0.6302
	(0.0992)	(0.0045)	(0.8916)	(0.1161)	(0.0264)	(0.0211)
	0.6646	219.8403	0.0209	5.2821	1.2245	29.9387
$\ln(Sales)_{t-2}$	-0.014254	-0.051183	0.0508	0.0693	0.0499	0.0371
	(0.2419)	(0.0364)	(0.7017)	(0.6677)	(0.0824)	(0.1498)
	-0.0589	-1.4044	0.0724	0.1038	0.6057	0.2475
$\ln(Sales)_{t-3}$	0.013006	0.012956	0.0023	0.2674	-0.0145	0.3110
	(0.3250)	(0.0213)	(0.6264)	(0.0980)	(0.0786)	(0.1587)
	0.0400	0.6095	0.0037	2.7296	-0.1851	1.9596
CondVarSales					143.7695	
					(1.0087)	
					142.5235	
CondStdInv	0.059356	-0.484677				
	(0.3693)	(0.5214)				
	0.1607	-0.9296				
CondStdSls	0.236807	0.407357	112.9825			
	(0.6850)	(0.3355)	(21.1568)			
	0.3457	1.2141	5.3402			
	CondVarInv	CondVarSls	CondVarInv	CondVarSls	CondVarInv	CondVarSls
Constant	0.000290	0.000832	0.0002613	0.0015	0.0014	0.0099
	(0.0003)	(0.0004)	(0.0041)	(0.0001)	0.0001402	(0.0000323)
	1.1287	2.2063	0.0635	17.9692	9.8760	305.8864
ARCH	0.855730	0.952993	0.4081	0.0004689	1.000	0.0011
	(0.8708)	(1.3163)	(1.1004)	(0.0003)	(0.6227)	(0.0004)
	0.9827	0.7240	0.3708	1.7144	1.6058	3.1410
GARCH	0.000000	0.014277	0.0000	0.2907	0.0000	0.0000
	(0.0053)	(0.3173)	(0.0758)	(0.3614)	(0.0138)	(0.0049)
	0.0000	0.0450	0.000	0.8044	0.000	0.000
Constant Corr	0.449732		-0.4233		-0.8878	
	(0.0968)		(0.8102)		(0.0059)	
	4.6480		-0.5224		-151.0772	

Table 6 (Continued)
Constant Correlation
Multivariate GARCH-in-Mean: ln(Auto) Retail Series
Mean Equation : VAR,
(Robust standard errors are reported in parentheses)

	Model E	
	Ln(Inv)t	Ln(Sls)t
Constant	-0.8814 (6.5727) -0.1341	-0.0183 (71.6906) -0.0003
$ln(Inv)_{t-1}$	1.0550 (0.3747) 2.8155	0.3533 (91.6906) 0.0039
$ln(Inv)_{t-2}$	-0.1285 (12.0703) -0.0106	-0.0314 (103.24) -0.0003
$ln(Inv)_{t-3}$	-0.0177 (6.3064) -0.0028	-0.2753 (9.8957) -0.0278
$ln(Sales)_{t-1}$	0.0793 (15.9693) 0.0050	0.6190 (63.2283) 0.0098
$ln(Sales)_{t-2}$	0.0096 (5.4733) 0.0018	0.0785 (30.3008) 0.0026
$ln(Sales)_{t-3}$	-0.0011 (2.8798) -0.0004	0.2499 (14.0426) 0.0178
CondStdInv	-41.0956 (84.7760) -0.4848	
CondStdSls	20.1711 (33.5636) 0.6010	
	CondVarInv	CondVarSls
Constant	0.0000 (0.0028) 0.000	0.0079 (0.0056) 1.4171
ARCH	0.0000 5.2488e-007 0.000	0.0014 (0.3349) 0.0041
GARCH	1.0000 (0.4267) 2.3434	0.0000 (2.0526) 0.000
Constant Corr	-0.4874 (3.2294) -0.1509	

APPENDIX 4
VAR Results for ln(Retail Series), Diagonal Models

Table 1
Diagonal Model
Multivariate GARCH-in-Mean: Auto Dealers
Mean Equation: VAR. (Robust Standard Errors of Estimates are in Parentheses)

	Ln(Auto) Model A		Ln(Auto) Model C		Ln(Auto) Model D	
	$Ln(Inv)_t$	*$Ln(Sls)_t$*	*$Ln(Inv)_t$*	*$Ln(Sls)_t$*	*$Ln(Inv)_t$*	*$Ln(Sls)_t$*
Constant	-0.563422 (0.2793) -2.0173	-1.6196 (0.7091) -2.2840	-1.7601 (0.0294) -59.9204	-0.0253 (0.0490) -0.5151	-1.0055 (0.1846) -5.4480	-0.2177 (0.0518) -4.2070
$Inventory_{t-1}$	0.958242 (0.0571) 16.7845	0.345237 (0.0691) 4.9968	1.1063 (0.0015) 748.5943	0.3681 (0.0798) 4.6136	1.0539 (0.0142) 74.4043	0.5545 (0.1664) 3.3333
$Inventory_{t-2}$	-0.016327 (0.0796) -0.2052	0.016598 (0.1429) 0.1161	-0.1020 (0.0159) -6.4197	-0.0690 (0.0948) -0.7283	0.0025 (0.0952) 0.0262	-0.2599 (0.2602) -0.9988
$Inventory_{t-3}$	-0.036403 (0.0413) -0.8812	-0.30961 (0.0474) -6.5333	-0.0753 (0.0201) -3.7478	-0.2612 (0.0628) -4.1586	-0.0670 (0.1066) -0.6270	-0.1207 (0.2683) -0.4500
$Sales_{t-1}$	0.05635 (0.0165) 3.4107	0.583248 (0.0557) 10.4792	0.0098 (0.0314) 0.3124	0.5925 (0.0361) 16.4057	-0.1370 (0.0710) -1.9291	0.6312 (0.1984) 3.1810
$Sales_{t-2}$	0.026523 (0.0559) 0.4748	0.050678 (0.1641) 0.3089	0.0440 (0.0368) 1.1940	0.1269 (0.1632) 0.7771	0.0331 (0.1111) 0.2980	0.3092 (0.2920) 1.0588
$Sales_{t-3}$	0.010851 (0.0427) 0.2542	0.309458 (0.1155) 2.6802	0.0166 (0.0293) 0.5670	0.2410 (0.0928) 2.5979	0.1187 (0.1115) 1.0649	-0.1061 (0.2684) -0.3952
CondVarInv						
CondVarSls					21.3210 (0.7015) 30.3942	
CondStdInv	-127.037223 (12.4524) -10.2018	-78.587267 (31.2484) -2.5149				
CondStdSls	67.421711 (2.7160) 24.8240	66.765744 (1.1243) 59.3859	22.0841 (0.6150) 35.9090			
	$CondVarInv_t$	$CondVarSls_t$	$CondVarInv_t$	$CondVarSls_t$	$CondVarInv_t$	$CondVarSls_t$
Constant	-0.010123 (2.186e-05) -6430.0	0.001885 (0.0018) 1.0519	0.0204 (0.0023) 9.0257	-0.0059 (0.0012) -4.7263	-0.0215 (0.0012) -18.1094	0.0560 (0.0022) 25.1503
ARCH	0.012185 (0.0014) 8.5970	0.032141 (0.0010) 31.6541	0.6016 (0.0505) 11.9184	-0.0689 (0.0030) -22.8426	0.3951 (0.1450) 2.7249	-0.1955 (0.0192) -10.1654
GARCH	0.876344 (9.613e-010) 9.1167e+08	-0.164308 (0.0300) -5.4794	-0.0512 (0.1377) -0.3719	0.6874 (0.0105) 65.3943	0.6671 (0.1918) 3.4780	0.7706 (0.0156) 49.5084

Table 1 (Continued)
Diagonal Model
Multivariate GARCH-in-Mean: Auto Dealers
Mean Equation: VAR.
(Robust Standard Errors of Estimates are in Parentheses)

	Model E	
	$Ln(Inv)_t$	*$Ln(Sls)_t$*
Constant	-2.9480 (0.1278) -23.0672	-0.0134 (0.0712) -0.1882
$Inventory_{t-1}$	1.0447 (0.0042) 247.3650	0.3477 (0.2885) 1.2051
$Inventory_{t-2}$	-0.1084 (0.0615) -1.7624	-0.0204 (0.3825) -0.0533
$Inventory_{t-3}$	-0.0285 (0.0462) -0.6174	-0.2738 (0.1238) -2.2122
$Sales_{t-1}$	0.0808 (0.1041) 0.7760	0.6035 (0.2393) 2.5224
$Sales_{t-2}$	0.0143 (0.1006) 0.1426	0.0727 (0.1958) 0.3714
$Sales_{t-3}$	-0.0039 (0.0309) -0.1277	0.2654 (0.0581) 4.5707
CondVarSls		
CondStdInv	-18.8492 (2.1020) -8.9671	
CondStdSls	64.8992 (1.5051) 43.1208	
	$CondVarInv_t$	$CondVarSls_t$
Constant	0.0076 (0.0000972) 77.8117	-0.0057 (0.0016) -3.5505
ARCH	-0.0213 (0.0016) -13.6633	0.0196 (0.0072) 2.6998
GARCH	0.9357 (0.000375) 2493.5	0.2837 (0.0159) 17.8068

Table 2
Diagonal Model
Multivariate GARCH-in-Mean: ln(Apparel Series)
Mean Equation: VAR. Robust Standard Errors of Estimates are in Parentheses

	Ln(Apparel) Model A		Ln(Apparel) Model C		Ln(Apparel) Model D	
	Ln(Inv)$_t$	*Ln(Sls)$_t$*	*Ln(Inv)$_t$*	*Ln(Sls)$_t$*	*Ln(Inv)$_t$*	*Ln(Sls)$_t$*
Constant	-13.142058 (3.2362) -4.0610	-3.44292 (0.1253) -27.4724	-21.4238 (15.1357) -1.4154	-0.0958 (0.2967) -0.3227	-5.8007 (1090.7) -0.0053	-0.0947 (8.4431) -0.0112
Inventory$_{t-1}$	-1.144812 (0.0881) -12.9965	-0.001372 (0.000282) -4.8595	1.4667 (4.6496) 0.3154	0.1690 (0.7241) 0.2334	1.0355 (82.0133) 0.0126	0.1729 (18.3838) 0.0094
Inventory$_{t-2}$	-1.23514 (0.3602) -3.4293	-0.221597 (0.0235) -9.4464	0.6090 (3.1430) 0.1938	-0.1393 (0.0491) -2.8346	0.1737 (3.8911) 0.0446	-0.1420 (25.3349) -0.0056
Sales$_{t-1}$	2.298684 (0.1649) 13.9408	0.954871 (0.0281) 34.0124	0.6016 (2.6768) 0.2247	0.6732 (0.1236) 5.4472	0.2069 (62.9441) 0.0033	0.6741 (7.6987) 0.0876
Sales$_{t-2}$	2.439554 (0.4897) 4.9818	0.545997 (0.0688) 7.9358	0.5477 (0.6618) 0.8276	0.2448 (0.9014) 0.2715	0.1489 (70.4707) 0.0021	0.2399 (77.6848) 0.0031
CondVarSls					-2.0703e-011 (4.8410e-09) -0.0043	
CondStdInv	0.002190 (0.000219) 9.9562	-0.002383 (0.000918) -2.5930				
CondStdSls	-0.000664 (0.0000229) -28.9302	0.007750 (0.00015) 50.6013	0.0000010164 (0.0000000239) 42.5994			
	CondVarInv$_t$	CondVarSls$_t$	CondVarInv$_t$	CondVarSls$_t$	CondVarInv$_t$	CondVarSls$_t$
Constant	5510571.74 (298781.9) 18.4435	1606311.93 (64534.27) 24.8908	5606800.00 (378440.0) 14.8154	1612900.00 (108870.0) 14.8154	5606800.0 (373250.0) 15.0213	1612900.0 (112050.0) 14.3947
ARCH	479.7146 (18.7364) 25.6034	-287.6892 (36.9713) -7.7814	473.4993 (2.2859) 207.1389	-282.5919 (11.6428) -24.2718	473.7099 (536.2029) 0.8835	-282.5919 (867.7974) -0.3255
GARCH	0.175388 (0.0016) 108.7213	-0.426138 (0.0505) -8.4447	-0.0000022635 (2.1032e-008) -107.6219	0.00002359 (0.00000173) 13.6161	0.00003478 (0.0000022) 15.8644	0.00004352 (0.0000013) 34.3735

