Uncertainty in Sales and Inventory Behaviour in the U.S. Trade Sectors
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Uncertainty in sales and inventory behaviour in the U.S. trade sectors

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Abstract. This paper investigates uncertainty in sales and inventory behaviour for the U.S. wholesale and retail trade sectors. First, using a vector error correction model with GARCH-M, we find that the uncertainty measured by forecast error variance in sales does not affect inventory behaviour in both trade sectors. Second, using forecast error variance decomposition and estimated permanent components, we observe that the uncertainty may be attributed more to demand shocks than to cost shocks.

Incertitude dans le comportement des ventes et des inventaires dans les secteurs commerciaux aux Etats-Unis. Ce mémoire examine l'incertitude dans le comportement des ventes et des inventaires dans les secteurs du commerce de gros et de détail aux Etats-Unis. D'abord, à l'aide d'un modèle vectoriel de correction d'erreurs avec GARCH-M, on établit que l'incertitude mesurée par la variance de l'erreur de prévision dans les ventes n'affecte pas le comportement des inventaires et ce dans les deux secteurs. Ensuite, à l'aide d'une décomposition de la variance de l'erreur de prévision et d'une évaluation des composantes permenentes, on montre que l'incertitude peut être attribuée bien davantage aux chocs du côté de la demande qu'aux chocs du côté des coûts.

I. INTRODUCTION

It is widely believed that changes in inventory investment may play a significant role in cyclical fluctuations. As indicated by Blinder and Maccini (1991), the drop in inventory investment has accounted for 87 per cent of the drop in GNP during the average postwar recession in the United States. Therefore, understanding the causes of changes in inventory investment and investigating how changes in inventory investment affect the level of economic activity is essential for understanding the cyclical fluctuations in output.

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Microeconomic theories of inventory behaviour specify several motives for holding inventories, such as production smoothing, minimizing stockout costs, reducing purchasing costs. The production-smoothing model suggests that a firm partially adjusts its production to variation in sales and lets the inventories absorb the change in sales. This action implies that production is less variable than sales. The evidence, however, does not provide much support for the production-smoothing hypothesis.

The dissatisfaction with the production-smoothing hypothesis has motivated other explanations. One of these explanations focuses on cost shocks and offers production cost smoothing as an alternative to production smoothing. As shown by Glick and Wihlborg (1985) and Blinder (1986), if there is a cost shock that the firm sees before it determines the level of production, then the firm may maximize its profits over time by increasing production and building inventories when costs are low and decreasing production and depleting inventories when costs are high. Eichenbaum (1989) examines this in the context of the production-cost-smoothing model, distinguishing it from the production-level-smoothing model.

Another explanation is based on the stockout-avoidance motive. As shown by Kahn (1987), if the firm can backlog excess demand, then volatility in production exceeds that of sales. This is so because firms hold inventories not to smooth production but rather because stockouts are costly. Kahn (1991) finds supporting evidence for the stockout-avoidance motive using data from the U.S. automobile industry.

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.

Although the motives for holding inventories have been studied carefully in the literature, both the role of sales uncertainty in determining inventory behaviour and the way inventory uncertainty affects economic activity have not received much attention. In this paper we investigate empirically how the change in inventories respond to the uncertainty in sales and how the uncertainty in inventories may affect the change in sales.

In order to investigate these issues we use a multivariate time-series model with time-varying conditional variances. Using the U.S. wholesale trade and retail trade data, we find that inventories and sales series are cointegrated. Therefore, we use a vector error correction model (VECM) with multivariate generalized autoregressive conditional heteroscedasticity in mean (GARCH-M) model of Engle et al. (1987).

In section II, we find that the behaviour 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 evidence in section III indicates, however, that uncertainty in sales does not have a significant effect on inventories in both of the U.S. 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 uncertainties in predicting the changes in sales.

Furthermore, in section IV, to investigate the sources of the uncertainty, we estimate the permanent components of inventories and sales series and compute the fraction of the forecast error variance of the series attributed to shocks to the permanent components. We find that the uncertainty may be due more to demand shocks than to cost shocks.

II. THE INITIAL MODEL: VECM

Monthly real (in 1982 dollars) inventory (I_t) and sales (s_t) series from 1967:1 to 1990:3 (279 observations) for the U.S. wholesale and retail trade are obtained from the Citibase. The series are seasonally adjusted at the source.

First, we implement the test for the unit root hypothesis on the series I_t and s_t, using the recent tests by Phillips (1987) and Phillips and Perron (1988). The results are presented in table 1. The results indicate that the unit root hypothesis cannot be rejected for the inventory and sales series in both of the U.S. trade sectors. This observation leads to a consideration of the presence of cointegration between the inventory and sales series. These stock-flow relationships have been studied by Granger and Lee (1989) using the concept of *multicointegration*. The tests involve the cointegrating regression $I_t = \hat{\alpha} + \hat{\beta}s_t + u_t$, and the unit root test for the OLS residual u_t. For the U.S. wholesale trade, the Durbin Watson statistics (DW) for u_t is 0.23 and the adjusted coefficient of determination ($\bar{R}^2$) of the regression is 0.98. Since u_t has a zero mean, the Phillips-Perron test based on the regression without a constant or a trend, $Z(t_{\hat{\alpha}})$, is computed. The statistic is -4.37. Using the 1 per cent critical value of -4.0 in Engle and Yoo (1987), we obtain the result that inventory and sales series are cointegrated at the 1 per cent level.

For the U.S. retail trade, DW $= 0.38$, $\bar{R}^2 = 0.98$, and $Z(t_{\hat{\alpha}}) = -5.67$. Thus, the inventory and sales series are cointegrated at the 1 per cent level.

We also use the Johansen (1988, 1991) test for $X_t = (I_t s_t)'$ to test for cointegration. The test allows us to determine the rank of cointegration (r). For the bivariate model employed in this paper, if the null hypothesis $r = 0$ is rejected, while $r = 1$ is not, $X_t = (I_t s_t)'$ is cointegrated. In table 1, the results for $k = 1, \ldots, 6$ are reported, where k is the number of lagged ΔX_t augmented in the error correction models to make the residual vector be serially uncorrelated vector white noise. In both trade sectors I_t and s_t are cointegrated.

The initial error correction models are specified as follows:

$$\Delta I_t = a_0 + a_1 u_{t-1} + \sum_{j=1}^{k}(a_{1+j}\Delta I_{t-j} + a_{1+k+j}\Delta s_{t-j}) + e_{1t}$$

$$\Delta s_t = b_0 + b_1 u_{t-1} + \sum_{j=1}^{k}(b_{1+j}\Delta I_{t-j} + b_{1+k+j}\Delta s_{t-j}) + e_{2t}.$$

The lag length k is determined using the Akaike information criteria (AIC), the Schwartz information criteria (SIC), the likelihood ratio (LR) statistics, and the Ljung-Box portmanteau test for up to the twentieth-order serial correlation in the residuals

TABLE 1
Testing for unit root and cointegration

	Phillips-Perron tests for a unit root			
	Wholesale		Retail	
Statistics[a]	I	s	I	s
$Z(t^*_\alpha)$	−0.03	−0.13	0.37	−0.09
$Z(t_{\tilde{\alpha}})$	−2.61	−3.23	−1.48	−2.26
	Johansen test for cointegration[b]			
	Wholesale		Retail	
	$r=0$	$r=1$	$r=0$	$r=1$
$k=1$	20.452**	0.004	36.697**	0.020
$k=2$	15.726*	0.003	29.823**	0.047
$k=3$	18.379*	0.018	27.744**	0.089
$k=4$	15.350*	0.053	22.699**	0.021
$k=5$	19.104**	0.097	24.994**	0.139
$k=6$	21.524**	0.084	22.809**	0.172

a (top) $Z(t^*_\alpha)$ and $Z(t_{\tilde{\alpha}})$ denote the Phillips-Perron statistics based on the regressions with a constant term and with both a constant and a time trend term, respectively. The Newey-West (1987) truncation lag used is equal to 12. The results are similar for the other values. The critical values are taken from Dickey and Fuller (1981) and Fuller (1976).

b (bottom) * and ** denote the significance at the 5 per cent and 1 per cent levels, respectively. The Johansen's *maximum eigenvalue* statistics are reported. The critical values are obtained from Osterwald-Lenum (1992).

(table 2). In both trade sectors, $k = 1$ is selected by the SIC and $k = 3$ is chosen using the AIC. The LR test for $k = 2$ vs. $k = 3$ is significant, but the LR test for $k = 3$ vs. $k = 4$ is not. The Ljung-Box tests also suggest a choice of k larger than one. We therefore select $k = 3$ for both U.S. trade sectors.[1]

To check if the error correction is non-symmetric, we test if the coefficients of u^+_{t-1} and u^-_{t-1} are equal, where $u^+ = \max(u, 0)$ and $u^- = \min(u, 0)$. Using the asymptotic chi-square statistics with White's (1980) heteroscedasticity consistent covariance matrix estimates, we find that the coefficients of u^+_{t-1} and u^-_{t-1} are significantly different in the inventory equation for the wholesale trade sector, whereby we employ a nonsymmetric error correction model (table 4).