Table 3
Diagonal Model
Multivariate GARCH-in-Mean: ln(Food Retail) Series
Mean Equation: VAR. Robust Standard Errors of Estimates are in Parentheses

	Model A		Model C		Model D	
	ln(Inv)$_t$	*ln(Sales)$_t$*	*ln(Inv)$_t$*	*ln(Sales)$_t$*	*ln(Inv)$_t$*	*ln(Sales)$_t$*
Constant	4.249913 (0.9472) 4.4866	-1.971099 (0.1072) -18.3837	2.8381 (4.2245) 0.6718	-2.0040 (0.1174) -17.0699	0.8067 (0.6492) 1.2426	0.5539 (0.0483) 11.4799
Ln(Inv)$_{t-1}$	-1.38809 (0.5868) -2.3654	-0.325611 (0.0475) -6.8562	3.8191 (2.0137) 1.8965	0.4498 (0.1098) 4.0968	4.4637 (0.7590) 5.8811	0.2108 (0.0372) 5.6679
Ln(Inv)$_{t-2}$	-6.91905 (1.1927) -5.801	-0.072976 (0.0383) -1.9059	0.9790 (8.0621) 0.1214	-2.4567 (0.0032) -766.6040	-8.1273 (1.0024) -8.1077	1.5606 (0.5183) 3.0112
Ln(Sales)$_{t-1}$	5.163103 (1.7435) 2.9613	1.24703 (0.0083) 150.5743	-5.0887 (0.7238) -7.0305	0.4695 (0.1345) 3.4912	3.5732 (0.6892) 5.1844	-1.1395 (0.4711) -2.4188
Ln(Sales)$_{t-2}$	2.038185 (0.2504) 8.1405	0.588181 (0.0281) 20.9184	0.5717 (7.5579) 0.0756	2.8674 (0.0022) 1275.70	0.3575 (0.1538) 2.3252	0.2274 (0.0883) 2.5760
CondVarInv						
CondVarSls					0.00001499 (3.696e-05) 0.4054	
CondStdInv	-0.163583 (0.0138) -11.8817	0.006477 (4.624e-04) 14.0074				
CondStdSls	2.501747 (0.1217) 20.5570	-0.097894 (0.0012) -78.5908	0.0094 (0.0005) 18.2560			
	CondVarInv$_t$	CondVarSls$_t$	CondVarInv$_t$	CondVarSls$_t$	CondVarInv$_t$	CondVarSls$_t$
Constant	8272.00282 (132.5292) 62.4165	0.009553 (0.0038) 2.5375	8414.500 (681.0064) 12.3560	0.0152 (0.0028) 5.4491	8415.400 (847.5492) 9.9291	0.0003168 (0.0009903) 0.3199
ARCH	-0.964264 (0.0134) -72.2104	-0.956692 (0.0096) -99.8828	0.3207 (0.0208) 15.4250	0.3670 (0.0302) 12.1375	1.4187 (0.0420) 33.7421	1.3881 (0.0263) 52.8184
GARCH	0.096193 (7.556e-05) 1273.00	0.096178 (7.577e-05) 1269.30	0.1615 (0.0001162) 1389.400	1.1614 (0.0001155) 1398.200	0.0754 (0.0004) 170.2377	0.0754 (0.0004435) 170.0703

Table 3 (Continued)
Diagonal Model
Multivariate GARCH-in-Mean: ln(Food Retail) Series
Mean Equation: VAR.
Robust Standard Errors of Estimates are in Parentheses

	Model F	
	ln(Inv)$_t$	*ln(Sales)$_t$*
Constant	1.4878 (5.7987) 0.2566	0.2698 (0.4326) 0.6238
Ln(Inv)$_{t-1}$	-4.3864 (5.6042) -0.7827	0.8909 (0.0390) 22.8272
Ln(Inv)$_{t-2}$	4.2008 (4.0333) 1.0415	0.1553 (0.0962) 1.6153
Ln(Sales)$_{t-1}$	-1.3991 (2.7993) -0.4998	0.5595 (0.0377) 14.8253
Ln(Sales)$_{t-2}$	1.9012 (2.5693) 0.7400	-0.7302 (0.0441) -16.5492
CondVarInv	-0.1573 (0.000278) -566.5740	
CondVarSls	2.1601 (0.0018) 1211.6	
CondStdInv		
CondStdSls		
	CondVarInv$_t$	CondVarSls$_t$
Constant	8412.9 (3.4744) 2421.4	-0.0101 (0.0035) 2.8604
ARCH	-0.3354 (0.046) -8.2598	-0.3640 (0.0848) -4.2917
GARCH	-0.4220 (0.000194) -2179.4	-0.4220 (0.000188) -2241.7

Table 4
Diagonal Model
Multivariate GARCH-in-Mean: ln(Furniture Retail Series)
Mean Equation: VAR. Robust Standard Errors of Estimates are in Parentheses

	Model C		Model D		Model E	
	ln(Inv)$_t$	*ln(Sales)$_t$*	*ln(Inv)$_t$*	*ln(Sales)$_t$*	*ln(Inv)$_t$*	*ln(Sales)$_t$*
Constant	8.6958 (0.0137) 636.0533	8.1178 (0.0115) 705.2890	3.6437 (0.0093) 393.4373	1.3120 (0.0423) 31.0268	-0.4329 (0.0231) -18.7535	-0.7762 (0.0494) -15.7052
Ln(Inv)$_{t-1}$	0.2515 (0.0014) 176.2208	-0.3802 (0.0054) -70.1841	0.6699 (0.0013) 523.6861	-0.0894 (0.0027) -33.3879	1.0088 (0.000841) 1199.4	0.2617 (0.0013) 197.9179
Ln(Sales)$_{t-1}$	-0.2238 (0.0015) -145.0373	0.4386 (0.0061) 72.4951	-0.1053 (0.0009) -122.8512	0.8997 (0.0612) 14.7018	-0.0235 (0.000726) -32.3252	0.7459 (0.0064) 115.760
CondVarInv						
CondVarSls			2.1777 (0.1491) 14.6011			
CondStdInv					0.4010 (0.1242) 3.2285	
CondStdSls	0.9229 (0.0178) 52.1067				1.0110 (0.0808) 12.5103	
	CondVarInv$_t$	CondVarSls$_t$	CondVarInv$_t$	CondVarSls$_t$	CondVarInv$_t$	CondVarSls$_t$
Constant	-0.0061 (0.000618) -9.8844	0.0064 (0.0020) 3.2795	0.0061 (0.0026) 2.3133	-0.0371 (0.0121) -3.0795	0.0077 (0.0024) 3.1607	-0.3154 (0.0094) -33.5822
ARCH	-0.7043 (0.0439) -16.0288	-0.5972 (0.0047) -128.3471	-0.5967 (1.6958) -0.3519	-0.2769 (0.0043) -64.9165	-0.9621 (0.1757) -5.4751	0.4013 (0.0075) 53.7166
GARCH	-0.6748 (0.0241) -27.9866	-0.8251 (0.0037) -222.1657	-0.6823 (0.9466) -0.7207	-0.9601 (0.0622) -15.4444	-0.4026 (0.2039) -1.9741	0.7229 (0.0220) 32.8572

Table 5
Diagonal Model
Multivariate GARCH-in-Mean: General Merchandise Retail Series
Mean Equation: VAR. Robust Standard Errors of Estimates are in Parentheses

	Model A		Model C		Model D	
	ln(Inv)$_t$	*ln(Sales)$_t$*	*ln(Inv)$_t$*	*ln(Sales)$_t$*	*ln(Inv)$_t$*	*ln(Sales)$_t$*
Constant	0.474845 (0.5786) 0.8206	0.431683 (0.2151) 2.0072	8.0383 (0.4729) 16.9987	0.5801 (0.0988) 5.8698	-15.8103 (0.5954) -26.5525	-2.0733 (0.3673) -5.6448
Ln(Inv)$_{t-1}$	0.483139 (0.4865) 0.9931	-0.510993 (0.1562) -3.2724	8.9192 (0.1532) 58.2186	1.8253 (0.0271) 67.4045	28.5944 (0.8441) 33.8753	3.3916 (0.0276) 123.0229
Ln(Inv)$_{t-2}$	-0.203314 (0.4998) -0.4068	0.123360 (0.2321) 0.5315	--12.1163 (0.1522) -79.5894	-2.4760 (0.0228) -108.3850	-22.8605 (0.7379) -30.9820	1.1368 (0.1291) 8.8079
Ln(Inv)$_{t-3}$	0.761182 (0.4554) 1.6716	-0.690546 (0.0202) -34.2106	-3.7760 (0.0851) -44.3551	-0.4273 (0.1761) -2.4263	0.7548 (0.0285) 26.5139	-4.5238 (0.3717) -12.1717
Ln(Sales)$_{t-1}$	-0.528177 (0.4757) -1.1102	1.351674 (0.0023) 577.7614	16.0088 (0.0581) 275.4071	2.3124 (0.0099) 234.3515	-13.1741 (0.0694) -189.6922	-1.0543 (0.0138) -76.2480
Ln(Sales)$_{t-2}$	-0.429173 (2.6737) -0.1605	-0.040527 (0.2012) -0.2014	-4.0333 (0.3918) -10.2943	0.0771 (0.0109) 7.0620	30.5280 (0.5769) 52.9162	6.4037 (0.4314) 14.8450
Ln(Sales)$_{t-3}$	0.530006 (3.6246) 0.1462	0.612987 (0.1856) 3.3026	-5.3633 (0.3626) -14.7909	-0.5009 (0.1745) -2.8696	-18.7474 (0.6446) -29.0846	-3.8604 (0.0688) -56.1009
CondVarInv						
CondVarSls					-7.5693e-006 (3.9103e-07) -19.3574	
CondStdInv	-0.021013 (0.0015) -14.4628	0.002183 (2.330e-08) 9367.3				
CondStdSls	0.156813 (0.0106) 14.8237	-0.015149 (7.389e-05) -205.0055	-0.0059 (3.125e-04) -18.9252			
	CondVarInv$_t$	CondVarSls$_t$	CondVarInv$_t$	CondVarSls$_t$	CondVarInv$_t$	CondVarSls$_t$
Constant	4809.60075 (3.2718) 1470.0	-0.004048 (0.0235) -0.1725	4805.7 (539.0457) 8.9152	-0.0126 (0.0013) -9.3685	4800.50 (199.7755) 24.0295	-0.0131 (0.0848) -0.1547
ARCH	2.157574 (0.7758) 2.7812	0.077479 (0.1619) 0.4787	0.2624 (0.0276) 9.4919	0.2513 (0.0173) 14.5198	3.1780 (0.1012) 31.3880	3.0167 (0.3437) 8.7782
GARCH	-0.023066 (3.978e-05) 580.00	-0.023095 (3.702e-05) 624.000	0.13000 (0.000514) 252.9473	0.13000 (0.00051408) 252.9105	0.1973 (0.0011) 173.9875	0.1973 (0.0011) 173.4236

Table 5 (Continued)
Diagonal Model
Multivariate GARCH-in-Mean: General Merchandise Retail Series
Mean Equation: VAR.
Robust Standard Errors of Estimates are in Parentheses

	Model E	
	$ln(Inv)_t$	*$ln(Sales)_t$*
Constant	0.6908 (0.4140) 1.6685	0.7694 (4.207e-05) 18289.0
$Ln(Inv)_{t-1}$	0.8098 (0.0033) 248.5378	0.4728 (0.0201) 23.5525
$Ln(Inv)_{t-2}$	-0.3450 (6.9749e-05) -4946.10	1.2797 (0.0787) 16.2590
$Ln(Inv)_{t-3}$	-0.2299 (0.0179) -12.8107	0.8119 (0.1993) 4.0744
$Ln(Sales)_{t-1}$	-0.0094 (0.0076) -1.2386	-0.3792 (0.0015) -249.7668
$Ln(Sales)_{t-2}$	0.2481 (0.1530) 1.6220	-1.0283 (0.1651) -6.2294
$Ln(Sales)_{t-3}$	0.1959 (0.0098) 19.9348	-1.1623 (0.2962) -3.9234
CondVarInv		
CondVarSls		
CondStdInv	-0.0459 (1.5194e-04) -301.9866	
CondStdSls	0.3404 (0.0011) 316.8558	
	$CondVarInv_t$	$CondVarSls_t$
Constant	4811.9 (0.9811) 4904.4	0.0000965 (0.0014) 0.0693
ARCH	2.1775 (0.1334) 16.3180	-0.7350 (0.0168) -43.7625
GARCH	0.1373 (3.0374e-05) 4519.80	0.1375 (2.853e-05) 4819.40

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Table 6
Diagonal Model
Multivariate GARCH-in-Mean: ln(Building Material Retail Series)
Mean Equation: VAR. Robust Standard Errors of Estimates are in Parentheses

	Model C		Model D	
	ln(Inv)$_t$	*ln(Sales)$_t$*	*ln(Inv)$_t$*	*ln(Sales)$_t$*
Constant	95.0591 (13.3887) 7.0999	-0.1771 (5.5871) -0.0317	1.1024e+08 (5.2618e+05) 209.5203	-2258.1 55.4241 -40.7426
Ln(Inv)$_{t-1}$	-4.4291 (2.7355) -1.6191	0.0472 (0.6452) 0.0732	-5.7663e+06 (5.0173e+04) -114.93	-77988.0 653.5276 -119.3334
Ln(Sales)$_{t-1}$	-4.8253 (2.3967) -2.0133	0.9009 (0.0790) 11.4004	-6.1068e+06 (6.4224e+04) -95.0850	86067.0 (712.5684) 120.7837
CondVarInv				
CondVarSls			0.00000378 (2.7354e-06) 1.3826	
CondStdInv				
CondStdSls	3.7182e-07 (1.772e-07) 2.0978			
	CondVarInv$_t$	CondVarSls$_t$	CondVarInv$_t$	CondVarSls$_t$
Constant	2.6223e+06 (1.7700e+05) 14.8154	6.8291e+05 (4.6095e+04) 14.8151	2.6228e+06 (7.8775e+05) 3.3295	1.4294e+05 (9605.6) 14.8806
ARCH	685.0120 (91.6105) 7.4774	-491.1601 (39.7338) -12.3613	14116.0 (1283.5) 10.9977	84.2149 (0.9856) 85.4485
GARCH	1.3577e-05 (1.686e-05) 0.8052	-8.5622e-06 (1.2428e-05) -0.6889	0.0049 (0.0284) 0.1738	-0.1405 (0.0064) -21.8335

Chapter 2. LIFE AND PROPERTY-CASUALTY INSURANCE INDUSTRY COMPARISONS FOUR YEARS AFTER THE ENACTMENT OF GLBA

1. INTRODUCTION

The Financial Services Modernization Act of 1999, also known as the Gramm-Leach-Bliley Act (GLBA), allows banks to enter insurance markets and to underwrite securities. This act substantially eliminates the barriers separating the banking, insurance, and securities industries. Section 104 of this act reaffirms the role of state insurance authorities as the functional regulators of insurance and requires compliance with State insurance licensing requirements, subject to nondiscrimination requirements.

The Gramm-Leach-Bliley Act (GLBA) of 1999 allows the creation of financial holding companies (FHCs) as a vehicle to engage in cross industry businesses and as a way to expand the businesses of bank holding companies (BHCs). The act allows a BHC, a holding company that controls one or more banks under the supervision of the Federal Reserve, to become an FHC with certain eligibility requirements. It is expected that the legislation will result in more competitive, stable, and efficient financial firms, and a better overall capital market (Santomero 2000).

Several benefits and costs of the Financial Service Modernization Act have been discussed in the literature including enhanced competition, increased efficiency, lower costs for consumers, improved access, and availability of new products and services (DiLorenzo 2003). DiLorenzo measures competition as the number of financial holding companies (FHCs) created, and observes that in 2002, banks have established a great number of these new entities, and few insurance or securities firms have done so.

Table 1.1 shows that the number of FHCs grew from 483 in 2000 to 636 in 2004 and have become potential entrants into insurance industries.

Table 1.1
Number of Financial Holding Companies 1999-2004

Year	Number of Domestic FHCs	Number of Foreign FHCs	Total
2000	462	21	483
2001	567	23	590
2002	602	30	632
2003	612	32	644
2004	600	36	636

Source: Financial Services Fact Book, Insurance Information Institute (from the Board of Governors of the Federal Reserve System). This source noted that there were 5,151 top tier BHCs in 2004; 12 percent had FHC status, according to the Federal Reserve.

White (2004) reported that the number of Bank Holding Companies (BHCs) with total assets $100 million or greater which underwrite insurance increased from 134 in 2001 to 171 (out of 251 BHCs' total) in 2002. This shows an increase of 24.6%. The author reported that in 2002, 45 engaged in property-casualty, and 72 engaged in life and health insurance.

Table 1.2
Bank-Produced Insurance Premiums, 1999-2003
(Billions of US$)

Year	Life & Health Insurance	Property-Casualty Insurance	Total
1999	$ 28.9	$ 7.5	$ 36.4
2000	35.8	9.1	44.9
2001	42.2	13.0	55.2
2002	53.0	16.5	69.5
2003	57.6	20.5	78.1

Source: Financial Services Fact Book, Insurance Information Institute (from American Bankers Insurance Association)

Table 1.2 shows a greater involvement of banks in life insurance than in property-casualty insurance. The table shows that in 1999 (before the enactment of GLBA), banks were already writing insurance. Yeager, Yeager and Harshman (2005) in section 2 also reported a greater involvement of FHCs in life insurance underwriting than in property-casualty insurance.

Previous studies suggest that banks would find life insurance more attractive than property-casualty insurance due to lower volatility return, lower selling expense, and higher demand than the property-casualty insurance. For example, Lown et al (2000) used pre-GLBA data on profitability at firm level in terms of equity rate of return as well as the risk factors in terms of standard deviation of return as measures of the attractiveness of life insurance for entrants. The authors recommended that banks enter the life insurance industry since they found that the combination of banks with life insurance firms was less risky in terms of lower standard deviation of return. Laderman (1999 p. 22) suggested that the life insurance industry's attraction for entrants (banks) is its low return variance, and based on pre-GLBA data the author recommended that banks enter into life insurance underwriting since it will reduce the probability of bankruptcy. Boyd & Graham (1988) also used pre-GLBA data and found that combining banks with life insurance firms could enable banks to reduce the probability of bankruptcy since the combination will reduce the volatility of profits. The pre-GLBA data used in these three studies shows that the standard deviation of return of life insurance was lower than that of property-casualty insurance. Yeager, Yeager & Harshman (2005) use the sensitivity of FHC's return to the fluctuation of market return (called beta) as a measure of return volatility. They show that the volatility of return decreases from 0.85 pre-GLBA (1996-

1999) to 0.31 in post-GLBA (2000-2003), and the return also decreases from 0.284 to 0.154.

This study uses different samples from capital market data to compare the return and variability of the life and health insurance with the property-casualty insurance companies before and after the enactment of GLBA. The enactment of GLBA may not have greatly affected the insurance industry, since GLBA did not address the regulation of price by state insurance commissions; a significant number of states require either prior approval or conditional approval of rates (DiLorenzo 2003, p. 328). GLBA was not complete deregulation, and this act is not a single event or law, but rather a relentless process of eroding the constraints placed on the financial marketplace (Santomero 2001). Also banking organizations had already exploited insurance activities before the enactment of GLBA, which simply made it easier for banks to continue the activities they had undertaken (Yeager, Yeager & Harshman 2005). The market structure of insurance industries did not change dramatically after the enactment of GLBA in terms of the number of companies in the market and the greater size of the life insurance premium relative to the property-casualty insurance premium, as reported in Table 1.3 and Table 1.4. This suggests that the profitability and volatility of life insurance may not differ substantially from the period prior to the enactment of GLBA. This study adds to the analysis tests of differences in mean and variances of return in life insurance and property-casualty insurance both before and after the enactment of GLBA.

In addition to lower earning variability, other attractions for entrants in the life insurance industry include the size of demand for insurance (Browne & Kim 1993); its faster growth in premiums than that of property and casualty insurance (Lown at al

2000); and its lower selling expenses (Carow 2001). In particular, this study examines the demand for insurance represented by the size of premium earned four years after the enactment of GLBA and observes whether the demand for life insurance is higher than that for property-casualty insurance. Since the theoretical background discussed in section 2 links higher revenue or demand with a safer or lower-risk financial institution (Berger 2000), this study could conclude that life insurance will be less risky than property insurance if the demand for life insurance is higher than the demand for property insurance. This indirectly supports previous recommendations for banks to enter life insurance.

As an analytical tool, this study uses two regression models, each for life and property-casualty insurance, with the premium size representing insurance demand at state levels as dependent variables. A pooled regression is not used because they have a different structure suggested by the Chow tests. This study uses four-year cross-sectional data from 15 states that consists of 12,000 observations. The factors affecting the demand for property-casualty and the demand for life insurance firms from previous studies are used as control variables. These include income, number of companies, and education.