In table 3 the asymptotic p-values for various specification tests for the above model are presented. These tests are: (a) Wooldridge's (1990) robust Lagrange multiplier (LM) test for autocorrelations (denoted by AR),[2] (b) LM tests for autore-

1 The results with $k = 1$, chosen by the SIC, are virtually the same as those with $k = 3$.

2 As noted by Domowitz and Hakkio (1986), Diebold (1987), Cumby and Huizinga (1992), and Wooldridge (1990, 1991), among others, the presence of time varying higher moments generally induces an incorrect size of specification tests. It usually leads to a rejection of the null too

TABLE 2
AIC, SIC, LR test, Ljung-Box test, and McLeod-Li test

	Wholesale trade[a]				Retail trade[a]			
k	AIC	SIC	LR	test	AIC	SIC	LR	test
1	1492.70	1524.65	2.58	(0.630)	1560.43	1588.83	17.54	(0.002)
2	1498.12	1544.26	19.55	(0.001)	1550.90	1593.49	8.95	(0.062)
3	1486.57	1546.90	3.96	(0.411)	1549.95	1606.74	3.74	(0.442)
4	1490.61	1565.14	8.67	(0.070)	1554.21	1625.19	9.24	(0.055)
5	1489.94	1578.67	4.61	(0.330)	1552.97	1638.15	2.32	(0.678)
6	1493.34	1596.26			1558.65	1658.03		

	Wholesale trade[b]				Retail trade[b]			
	Ljung-Box		McLeod-Li		Ljung-Box		McLeod-Li	
k	ΔI	Δs	ΔI	Δs	ΔI	Δs	ΔI	Δs
1	0.008	0.177	0.000	0.002	0.000	0.096	0.000	0.000
2	0.011	0.255	0.000	0.003	0.000	0.798	0.000	0.000
3	0.168	0.677	0.000	0.012	0.023	0.891	0.023	0.000
4	0.203	0.661	0.000	0.011	0.042	0.947	0.019	0.000
5	0.323	0.958	0.000	0.071	0.257	0.938	0.115	0.000
6	0.417	0.967	0.000	0.052	0.340	0.919	0.043	0.000

a Note that these figures are computed under homoscedasticity assumption. The likelihood ratio (LR) test statistics test the hypotheses of the lag lengths k vs $k+1$. The p-values from $\chi^2(4)$ are shown in ( ). But it may be noted that the LR tests do not follow an asymptotic chi-square distribution in the presence of ARCH, misspecification in conditional mean, or non-normality.

b Both Ljung-Box and McLeod-Li test statistics are asymptotically $\chi^2(20)$. The asymptotic p-values are reported.

gressive conditional heteroscedasticity (ARCH), (c) White's (1989) neural network test for neglected non-linearity, (d) Jarque-Bera (1980) test for normality, and (e) a test for non-symmetric error correction model.

Using the number of lags in the VECM selected, the residuals are not serially correlated. However, the McLeod-Li (1983) statistics (table 2) and the LM tests (table 3) are sufficiently significant to question the presence of ARCH.

III. BIVARIATE GARCH-M IN VECM

The analysis in this paper focuses on the relationship between inventory behaviour and uncertainty in sales, measured as conditional heteroscedasticity, as well as the relationship between sales and volatility in inventories. For this purpose, a bivariate GARCH-M is specified in the VECM.

often. If, for example, the conditional mean is the object of interest, the test for the null that the conditional mean is correctly specified may be affected by the misspecification in the conditional variance. We therefore use the LM test of Wooldridge, which is robust to neglected misspecification.

TABLE 3
Initial diagnostics

	Wholesale		Retail	
Statistics	ΔI	Δs	ΔI	Δs
AR(1)	0.836	0.948	0.968	0.219
AR(2)	0.913	0.128	0.905	1.000
AR(5)	0.999	0.883	0.994	0.997
AR(10)	1.000	1.000	1.000	1.000
ARCH(1)	0.005	0.902	0.000	0.000
ARCH(2)	0.000	0.924	0.000	0.000
ARCH(5)	0.001	0.011	0.000	0.000
ARCH(10)	0.004	0.082	0.000	0.000
Neural(3)	0.263	0.828	0.270	0.004
Jarque-Bera(2)	0.001	0.012	0.290	0.000
Non-symmetric(1)	0.047	0.340	0.631	0.120

NOTES: AR and ARCH denote the LM tests for autocorrelation and ARCH, respectively, and Non-symmetric denotes the test for non-symmetric ECM. The number in ( ) is the degree of freedom of each test. The asymptotic p-values are reported. For the neural network test we use ten phantom hidden units, three principal components of them, and five draws of the test in computing the Hochberg Bonferroni bound (see Lee, White, and Granger 1993). $k = 3$.

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. We use Bollerslev's (1990) model and assume the conditional correlations to be constant so that all the variations over time in conditional covariance are due to changes in two conditional variances. The constant correlation model has been applied successfully by Bollerslev (1990) and Baillie and Bollerslev (1990a, 1990b).

The model is now as follows:

$$\Delta I_t = a_0 + a_1 u_{t-1} + \sum_{j=1}^{k} (a_{1+j} \Delta I_{t-j} + a_{1+k+j} \Delta s_{t-j}) + \delta_1 h_{11t}^{1/2} + \delta_2 h_{22t}^{1/2} + e_{1t}$$

$$\Delta s_t = b_0 + b_1 u_{t-1} + \sum_{j=1}^{k} (b_{1+j} \Delta I_{t-j} + b_{1+k+j} \Delta s_{t-j}) + \delta_3 h_{11t}^{1/2} + \delta_4 h_{22t}^{1/2} + e_{2t}$$

$$h_{iit} = \omega_i + \alpha_i e_{i,t-1}^2 + \beta_i h_{ii,t-1} \qquad i = 1, 2$$

$$\rho = h_{12t}(h_{11t} h_{22t})^{-1/2},$$

where $h_{ijt} \equiv E(e_{it}e_{jt}|\mathrm{F}_{t-1})$ and F_{t-1} is the σ-field generated by all the information available at time $t-1$. Thus the formulation allows conditional time-varying variances and covariances. However, we assume that the conditional correlation is constant through time.

The parameter estimates are obtained by maximizing the quasi (normal) log-likelihood function using the scoring algorithm with only first numerical derivatives being used, à la Bollerslev and Wooldridge (1992).[3] The results are presented in table 4. The *robust* asymptotic standard errors are obtained à la White (1982) and Bollerslev and Wooldridge (1992), and the asymptotic t-values are reported in parentheses, which allow inferences that are valid when the assumption of conditional normality is violated.[4] The GARCH parameters are almost always highly significant, 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.[5]

For the wholesale trade sector, the stock-adjustment is non-symmetric with insignificant GARCH-M terms in the inventory equation. The coefficient of u_{t-1}^{+} is significant, which means that excess inventory holding leads to a significant reduction in inventories in the next period. In the sales equation, the coefficients of u_{t-1}^{+} and u_{t-1}^{-} were not significantly different from each other. Therefore, a symmetric error correction model was employed. The coefficient of the term u_{t-1} is positive and significant at the 10 per cent level, implying that inventories are above (below) the long run equilibrium level because sales are expected to rise (fall).

For the retail trade sector, the coefficient of u_{t-1} in the inventory equation is negative and significant. Thus when the inventory level exceeds its long-run equilibrium level, the firm adjusts by reducing its inventories. The GARCH-M terms are not significant in either equation.

In order to test the validity of the models a series of specification tests for the models standardized by $h_{iit}^{1/2}$ are presented in table 5. From the tests for the conditional second moments, the GARCH(1, 1) specification for each system also seems reasonable. The LM tests for ARCH and the McLeod-Li tests for the standardized residuals are not significant in all cases. Under the assumption of constant conditional correlations, the cross-product of the standardized residuals, $e_{it}e_{jt}(h_{iit}h_{jjt})^{-1/2}$, $i \neq j$, should also be serially uncorrelated. The LM tests for the serial correlation

3 Lumsdaine (1991) and Lee and Hansen (1992) show that the quasi maximum likelihood estimator (QMLE) is consistent and asymptotically normal under some fairly weak conditions. A Monte Carlo study by Bollerslev and Wooldridge (1992) indicates that the asymptotic results also carry over to finite samples.

4 We report only robust statistics. All the non-robust counterparts (reported in the earlier version of the paper) may be obtained from the authors on request, which show very similar results.

5 As none of the GARCH-M coefficients reported in table 4 is significant, while the ARCH tests reported in table 2 and table 3 are very significant, one may wonder if the VECM-GARCH-M is overfitting the data with resulting less significant ARCH effects in the residuals of VECM-GARCH-M. We thus test the presence of ARCH in the (non-standardized) residuals of the model and find very strong ARCH. The GARCH(1, 1) parameter estimates are also generally very significant. These indicate that the insignificant GARCH-M parameter estimates are not because of possibly reduced conditional heteroscedasticity due to overfitted GARCH-M.