In the literature, in addition to equity rate of return, other measures of insurance performance include return on assets (Laderman 1999), underwriting margin (Doherty & Garven 1995) and the loss ratio. The underwriting margin is defined as (Premium–Loss)/Premium, and the loss ratio is defined as Loss/Premium. The loss ratio used in this study is defined as (Incurred Loss/Earned Premium)*100, or alternatively one minus underwriting margin. The measures of the industry’s attractiveness used in this study, premium collected and the loss ratio, relate to one another. The premium earned is a component in the formula for the loss ratio. This study compares life and property-casualty insurance in terms of loss ratio using two regression models each for life and property-casualty insurance. Two separate regressions are run because they have different structures. This study follows Gron's (1994) naïve assumption that underwriting margin rises when there is an increase in premiums and falls when there is a decrease in premiums. Thus, the variables that affect the premiums earned are also assumed to affect the loss ratio. Carow (2001) argues that since banks are predicted to emphasize the sale of life insurance products, there will be increasing competition in the life insurance segment. This increased competition will result in lower profits for life insurance companies than property-casualty insurance companies.

This study uses loss ratio as a measure of insurance performance rather than a firm-wide profitability because the firm-wide profitability data is not available at the state level. The second reason is that many insurance companies operate business in both life and in property-casualty insurance businesses so that there is an operating expense that must be segmented. The data on segmented expenses are not available. Also the loss ratio is most extensively used in evaluating underwriting results and in insurance decision making (Kahane & Porat 1984). Finally, higher loss ratios may indicate not only lower underwriting profitability but also a reduction in funds available to invest by insurance companies.

This study finds that the return and variance of return in each and between life and property-casualty insurance industries do not differ significantly before and after the enactment of GLBA. Using premiums earned as a measure for the industry's demand, this study finds that life insurance collects more premiums than property-casualty insurance. The premium earned by life insurance firms is significantly higher than property-casualty insurance firms in any year during the four-year period upon the enactment of the GLBA.

Table 1.3
Insurance Premium for Selected Years
Millions US Dollars

Year	Property-Casualty**	Life and Health*
1970	32,579	36,767
1975	48,706	58,575
1980	92,397	92,624
1985	138,505	155,863
1990	210,203	264,010

Source: *) Economics and Statistics Administration, Office of Policy Development, ESA/OPD 96-2, from the American Council of Life Insurance
**) Economics and Statistics Administration, Office of Policy Development, ESA/OPD 96-2, from the Bests' Aggregates and Averages, 1994

Table 1.4
Insurance Premium and Computations of Its Growth
from 1992 to 2003

	Property-Casualty Insurance		Life & Health Insurance	
Year	Premium (000s)	Growth from previous year	Premium (000s)	Growth from previous year
1992	249,577,659	---	293,174,845	---
1993	262,756,158	5.28 %	319,458,164	8.97 %
1994	273,766,045	4.19 %	345,439,186	8.13 %
1995	280,971,191	2.63 %	358,619,388	3.82 %
1996	288,665,073	2.74 %	383,068,419	6.82 %
1997	293,853,688	1.80 %	419,262,523	9.45 %
1998	300,062,051	2.11 %	459,039,518	9.49 %
1999	311,522,554	3.82 %	509,602,103	11.04 %
2000	326,731,997	4.88 %	555,893,398	9.08 %
2001	368,073,661	12.65 %	584,307,446	5.11 %
2002	422,094,458	14.68%	615,452,794	5.33%
2003	462,130,431	9.49%	631,232,155	2.56%
	Average growth	5.84 %	Average growth	7.25 %

Source of the Premium Figures: The Website of the National Association of Insurance Commissioners

The regression results also find that per capita income and population significantly increase premiums in both segments of the industry. The domicile of companies is also a significant determinant, with domestic companies collecting more premiums than foreign companies. Firms in states with elected insurance commissioners collect more premiums than those in states with appointed commissioners. Education does not affect premiums earned in life insurance but it does in the property-casualty insurance industry.

This study finds that the loss ratio is higher for life insurance than property-casualty insurance in the four years after the enactment of GLBA. The lower loss ratio for property-casualty insurance is also suggested by Standard & Poor's. For example, Standard & Poor's Industry Survey (January 13, 2000 p. 21) reported that in property-casualty, loss ratio typically ranges from 60% to 80%. In life insurance, the average benefit (loss) ratios in the years 1999 and 2000 were 87.05% and 83.04%, respectively (Standard & Poor's Industry Survey 2002). The value of F-statistic is higher for the regression in life insurance, which means that the premium earned and loss ratio in the life insurance industry is more predictable than in the property-casualty insurance industry. Following Berger (2000), these higher premiums earned in life insurance should mean that the life insurance business is less risky than the property-casualty insurance business.

2. PREVIOUS STUDIES ON RECOMMENDING BANKS TO ENTER THE LIFE INSURANCE INDUSTRY

Previous studies suggested that financial institutions seek to achieve a low earning variability and based on this goal recommended that banks enter the life insurance industry.

2.1. The Low Earning Variability as a Desired Goal at Firm's Levels.

The GLBA's stated purpose was "to enhance competition in the financial services industry by providing a prudential framework for the affiliation of banks, securities firms, and other financial service providers, and for other purposes" (The GLBA S.900). The biggest potential benefit of the GLBA is that it allows financial institutions to exploit the revenue efficiencies and scale and scope economies that were unavailable before deregulation (Yeagers and Harshman 2005). For firms, their interests naturally will focus on the impact of the GLBA on their own competitive positioning (Santomero and Eckles, 2000).

The literature suggests that having a safe and stable operation or earnings is a desired objective for a financial institution. For example, Barth, Brumbaugh, and Wilcox (2000) predict several benefits for banks that expand activities under the GLBA. The greater profitability is expected from scope economies since certain fixed overhead costs can be used across a range of financial services. The existing technology, personnel, and networks will enable banks to distribute securities and insurance services at a low marginal cost. The authors predicted that a broad banking company may have a lower profit variance after entering insurance, which can reduce the likelihood of insolvency and in turn result in paying low interest rates on its funds.

Santomero and Eckles (2000) offered the advantages of reducing variability of income lending activity in addition to making an FHC safer and less susceptible to insolvency. Reduced risk directly reduces expected funding costs and directly affects reported earnings. Also earnings from lines of business in which customers value a bank's reputation for stability may increase as well. Finally, the firm may be able to increase the level of some risky, yet profitable, activities, such as commercial lending, without needing additional capital.

Berger (2000) provides the theoretical foundation that relates a higher demand for products of a financial institution and a low-risk firm. A firm seeks to diversify to reduce risk because this will improve cost efficiency and revenue efficiency. Three generally accepted concepts of efficiency are relevant in discussing the joining of two or more financial services organizations: cost efficiency, revenue efficiency, and profit efficiency. Cost efficiency is indicated by the closeness of a firm's costs to a best-practice firm, revenue efficiency is reflected by the customers' preferences and willingness to pay for a firm's outputs, and profit efficiency embodies both cost and revenue efficiency. In this case, the potential source of cost, revenue, and profit efficiency is the gain from integration. Particularly there are three main types of cost efficiency: scale efficiency, scope efficiency, and X-efficiency. The author argues that risk diversification is a source of efficiency and identified five market imperfections that encourage financial institutions to diversify risk. First, informational opacity of assets monitored motivates a financial institution to improve credibility by reducing risk by diversifying products. Second, asymmetric information relates to the capacity of a financial institution to honor a financial promise and guarantee a payment it makes. The value of the financial guarantee and the capacity to provide it depends on the ability of a firm to control the risk. Third, imperfect information exists about the cost of financial distress in the event of a financial failure or closure. The reduction of risk can reduce the expected cost of the failure. Fourth, government regulation or supervision also motivates a financial institution to reduce the risk in the form of government penalties, government actions, or closures.

Fifth, the illiquidity (for small financial institution shares) might cause the shareholders to prefer that the institution be managed in a risk-averse fashion. The improved cost and revenue efficiency include a lower cost of compliance with prudential regulation or supervision and increased revenue resulting from being a more credible and safer financial institution.

The importance of controlling risk is also inferred from the GLBA. Mamun, Hassan, and Maroney (2005) listed efforts by the GLBA to reduce exposure to systematic risk across the banking industry through gaining diversification benefits by removing barriers to entry, providing safeguards against excessive risk taking, establishing financial health criteria for expanding business into other sectors, assigning the FED the responsibility of FHC supervision and regulation, giving the FED access to risk data across the entire organization, and using other means to discipline institutions.

2.2. Recommendation for Entrants into the Insurance Industry

Several studies attempted to predict the effects of the GLBA on the relevent industries, including Hendershott, Lee, and Tompkins (2002), Carow and Heron (2001), Carow (2001), Cowen, Howell, and Power (2001), and Strahan and Sufi (2001). These papers use event study methodology to predict which industry will gain from GLBA. Hendershott, Lee, and Tompkins (2002) predicted that the impact of GLBA is asymmetric since commercial banks have been allowed to enter insurance and investment banking prior to the enactment of GLBA. They expected that the greatest effect of GLBA is on insurance companies and investment banks and found the largest abnormal returns among insurance companies and investment banks. The authors do not separate the insurance industry into life-health and property-casualty insurances. Carow and Heron

(2001) argue that banks will benefit by entering the insurance industry, but also do not differentiate life insurance from property-casualty insurance industries.

The following studies separated insurance firms into life-health and property-casualty insurance firms and recommended banks enter the life-health insurance industry. In general the studies made this recommendation because combining banking with life insurance will provide a less risky operation in terms of lower earnings variability. Table 2.1. reports the findings of these studies, which compared the profitability and volatility of life and property-casualty insurance prior to the enactment of GLBA.

Table 2.1
The Characteristics of Insurance Industries Prior to the Enactment of GLBA

Source	Life-Health		Property-casualty	
	Median Return	Std Deviation	Median Return	Std Deviation
Lown et. al. (2000)*)				
1971-1984	0.1282	0.0261	0.1344	0.0467
1984-1998	0.1058	0.0453	0.1117	0.0691
1992-1998	0.1123	0.0245	0.1173	0.0449
Laderman (1999)**)				
1979-1986	0.022985	0.006319	0.036977	0.023724
1987-1997	0.01204	0.005631	0.028082	0.015217
Boyd and Graham (1988)*)				
1971-1984	0.1282	0.0261	0.1344	0.0467

Note: *) Return is defined as return on equity
**) Return is defined as return on assets

This table shows that the returns experienced by the life-health insurance industry were lower than property-casualty insurance in all samples and regardless of the measurement used. Lown et.al (2000) reported that life insurance returns during 1971-1984, 1984-1998, and 1992-1998 were 0.1282, 0.1058 and 0.1123 respectively, and these were lower than the property-casualty insurance returns in the same period which were 0.1344, 0.1117 and 0.1173 respectively. The corresponding standard deviations of return in life insurance of 0.0261, 0.0453 and 0.0245 were lower than the standard deviations of return in property-casualty insurance which were 0.0467, 0.0691 and 0.0449. Laderman (1999) reported the return in life insurance for periods 1979-1986 and 1987-1997 were 0.022985 and 0.01204 respectively. These returns were lower than the returns in property-casualty insurance for the same periods which were 0.036977 and 0.028082. The corresponding standard deviations of return for life insurance for the periods 1979-1986 and 1987-1997 were lower at 0.006319 and 0.005631 than the standard deviations of return for property-casualty insurance at 0.023724 and 0.015217. Boyd and Graham (1988) reported the same figures as Lown et.al (2000).

A study by Lown et.al. (2000) examined the risk return profile that affects a BHC's merger. They used financial data of bank holding companies, securities, property and casualty insurance, life insurance, insurance agent/brokers, investment advice, real estate development, and other real estate firms for simulated mergers between BHCs and firms from a subset of the remaining financial services industries: life insurance, property and casualty insurance, and securities. In their study, the authors define rate of return as the equity rate of returns and risk as the standard deviation of that return. Their study shows that mergers between bank holding companies (BHCs) and life insurance firms produced firms that are less risky (and no less profitable) than either of the two individual industries: property-casualty insurance and securities. The results pointed most strongly to combinations of banks and life insurance companies.

To support their findings, Lown et al. (2000) compared the result with evidence from experience in Europe. In Europe between 1990-1999, banks and property-casualty insurance companies almost never combined, while mergers between banks and life insurance companies constituted more than 10% of the total business combination activities in financial services. The authors argue that the average growth in property-casualty premiums was slower than growth in life insurance premiums. According to the authors, one of many reasons for the sustainable growth of life insurance in Europe is rising income and wealth and an increasing proportion of older people.

Boyd and Graham (1988) simulated combinations between banks and non-bank financial firms and used the return on equity and its standard deviation as a measure of profitability and risk. They used 1971-1984 data from 146 BHCs, 15 property-casualty firms, 30 life insurance firms, and data from other firms that ranged from 5 to 31 firms. Hypothetical mergers were simulated between BHCs and property-casualty insurance, life insurance, securities, insurance agents and brokers, real estate development, and other real estate. Then a random selection of combined BHC and non-bank companies were repeatedly drawn to obtain relevant statistics from the two firms' historical data. The authors summed the profit and equity of the BHC and its non-bank partner to get the return on equity. Bankruptcy was defined as the situation where losses exceed equity. The results showed that even though its profitability was not the highest, the standard deviation on the return on equity was the lowest for the merger between BHC and life insurance firms. A calculation of the probability of bankruptcy was made in each pair of hypothetical bank/non bank industries. The authors concluded that combining bank holding companies and life-health insurance firms would reduce the volatility of returns and the risk of failure.

Laderman (1999) also simulated mergers between a BHC and individual non-bank firms. Instead of using the return on equity and its standard deviation, the author used the return on assets and standard deviation of assets as a measure of profitability and risk. A diversification benefit is defined as a decrease in the variance of return of assets below what it is for BHC alone. Bankruptcy is defined as the situation if losses exceed capital. The sample is divided into two periods. The first uses 1979-1986 data in which the number of BHCs was 200 (including 151 large BHCs with total assets of $ 1 billion or more), life insurance firms was 29, property-casualty firms was 33, and other firms was between 7 to 100. The second sample uses 1987-1997 data in which the number of BHCs was 422 (including 126 large BHCs), life insurance firms 50, property-casualty 103, and others between 24 to 95 firms. With the results from the first sample data, the author recommended banks enter life-health insurance firms; as a result of the second sample data, the author recommended banks enter either life-health or property-casualty insurance. A substantial level of investment in life insurance is needed to obtain optimal reduction in risk and appreciable levels on investment for optimal reduction in probability of bankruptcy.

Carow (2001) sees other reasons that banks might enter life insurance: insurance companies distribute their products through direct writers, exclusive agents, independent agents, and brokers. The author refers to the General Accounting Office Study (GAO, 1997), which found that a brokerage system has a higher cost in delivering property-casualty insurance; therefore, the author predicts that banks are expected to concentrate more heavily on life insurance activities.

Yeager, Yeager and Harshman (2005) use ex-post data to test the prediction that entering life and health insurance provided a less risky operation. The authors compare the performance of FHCs before and after the enactment of the GLBA. Unlike previous studies that used standard deviation of return as a measure of return volatility, these authors use the sensitivity of FHCs' return to the fluctuation of market return (beta) as a measure of return volatility. The authors show that FHCs were more involved in life-health insurance than in the property-casualty insurance between 2000 and 2003. The mean percentage of FHCs' total assets in life and health underwriting was 0.28% but only 0.6% in property-casualty underwriting. The authors show that the volatility of return by FHCs decreased from 0.85 pre GLBA (1996-1999) to 0.31 post GLBA (2000-2003).

These previous studies used historical data in their simulation in which the standard deviation of life insurance was lower than that of property-casualty insurance. Since this characteristic of data may change over time and over different samples, this study examines the profitability and variability of life and property-casualty insurance industry four years after the enactment of the GLBA using a different sample and different measurement of returns.

3. FACTORS AFFECTING THE DEMAND FOR INSURANCE

Several different models on the determinants of life insurance and property-casualty insurance demands have been developed in previous studies. These models enable this study to identify common variables that affect both the demand for life and property-casualty insurance.

3.1. Previous Studies Examining the Determinants of Life Insurance Demand

Schlag (2003) summarized the factors affecting life insurance demand used in the literature, which include macroeconomic, demographic, socio psychological and institutional variables, as well as insurer actions. Three measures of insurance demand commonly used in empirical studies are the number of insurance policies, the premium volumes, and the sums insured. Lim and Haberman (2004) examined the influence of macroeconomic variables affecting the demand for life insurance in Malaysia. They found that a combination of macroeconomic and demographic variables significantly affect the demand for life insurance. Inflation, fertility and crude live-birth rates, growth in GDP, improved financial development and a distressed stock market all significantly increase life insurance demand. Price of insurance and life expectancy had significant negative signs, and change in savings rate provided a mixed result depending on the measure of demand used.

Truett and Truett (1990) included only three variables in their study on the determinants of life insurance demand using Mexico data (1964–1979) and US data (1960-1982). Their study reported that education, real per capita income, and population within twenty-five to sixty-four years of age as a percent of total population had a positively significant effect on demand. Beck and Webb (2002) combined the macroeconomic and demographic variables from 68 countries as independent variables in their study on factors affecting life insurance demand. The results showed that income level, education, a higher share of young population, a higher level of banking sector, and larger shares of older population all increased life insurance consumption, while the inflation rate decreased life insurance demand. Browne and Kim (1993) examined life insurance demand using data from 45 countries. The number of dependents, income per capita, social security expenditures per capita, and third level education had a positive and significant effect on life insurance demand. Expected inflation rate and Islamic religion had negative signs and are significant. The authors found that life expectancy had no significant coefficient.

Outreville (1996) used data from developing countries to examine factors affecting premium income. GDP per capita, life expectancy, and level of financial development increased life insurance demand, while inflation and a monopolistic market had significant negative signs. The remaining control variables, including the real interest rate, foreign companies in the market, percentage of rural population, education level, health status, religion (Moslem population), social security, dependency ratio, and growth rate of population, all did not significantly affect life insurance demand.

3.2. Previous Studies Examining the Determinants of Property-Casualty Insurance Demand

Esho et al (2004) examined the determinants of demand for property-casualty insurance using a panel data consisting of 44 countries. The authors found that real GDP per capita, urbanization as proxy for loss probability (greater urbanization means greater loss probability), theft, and protection of property rights all have a significant, positive effect on the property-casualty insurance consumption. They also found that education (defined as the proportion of the population completing secondary education) and price did not affect insurance demand significantly.

Ma and Pope (2003) investigated important market characteristics or factors of foreign countries in the OECD that affect the demand for property-casualty insurance.

The authors use GDP per capita as a proxy for insurance demand based on their finding that an increase in GDP by 1 percent caused the premium written by foreign insurers to increase by 1.11 percent. The real interest rate in a host country has a significant positive effect on the premium written. Other findings were that a market that is not competitive had a significantly positive relation with the premium volume, but profitability variable had a significantly negative effect. Beenstock, Dickinson, and Kajura (1988) investigate the relations between property-liability premium per capita and GNP per capita as well as interest rate for 45 developed and developing countries in 1981. The authors found that the property-liability premium per capita rises significantly when income rises and varies directly with real interest rates.

Outreville (1990) investigated the effect of economic and financial developments on the property-liability insurance premium using cross-section data from 55 developing countries. The author found that GDP per capita and financial development (defined as the ratio of M2 to GDP) were the only factors that positively and significantly explained the level of property-liability insurance demand. The price of insurance had a negative sign but was insignificant. Education negatively and significantly affected property-liability insurance demand.

Browne, Chung, and Frees (2000) examined factors affecting property-liability insurance premiums per capita in the OECD countries. They found that property-liability insurance purchases were significantly higher in higher income, common law countries with a higher market share of foreign companies (which created a highly competitive insurance market). Wealth per capita, however, significantly reduced premium per capita while education and urbanization were insignificant.

3.3. Common Variables Affecting Both Life Insurance and Property-Casualty Insurance Demands.

This study needs to find a set of independent (common) variables that affect both property-casualty and life insurance firm performance. The use of common variables enables this study to see whether one industry performs better than another when facing the same environment represented by the common variables. This study uses the variables that appeared as independent variables in both life insurance and property-casualty insurance performance in previous studies, which are available in a state.

3.3.1. Income

The first common variable is income, which is expected to have a positive impact on premiums and insurance profitability. Numerous studies have used a version of income as a control variable in the analysis of life or property-casualty premiums. Table 3.1 reports studies that have included income as a control variable and the exact definition of income used in each study (GDP per capita, income per capita, etc). In all of these studies, the measure of income positively and significantly affects the demand for life and property-casualty insurance.

3.3.2. Education

The second variable is education. The relationship between education and demand for insurance is expected to be positive for two different reasons. Truett and Truett (1990) hypothesize that more highly educated people would recognize the various types of life insurance available and perhaps have a stronger desire to protect dependents. Browne, Chung, and Frees (2000) and Browne and Kim (1993) hypothesize that more education

Table 3.1
List of Income Variables Affecting Life and Property-casualty Insurance Performance from Previous Studies

Independent Variables	Affect Life Insurance Performance		Affect Property-Casualty Performance	
	Dependent Variable	Articles	Dependent Variable	Articles
National Income as a proxy of disposable income	Insurance Premium	Mark J. Browne and Kihong Kim (1993)		
GNP per capita			Insurance Premium per capita	Mark J Browne, Jae Wook Chung, and Edward W Frees (2000)
Log(GDP)			Demand (premium written per capita)	Yu-Luen M and Nat Pope (2003)
GDP per capita	Gross Life Insurance premium per capita	J. Francois Outreville (1996)		
Log (GDP per capita)	Life insurance consumption	Thorsten Beck and Ian Webb (2002)	Total Gross Premium	J. Francois Outreville (1990)
Real GDP			PC Insurance Consumption	Esho, Neil et al (2004)
Real per capita Income	Average dollar life insurance per family	Dale B Truett and Lila J Truett (1990)		
Income per capita			P-L Premiums	Michael Beenstock, Gerry Dickinson, and Sajay Khajura (1988)
Growth in GDP	Premium	Chee Chee Lim and Steven Haberman (2004)		

could lead to greater risk aversion and thus a greater awareness of the necessity of insurance. Table 3.2 lists previous studies that have included education as an independent variable. The definition of education varied among previous studies as reported in Table 3.2. The measure of education positively and significantly affects the demand for life and property-casualty insurance in Truett and Truett (1990), Browne and Kim (1993), and Beck and Webb (2002). A negative and significant effect was reported in Outreville (1990) and an insignificant effect was reported in Outreville (1996), Browne et al. (2000) and Esho et.al. (2004).

Table 3.2
List of Education Variables Affecting Life and Property-Casualty Insurance Performance from Previous Studies

Independent Variables	Affect Life Insurance Performance		Affect Property-Casualty Performance	
	Dependent Variable	Articles	Dependent Variable	Articles
Median School Years	Average dollar life insurance per family	Dale B Truett and Lila J Truett (1990)		
Percentage of labor force with higher education	Gross Life Insurance premium per capita	J. Francois Outreville (1996)	Premium per capita	J. Francois Outreville (1990)
Third level education enrollment percentage	Premium Volume	Mark J. Browne and Kihong Kim (1993)	Premium per capita	Mark J Browne, Jae Wook Chung, and Edward W Frees (2000)
Proportion of the population completing secondary education			Demand for PC	Esho et al (2004)
Average year of schooling	Life insurance consumption	Thorsten Beck and Ian Webb (2002)		

3.3.3. Number of Companies

The third variable is the number of companies per 100,000 state population. Theoretically the structure of a market affects a firm's performance. Since the performance of insurance firms is measured by total premium earned and loss ratio experienced, the objective is to examine whether the market structure represented by the number of companies affects the performance of insurers. Previous studies include the number of companies as an independent variable to explain the loss ratio of life insurance

(Meier 1988, p. 151), the insolvency rate of life insurance (Browne, Carson, & Hoyt, 1999), the loss ratio of property-liability insurance (Meier, 1988 p. 154), and the insolvency rate of property-liability insurance (Browne and Hoyt, 1995). Meier (1988, p. 144) used the number of insurance companies per 100,000 state population as an indicator of regulatory stringency; that is, a state can limit the insurance business to only the most solvent companies. This interpretation should mean that the smaller the number of insurance companies per 100,000 population, the more profitable they are. According to Browne et.al. (1999) and Browne and Hoyt (1995), if the number of companies proxies the stringency of the regulatory environment, the insolvency rate would be expected to increase with the number of companies. The number of companies also may proxy the degree of competition in the insurance market. Increased competition could increase the rate of insolvency.

The inclusion of a number of companies in this study may also be reasonable since insurance is not a perfectly competitive industry. Harrington (1984) refers to several studies that conclude the market structure of the property-liability insurance industry is characterized by ease of entry, low moderate return to scale, large number of sellers, and relatively low levels of concentration. But Harrington (1984) argued that there are no definitive answers with regard to the competitive nature of the property-liability insurance market. There are several aspects of the property-liability insurance industry that make the identification of its market structure inconclusive. Joskow (1973) and Smallwood (1975) argue that significant entry barriers may exist for insurers with direct writer (exclusive agent or insurer employee) distribution systems. The evidence on market concentration is inconclusive (Harrington 1984, p. 578; Meier 1988, p. 12). Many firms offer only a few lines of insurance (Meier 1988, p. 13). Informational imperfections in the property-liability insurance market could result in noncompetitive outcomes regardless of market structure. These imperfections include differences in services (especially claim policy), insurers' solidity, imperfect and asymmetric information concerning a potential buyer's expected loss (Harrington 1984, p. 579), individual lines of insurance that have unique characteristics (Meier 1988, p. 17), and unequal bargaining power between insurers and consumers (Klein 1995, p. 366).

Interest group theory argues that groups lobby politicians for favorable regulatory changes. Their effectiveness in overcoming free-rider organizational problems is generally a function of group size and per capita stakes (Teske 1991, p. 140). Klein (1995) notes that the typical state has 1000 to 1500 licensed insurers operating within its borders, most of which will be domiciled in other states. Meier (1988) found that overall, these industries, except for medical malpractice insurance, are only moderately concentrated, barriers to entry and exit are generally low, and profits are good but vary. Lereah (1985) also argues that although statistics are far from conclusive, the property-liability industry exhibits all the basic structural characteristics of the competitive market: a large number of firms, moderate concentration ratios, low capital requirements, and no substantial barriers to entry.

Previous studies also employed number-of-companies-related variables as an independent variable to examine factors affecting insurance performance. For example, a monopolistic market positively and significantly affects life insurance premiums (Outreville 1996), and a non competitive market structure positively and significantly affects property-casualty insurance premiums (Ma & Pope 2003) and affects the property-casualty insurance loss ratios using a 4-firm concentration (Chidambaran, Pugel, & Saunders, 1997) and using a 3-firm concentration (Meier 1988, p. 154).

3.3.4. Regulatory Variables

This study employs regulatory variables including the domicile of companies (domestic and foreign) and the status of insurance commissioners (appointed and elected). The first regulatory variable is Domicile, a dummy variable that equals one if the company is domiciled in the state and zero if it is domiciled in another state. State regulators might treat domestic companies differently from those domiciled in other states in several ways. Klein (1995) argues because of the cost of closely monitoring all of its licensed insurers for solvency, states tend to concentrate oversight on their domestic insurers and defer the responsibility for other insurers to their domiciliary jurisdiction. Meier (1988) hypothesizes that support from domestic insurance companies is more valuable to regulators than support from foreign insurance companies because in-state insurance companies are more likely to commit a greater portion of their assets to a state. According to Meier (1988), since the banning of foreign companies and the discriminatory practices of premium taxes are no longer legal after 1985, local protectionism may have become more subtle. Meier (1991, p. 702) hypothesizes that local companies are more likely to be consulted on policy questions and their complaints about regulation are more likely to be heard. Similar arguments are made by Klein (1995, p. 381). According to Klein, domiciliary and non-domiciliary states have somewhat different incentives in regulating the solvency of an insurer. Like Meier, Klein argues that a state has a strong interest in the expansion of a domestic company to the extent that the company's expansion boosts employment, income, and tax revenues in the state.

The second regulatory variable is Elected, a dummy variable that equals 1 if the state insurance commissioner is elected and 0 otherwise. The expectation of most scholars is that elected commissioners are more likely to favor consumers' short-term interest by not changing rate structure and by allowing competitive entry (Teske 1991, p.145). This study predicts that through an expected lower price, insurance companies in states with elected commissioners will have a higher loss ratio.

4. DATA AND MODEL ANALYSES

4.1. Sample

This chapter performs two types of analysis of insurance companies, a capital market analysis of company profitability and an analysis of premiums and loss experienced by companies' operation in state. The profitability and variability of life-health insurance and property-casualty insurance companies uses data from *Standard & Poor's Security Price Index Record,* 2004 edition. The number of stocks included in the life and health stock price index is 8 and in the property-casualty stock price index is 11, which are the components of 500 stocks in the S&P500 stock index. The companies included in the index changes over time due to the fluctuation of their market capitalization. Data on monthly price index for these two segments of the insurance industry are available for a four-year period after the enactment of GLBA. Two characteristics of the insurance industry, monthly returns and standard deviation of returns, are calculated from these data. The monthly return is (Ending index – Beginning Index)/Beginning Index. A vertical comparison examines if there is a difference in industry returns and standard deviation in the same industry four years after and before the enactment of GLBA. A horizontal comparison examines the difference between the industry returns and standard deviation of returns for life-health insurance versus property-casualty insurance. These results are compared with earlier studies of the profitability and variability of insurance companies.

The performance of insurance companies and the influence of state regulation on performance is examined using premiums earned by the company and the loss ratio. The term loss ratio is generally used for property-casualty insurance, and benefits ratio sometimes is used for life insurance. Data on premiums and losses by state for individual companies come from state insurance departments. This study uses cross-sectional data from a sample of 15 states from the years 2000 to 2003[2]. The sample data consists of 100 top life insurance companies and 100 top property-casualty insurance companies for each year and each state. The data set excludes companies with a loss ratio of 300% or greater because these may be regarded as outliers and a few companies reporting a negative loss ratio. The negative loss ratio may result from a temporary bookkeeping entry from unusual circumstances before being corrected.

The two segments of the industry differ in their operations. Property and casualty insurers collect payments in the form of premiums from people who face similar risks. A portion of these payments covers policyholders' losses. Therefore, earned premiums are typically an insurer's primary revenue source in addition to income from the invested premiums. A policy is recorded on the insurer's books as a written premium when the policy is issued. Premiums earned over the life of the policy are recognized as revenue. There is usually a lag of about 12 months between the time a policy is written and the

[2] These 15 states are Oregon, Idaho, Missouri, Wisconsin, Mississippi, Colorado, Hawaii, North Carolina, Utah, South Dakota, New Jersey, Alaska, Oklahoma, Nebraska, and Iowa.

time the full premium is recognized as revenue. Commissions paid to insurance agents for selling policies are usually deducted immediately from the collected premium (Standard & Poor's Industry Survey, January 13, 2000). Life insurers collect premiums from policyholders, invest those premiums, and share some of that income with policyholders in the form of policy dividends, income from annuity, or cash value. Eventually, life insurers give policyholders some form of financial reimbursement, either upon the policyholder's death or when a policy or an annuity matures. Included in benefits are death benefits, annuity benefits, disability benefits, and accident and health benefits. The largest component is surrender benefits, which are paid out to policyholders when they relinquish their policies for their cash surrender value (Standard & Poor's Industry Survey, April 2002, p. 10).

This study obtains data from several sources. Two widely recognized sources for insurance data are AM Best and the National Association of Insurance Commissioners (NAIC). Statistics for premiums and losses are available for property-casualty insurance while only statistics for premiums are available for life insurance. Since this study examines the effect of state regulation on firm's performance and the actual markets are in the state, the firm's data in the state level from the state insurance departments are used. Most states provide loss ratios data or their components for calculation for property-casualty but not for life insurance. Thus, this study is able to gather data for life insurance only from 15 states as listed in Table 4.1. Even though more data than these 15 states are available for property-casualty insurance, this study uses only those 15 states since the objective is to compare the characteristics of property-casualty and life insurance. Other data taken from state insurance departments' publications include the domicile of companies and number of companies operating in each state. Table 4.1 reports the number of active insurance companies with non-zero premiums in 15 states.

Table 4.1
Number of Active Insurance Companies in 15 States
During Years 1999–2003

States	Number of Property-Casualty Insurance Companies				Number of Life Insurance Companies			
	2000	2001	2002	2003	2000	2001	2002	2003
Oregon	637	644	632	629	584	572	554	554
Idaho	784	765	781	768	570	547	543	524
Missouri	704	703	708	721	565	553	537	515
Wisconsin	918	933	907	930	572	571	557	540
Mississippi	793	803	805	808	624	612	594	597
Colorado	709	726	722	732	589	575	562	539
Hawaii	519	516	528	539	478	472	461	448
North Carolina	768	806	807	795	537	554	570	602
Utah	789	794	808	814	609	592	575	555
South Dakota	819	819	791	810	528	528	520	527
New Jersey	668	671	697	698	412	416	414	407
Alaska	410	401	409	413	358	353	340	325
Oklahoma	843	873	876	843	628	621	614	575
Nebraska	855	861	864	859	605	614	616	615
Iowa	847	849	849	850	542	530	519	498

Note: The number of companies in 1999 in the states of Oregon, Idaho, Missouri, North Carolina, and Alaska are 632, 781, 698, 762, and 413 for property-casualty and 600, 574, 549, 561, and 333 for life insurance, respectively. These are an example of no significant changes in the number of companies upon the enactment of GLBA.
Source: Lists of Companies in the State Insurance Division's Annual Reports

Whether the insurance commissioners are appointed or elected is obtained from state laws, which are available on the state websites. Data on state populations, education, and per capita income are obtained from the US Census Bureau's annual population estimates by state. This study requires the population data to obtain the number of insurance companies per 100K population (company density) and the percentage of population with college education.

4.2. Model Analysis

For comparing the demand for life insurance and the demand for property-casualty insurance in terms of premium earned by company, this study considers a pooled regression model with the use of a dummy variable for distinguishing these two types of insurance industries. Alternatively, this study may use a separate regression for each insurance industry and compare the coefficient of the common variables affecting both. The regression with pooled data assumes that an independent variable has the same effect on either life insurance demand or property-casualty demand. If the structure is not the same for both industries, a separate regression should be run. This study conducts the Chow test (an application of F-test) to see which approach is more suitable with the data on hand. This test examines whether using pooled regression reduces the residual sum of squares. The pooled regression function is an inadequate specification if it produces a higher residual sum of squares and consequently, the study should run separate regression for the two insurance segments.

Including constant, company density, per capita income, and education as predictors, the Chow tests for the regression of premium-earned and loss ratio produce $F(4, 11992)$ values of 37.01 and 22.03, respectively. The critical F value at 5% alpha is 2.37.

Therefore, this test rejects the null of common structure in the life insurance and property-casualty insurance regressions both for insurance premium and for loss ratio. Thus, the pooled regression is an inadequate specification, and this should run separate regressions for life and property-casualty insurance demands and life and property-insurance loss ratios. The Chow tests with all dummy variables included produce the same conclusions, that is, F(10,11980) values of 32.38 and 21.25 for premium and loss ratio equations, respectively and each with a p-value of 0.00000 .

Heteroscedasticity, or unequal variances of the error terms for different observations, may be a potential problem. In the presence of heteroscedasticity, even though OLS estimators are still linear and unbiased, there are undesired effects of heteroscedasticity, which makes the t- and F-test unreliable due to incorrect standard errors of the estimates. Heteroscedasticity makes the statistical inference invalid, and the OLS is not the best estimator of regression coefficients.

The formal tests to detect the existence of heteroscedasticity include Park, Glejser, Goldfeld–Quandt, Breusch–Pagan–Godfrey, and White tests. The null is no heteroscedasticy (homoscedasticity) exists. The Goldfeld–Quandt test assumes that the variance of residuals is monotonically associated with some variable. The Breusch–Pagan–Godfrey test assumes that the variance of residuals is a linear function of a set of variables or a function of a linear combination of variables. The White test assumes that the sources of heteroscedasticity are unknown, but heteroscedasticity exists.

This study uses the White test to examine the existence of heteroscedasticity in the regression results. The White heteroscedasticity test statistic is nR^2 (number of observations times the R-squared), which follows the chi-square distribution with degrees of freedom equal to the number of regressors in the auxiliary equation. The auxiliary regression is defined as the regression of squared residuals on the original regressors of the model, on the original regressors' squared values, and on their cross products. There is no heteroscedasticity if all coefficients in the auxiliary regression are zeros**.** The White heteroscedasticity test statistics for the regressions with premiums as dependent variable are 48.16 for life and 148.33 for property-casualty both with probability chi-square (p-value) = 0.000, which fail to accept the null of homoscedasticity at 1%. For the regressions with loss ratio as dependent variable, the White statistics are 16.25 for life with p-value = 0.012 and 20.34 for property-casualty with p-value = 0.0024, which reject the null of homoscedasticity at 5% and 1%, respectively. The White test for the full models with all dummies included also found that they are not free from heteroscedasticity. For premium regression, the White statistic for life is 23.89 with p-value of 0.000 and the White statistic for property-casualty insurance is 4.59 with p-value of 0.0000. For loss ratio regression, the White statistics for life and property-casualty insurance are 1.56 with p-value 0.011 and 3.62 with p-value 0.000, respectively. Correcting heteroscedasticity, this study uses the robust (White's) standard errors since the functional form of the heteroscedasticity is unknown.

To evaluate whether a particular year affects insurance demand differently from other years, the model adds seasonal dummies as regressors. The seasonal dummy is added in the model to examine possible differences in demand patterns of insurance from one year to another. To avoid perfect collinearity with the constant associated with the intercept, only three out of four dummy variables will be used. That is, four years are indicated with only three dummies: *Year00*, *Year01*, and *Year02*. The structure of the model with three different year dummy variables and X representing other variables is $InsDemand = \beta_0 + \beta_1 X + \delta_1 Year00 + \delta_2 Year01 + \delta_3 Year03 + \varepsilon$. The alternative is to include all four dummy variables in the model but, in this case, the constant term should be excluded in the equation.

There may be an interaction between variables in the model. For example, the use of the dummy variable *Elected* = 1 if a commissioner is elected and *Domicile* = 1 if a company is domestic, implicitly assumes that the effect of *Elected* is constant across the domicile of a company and *Domicile* effect is constant across the *Elected*. To test for this possibility, one dummy variable, which is the product of *Domicile*Elected* is added. Thus the effect of an elected commissioner on premiums may interact with the domicile of an insurance company. The coefficient of *Domicile*Elected* represents a differential effect of being a domestic insurer in the state in which the insurance commissioner is elected.

The final empirical model for this study can be constructed as follows:

$$\begin{aligned} InsDemand = {} & \lambda_0 + \lambda_1 Domicile + \lambda_2 Elected + \lambda_3 (Domicile * Elected) + \lambda_4 Year00 \\ & + \lambda_5 Year01 + \lambda_6 Year02 + \lambda_7 CompDensity + \lambda_8 PercentPopWCollege \\ & + \lambda_9 PCIncome + \varepsilon \end{aligned}$$

Table 4.2 provides the explanation of the variables in this model. The next section presents the empirical results.

5. EMPIRICAL RESULTS

This study uses two analytical tools to examine the life and property insurance industries: direct comparison using capital market data and regression analysis of premiums and loss ratios. The capital market analysis suggests that there are no

Table 4.2
List Independent Variables

Variable	Explanation
Year00	Dummy variable with a value of 1 if the year is 2000 and 0 otherwise
Year01	Dummy variable with a value of 1 if the year is 2001 and 0 otherwise
Year02	Dummy variable with a value of 1 if the year is 2002 and 0 otherwise
Domicile	Dummy variable with a value of 1 if domestic company, and a value of 0, otherwise
Elected	Dummy variable with a value of 1 if the insurance commissioner is elected, and a value of 0, otherwise
*Domicile*Elected*	Interactive dummy variable
Percent Pop w College	Percentage of citizens 25 years old or older with college education to the number of population.
Company Density	Number of companies per 100,000 population
Per Capita Income	Per capita income in a particular state

differences in mean returns and variances before and after the enactment of GLBA in two insurance industries. The regression results, on the other hand, suggest that life insurance is more attractive since it earns higher premiums and a more predictable loss ratio than property-casualty insurance.

5.1. Results from Capital Market Data

As reported in Table 2.1, several studies found that the standard deviation of returns was lower in life insurance than in property-casualty insurance prior to the enactment of

GLBA. On the other hand, the mean returns were lower for life insurance than property-casualty insurance.

This study is interested in examining if there is a difference in return and variance of return in these two insurance industries before and after the enactment of GLBA. Table 5.1 reports the mean and standard deviation of monthly returns on stock price index for life-health insurance and for property-casualty insurance four years before and after the enactment of GLBA. Table 5.1 also reports the average monthly return and its variance on stock price index during 48 months or four years before and after the enactment of GLBA.

Table 5.1
The Characteristics of Property-Casualty and Life-Health Insurance Industries Four Years Before and After the Enactment of GLBA based on Stock Price Index

Year	Property-Casualty Insurance		Life and Health Insurance	
	Monthly Return	Std Deviation	Monthly Return	Std Deviation
Before GLBA				
1996	0.0158805	0.039358	0.013641	0.031536
1997	0.0300959	0.0453414	0.019691	0.041527
1998	-0.0045441	0.0497738	0.0023960	0.065803
1999	-0.0235471	0.0691128	-0.011597	0.068119
Average (4 years)	0.004452	0.054553	0.006033	0.054166
Return variance	------	0.002976	------	0.002934
After GLBA				
2000	0.035741	0.078754	0.01204	0.069460
2001	-0.006026	0.056376	-0.00720	0.044343
2002	-0.005617	0.048870	-0.01244	0.044145
2003	0.013563	0.045851	0.011780	0.003507
Average (4 years)	0.009415	0.059548	0.002546	0.049973
Return variance	------	0.003546	-----	0.0024973

Note: Data are obtained from Security Price Index Record, Standard & Poor's, 2004 edition.

The average monthly returns during 1996-1999 (before GLBA) were 0.006033 and 0.004452 in life and property-casualty insurance industries, respectively, and their corresponding standard deviations of return were 0.054166 and 0.054553. The average monthly returns during 2000-2003 (after GLBA) were 0.002546 and 0.009415 in life and property-casualty insurance industries respectively, and their corresponding standard deviations were 0.049973 and 0.059548. During 1996-1999 (before GLBA) the returns in life insurance varied from 0.013641 to -0.011597 while in property-casualty, the returns varied from 0.0158805 to -0.0235471.

The standard deviations in life insurance varied from 0.031536 to 0.068119 while in property-casualty the variation ranged from 0.039358 to 0.0691128. During this period, the returns in both industries increased from 1996 to 1997 and decreased further in 1998 and 1999. The standard deviations of return in life insurance were always lower than property-casualty insurance.

In the years after GLBA, the returns in life and property-casualty insurance followed the same pattern. Both returns were positive in 2000 and 2003 and negative in 2001 and 2002. As in the period before GLBA, the standard deviations of return in life insurance were higher in all years after GLBA.

Statistical tests are employed to see if the mean returns in each insurance sector before and after GLBA statistically differ. Using Minitab the tests show that life insurance returns before and after the enactment of GLBA did not differ significantly with a t-value of 0.33 and a p-value of 0.744. This study also observes the same results in property-casualty insurance in which the t-value is -0.43 with a p-value of 0.671. Before the GLBA, life insurance return and its property-casualty counterpart return also do not differ significantly with a t-value of 0.14 and a p-value of 0.887. After the GLBA, the returns between these two insurance sectors again do not differ significantly with a t-value of -0.61 and a p-value 0.542. All tests are conducted with the null that the two returns are equal with alpha of 5%.

The difference in variances of return before and after GLBA for life insurance was statistically insignificant. The F-statistic is 1.17 with a p-value of 0.583. The difference in variances of return before and after GLBA is also insignificant in property-casualty insurance. The F-statistic is 1.10 with a p-value of 0.550. The variances of return between life and property-casualty insurance also do not differ either before GLBA or after GLBA. The F-statistic before GLBA is 1.01 with a p-value of 0.961 and after GLBA is 1.42 with a p-value of 0.233. All of these results are based on 5% significant levels.

The difference between the results in this study and data reported by previous studies might be due to differences in sample and measurement of return. Previous studies used median instead of the arithmetic mean of return, and used annual performance instead of monthly performance.

5.2 Regression Results

Table 5.2 reports two regressions with demand, in terms of total premium earned by company, as dependent variables, for life and for property-casualty insurance. The regression results reported in this table support the claim that premiums earned by life insurance companies are higher than premiums earned by property-casualty insurance companies. The constant term in the premium equation for life insurance is -42.86 million while for property-casualty it is -73.43 million, which is lower. In the period of four years after the enactment of GLBA, the premiums earned by life insurance

Table 5.2
Regression with Premium Earned by Company as Dependent Variable
Robust Standard Errors Reported in the Parentheses Followed by t-ratio

	Demand for Life (Prem. Earned by Company)	Demand for P/C (Prem. Earned by Company)
Observations	6000	6000
Constant	-42862400.0 (17652989.0) -2.428053	-73436440.0 (13159520.0) -5.580480
Year00	27176467.0 (5310478.0) 5.117518	16312507.0 (4088142.0) 3.990201
Year01	30571332.0 (5446651.0) 5.612868	19235860 (4090464) 4.702611
Year02	1895441.0 (3685083.0) 0.514355	-382141.8 (2723383) -0.140319
Domicile	91450141.0 (16259567.0) 5.624390	332480.0 (4077268) 8.154489
Elected	7028221.0 (4061519.0) 1.730441*)	18410027 (3246540.0) 5.670661
Domicile*Elected	-11304273.0 (37190357.0) -0.303957	-11313430.0 (8580567.0) -1.318494
Company Density	-1304413.0 (59247.92) -22.01618	-457190.9 (30788.94) -14.84919
Percent Pop with College	-65239.48 (549927.3) -0.118633	1398008.0 (374392.8) 3.734069
Percapita Income	4272.121 (509.4403) 8.385912	2884.157 (416.6236) 6.922693
F-statistic Probability Adjusted R-squared	108.6933 0.00000 0.139094	84.92676 0.00000 0.112163

Note: *) Significant at 10 percent

companies in any year were persistently higher than property-casualty insurance. This can be observed from the higher coefficient of dummy variables Year00, Year01 and Year02 in the premium equation for life insurance, which are 27.18, 30.57, and 1.89, respectively. The corresponding coefficients in the property-casualty segment are 16.31, 19.24 and -0.38 millions, respectively.

The dummy variable *Domicile* has a positive and significant sign in both life and property-casualty regressions with t-values of 5.62 and 8.15, respectively. The positive signs of the coefficient are as expected, which means that domestic companies earned more premiums than their foreign counterparts operating in the same states. In particular, for regulators, the role of domestic life and property-casualty companies is important because on average they collect \$91.5 million and \$0.33 million more premiums, respectively, than foreign insurance companies. The positive effect of a domestic company is greater on life insurance premiums than on property-casualty insurance premiums.

The dummy variable *Elected* has a positive and significant sign at 10% alpha in life and at 1% alpha in property-casualty regression. The expectation was that insurance price should be lower so that it is more affordable in the states in which insurance commissioners are elected. A lower price may increase the amount of premium earned if the purchase of insurance is price elastic. In this case, life and property-casualty insurance companies in states with elected commissioners collected more premiums by as much as \$7.03 million and \$18.41 million, respectively, than in states with appointed commissioners.

The coefficient of the interactive dummy variable *Domicile*Elected* has a negative sign of -11.3 million in life and 0.46 million in property-casualty insurance, which means that domestic companies operating in the states where the insurance commissioners are elected collect less premiums than those in states where the insurance commissioners are appointed; however, the coefficient is not significant in both equations.

Company Density (number of companies per 100,000 people) and *Per-capita Income*, have a significant effect on premiums earned by both life and property-casualty insurance companies. The negative sign for company density and the positive sign for per capita income are as expected. The greater the number of companies in the market per 100,000 population, the less premiums an insurance company earned. However, the magnitude of coefficients of company density differs; it is -1,304,413 in life insurance and is only -457,191 in property-casualty insurance. Thus, on average, adding one life insurance company reduces the premium earned by $1.3 million while adding one property-casualty insurance reduces the premium earned by only $0.46 million. Thus, the number of companies in the life insurance sector has a greater effect on premiums earned than in the property-casualty insurance sector.

The coefficients of *Per-capita Income* are 4,272 in life and 2,884 in property-casualty regression. Income per capita has a greater positive effect on premiums earned by life insurance firms than by property-casualty insurance firms. On average, a dollar increase in income per capita produces a $4,272 increase in life insurance premium earned and only a $2,884 increase in property-casualty insurance premium earned by the company. Therefore, facing these two variables, the life insurance firms are at a more advantageous position.

Education has a significantly positive coefficient as expected in property-casualty with a t-ratio of 3.73 but has an insignificant negative coefficient in life insurance with t-ratio of -0.12. A one percent increase in population with college education increases premium earned by property-casualty insurance company by $1.4 million. The effect of a one percent increase in the population with college education is negligible. These results show that people with property-casualty insurance are more risk averse than people with life insurance.

Overall, the F-statistics in both equations are significant. The value of the F-statistic in the regression of demand for life insurance is higher; it is 108.69, while for property-casualty insurance, the value of F-statistic is 84.93, and both are significant at 1 percent alpha. Adjusted R-squared in life premium regression of 0.139 is higher than in property-casualty insurance, which is only 0.112. The greater value of the F-statistic and adjusted R-squared in the life insurance equation may indicate that facing the set of common variables, the premium earned in the life insurance business is more predictable than property-casualty insurance.

Table 5.3 reports the regression results with Loss Ratio as dependent variables for life and property-casualty insurance industries. The regression results for Loss Ratio reported in this study support the claim that the loss ratio for life insurance is higher than for property-casualty insurance.

Over the period of four years after the enactment of GLBA, the loss ratios for life and property-casualty insurance do not follow the same behavior. Their different behavior can be observed by the coefficients of dummy variables *Year00* and *Year01* and *Year02*. In the loss ratio equation for property-casualty insurance, the coefficients of

Table 5.3
Regression with Loss Ratio as Dependent Variable
Robust Standard Errors Reported in the Parentheses Followed by t-ratios

	Loss Ratio Life Ins.	Loss Ratio P/C Ins.
Observations	6000	6000
Constant	162.2521 (6.697811) 24.22465	65.92965 (4.910177) 13.42714
Year00	-12.49903 (2.511477) -4.976765	8.875262 (1.860279) 4.770930
Year01	-20.08157 (2.311693) -8.686953	10.51181 (1.911588) 5.498992
Year02	-2.149575 (1.744078) -1.232500	3.052768 (1.070148) 2.852661
Domicile	8.932368 (2.419767) 3.691417	-0.974298 (1.087726) -0.895720
Elected	-14.96384 (2.273899) -6.580696	0.563275 (1.405844) 0.400667
Domicile*Elected	-7.711165 (6.367317) -1.211054	4.907706 (3.518999) 1.394631
Company Density	-0.059307 (0.039530) -1.500299	-0.093725 (0.020146) -4.652196
Percent Pop with College	-1.374444 (0.217408) -6.321970	-0.214307 (0.168847) -1.269240
Percapita Income	-0.002050 (0.000211) -9.702487	0.0000593 (0.000171) -0.346206
F-statistic	29.07957	17.18737
Probability	0.00000	0.00000
Adjusted R-squared	0.040423	0.023787

these three dummies are 8.88, 10.51 and 3.05, which are all significant and positive. These coefficients are negative in the loss ratio equation for life insurance: -12.50, -20.08 and -2.15. Only the first two coefficients are significant.

The dummy variable *Domicile* has a positive and significant coefficient of 8.93 in life insurance. However, in the loss ratio equation for property-casualty insurance, the variable *Domicile* has a negative and insignificant coefficient of -0.97. The dummy variable *Elected* has a negative and significant coefficient of -14.96 in the loss ratio for life insurance. This dummy variable has a positive coefficient of 0.56 in the loss ratio for property-casualty insurance, but it is insignificant. The expectation was that the insurance price should be lower in the state in which insurance commissioners are elected so that the expected sign should be negative. The interactive dummy variable *Domicile*Elected* has a coefficient of -7.71 in life insurance and a positive sign of 4.91 in property-casualty insurance. These mean that life domestic companies operating in the states where the insurance commissioners are elected experienced a lower loss ratio than in those states where the insurance commissioners are appointed; however, the coefficient is not significant.

The *Company Density* (the number of companies per 100K population) has a coefficient of -0.06 (insignificant) in life insurance and -0.09 (significant) in property-casualty loss ratio equation. These coefficients suggest that the effect of company density on loss ratio is very small.

Two independent variables, *Education* (percent of the population with college education) and *Percapita Income*, have a significant coefficient on the loss ratio for life insurance companies. The effect of education on loss ratio in life insurance is material, but the effect of per capita income is negligible. In property-casualty, *Education* and *Percapita Income* have insignificant coefficients of -0.214 and -0.0000593. Their effects on loss ratio are very small even though their negative signs are as expected.

The value of the F-statistic in the regression of loss ratio for life insurance is 29.08, which is higher than the value of the F-statistic for the property-casualty insurance, which is 17.19. Both are significant at 1 percent alpha. The adjusted R-squared in both the life insurance equation and property insurance equation are only 0.04 and 0.024, respectively.

6. CONCLUSION

This study finds that life insurance companies are more attractive than property-casualty insurance companies in terms of higher premiums earned but not in terms of loss ratio, since life insurance experiences higher loss ratio than property-casualty insurance. This study also finds that earning variability in life insurance does not differ from earning variability in property-casualty insurance before and after the enactment of GLBA.

Previous studies recommended banks enter the life insurance business since it produces a lower return variability than the property-casualty insurance business. Their results were based on pre-GLBA samples in which the variability of return in life insurance was lower than property-casualty insurance. The results from capital market data show that the life insurance industry produced a lower return and lower volatility in terms of standard deviation of return, relative to the property-casualty insurance industry. However, the differences are not significant both before and after the enactment of GLBA, either in each insurance industry segment or between two insurance industry segments. These results suggest that the recommendation for banks to enter life insurance business rather than property-casualty insurance is not robust to differences in sample.

The regression results show that premium earned by life insurance firms is higher in any year during the four-year period after the enactment of GLBA. On the other hand, the loss ratio experienced by the life insurance industry is also higher than the loss ratio experienced by the property-casualty insurance industry.

The regression results show that premiums earned by life insurance and property-casualty insurance respond with different magnitude to the same variables. So do the loss ratios experienced by life and property insurance. This study shows that per capita income positively affects the premiums earned by insurance companies. Education significantly and positively affects premiums earned in property-casualty insurance but not in life insurance. The greater the number of companies in the markets, the less the amount of premiums earned by companies. Insurance companies operating in states in which the insurance commissioners are elected collect more premiums than those operating in states in which the insurance commissioners are appointed. Finally, domestic companies collect more premiums than their foreign company counterparts.

This empirical study shows that the life insurance industry is more attractive than the property-casualty insurance industry in terms of higher premiums collected. The higher premiums collected by life insurance has been higher even before the enactment of GLBA in 1999. This implies that the recommendations offered in previous studies that banks enters life insurance should still be acceptable four years after the enactment of GLBA based on premiums instead of risk factors.

The regression results for Loss Ratio reported in this study support the claim that the loss ratio for life insurance is higher than for property-casualty insurance. Over the period of four years after the enactment of GLBA, the loss ratios for life and property-casualty insurance do not follow the same behavior. A domestic company in the life insurance segment experiences a higher loss ratio than in property insurance. In property-casualty insurance, the effect of company domicile on loss ratio is not significant. Domestic life insurance companies operating in the states where the insurance commissioners are elected experienced a lower loss ratio than in those states where the insurance commissioners are appointed; however, the coefficient is not significant. This study finds that the effect of company density on loss ratio is very small. The effect of education on loss ratio in life insurance is material but the effect of per capita income is negligible. In property-casualty the effects on loss ratio are very small even though the negative signs are as expected. The F-statistics in the premiums and the loss ratio equations for life and property-casualty are all significant.

Some limitations of this study include a small sample size in the number of stocks used in analyzing return and variability, the small number of years in cross-sectional data on premiums and loss ratio, and the small number of states included in this study. The low value of adjusted R-squared in the regression models requires more relevant variables. Therefore, a greater sample size with longer duration of data as well as additional variables should be included for future studies.

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