TABLE 4
Estimated VECM with GARCH-M

Wholesale trade

$$\Delta I_t = \underset{(0.425)}{0.209} - \underset{(-5.875)}{0.115}\, u^+_{t-1} - \underset{(-0.212)}{0.005}\, u^-_{t-1} + \cdots - \underset{(-0.315)}{0.086}\, h^{1/2}_{11t} + \underset{(0.374)}{0.181}\, h^{1/2}_{22t} + e_{1t}$$

$$\Delta s_t = \underset{(0.115)}{0.250} + \underset{(1.871)}{0.050}\, u_{t-1} + \cdots - \underset{(-0.267)}{0.516}\, h^{1/2}_{11t} + \underset{(0.151)}{0.263}\, h^{1/2}_{22t} + e_{2t}$$

$$h_{11t} = \underset{(2.002)}{0.028} + \underset{(3.404)}{0.247}\, e^2_{1,t-1} + \underset{(12.791)}{0.730}\, h_{11,t-1}$$

$$h_{22t} = \underset{(0.782)}{0.077} + \underset{(1.900)}{0.062}\, e^2_{2,t-1} + \underset{(12.306)}{0.894}\, h_{22,t-1}$$

$$\rho = \underset{(1.769)}{0.094}$$

Retail trade

$$\Delta I_t = \underset{(0.316)}{0.189} - \underset{(-5.493)}{0.083}\, u_{t-1} + \cdots - \underset{(-0.635)}{0.123}\, h^{1/2}_{11t} + \underset{(0.324)}{0.141}\, h^{1/2}_{22t} + e_{1t}.$$

$$\Delta s_t = \underset{(0.288)}{0.229} + \underset{(0.366)}{0.006}\, u_{t-1} + \cdots - \underset{(-0.780)}{0.220}\, h^{1/2}_{11t} + \underset{(0.183)}{0.090}\, h^{1/2}_{22t} + e_{2t}.$$

$$h_{11t} = \underset{(0.884)}{0.036} + \underset{(1.979)}{0.132}\, e^2_{1,t-1} + \underset{(7.930)}{0.832}\, h_{11,t-1}.$$

$$h_{22t} = \underset{(3.538)}{0.552} + \underset{(2.211)}{0.573}\, e^2_{2,t-1} + \underset{(0.898)}{0.129}\, h_{22,t-1}.$$

$$\rho = \underset{(-1.556)}{-0.100}.$$

NOTES: $u^+ = \max(u, 0)$, $u^- = \min(u, 0)$. The robust asymptotic t-values are in ( ). The coefficient estimates for the three lagged differences of each series are not reported but are available upon request. $k = 3$.

in the cross-product of the standardized residuals of orders up to 1, 2, 5, 10 are reported with the notation $\rho(1)$, $\rho(2)$, $\rho(5)$, $\rho(10)$. The above diagnostics for the specification do not present any serious evidence against the model specification using bivariate GARCH(1, 1)-M in the system of the error correction models with the constant conditional correlation assumption.

IV. SOURCES OF UNCERTAINTY[6]

In the previous section we have aimed to measure the impact of uncertainty in sales and inventories on the behaviour of the series. Uncertainty is measured by estimating one-period-ahead forecast error variance in the VECM using GARCH(1, 1) specification. We find that costs involved in maintaining inventories have predominant influences on sales and inventory behaviour but the contribution of uncertainty is minimal.

6 We thank a referee for suggesting to extend our research along these lines. All the computations in this paper are done using GAUSS386i Version 3.0.

TABLE 5
Specification tests for the standardized residuals

	Wholesale		Retail	
Statistics	ΔI	Δs	ΔI	Δs
Ljung-Box(20)	0.016	0.847	0.002	0.046
McLeod-Li(20)	0.644	0.245	0.486	0.412
ARCH(1)	0.444	0.379	0.836	0.683
ARCH(2)	0.673	0.618	0.269	0.164
ARCH(5)	0.406	0.522	0.673	0.389
ARCH(10)	0.375	0.424	0.587	0.167
$\rho(1)$	0.300		0.052	
$\rho(2)$	0.577		0.065	
$\rho(5)$	0.770		0.167	
$\rho(10)$	0.317		0.424	

NOTES: ARCH and ρ denote the LM tests for autocorrelations in the squared standardized residuals and in the cross product of standardized residuals, respectively. The number in ( ) is the degree of freedom of each test. The asymptotic p-values are reported. $k = 3$.

As the VECM provides an environment in which forecast error variance decomposition can be performed, it may yield interesting information about the relative importance of the common stochastic trend in uncertainty of sales and inventories. Thus we estimate the initial model (VECM with $k = 3$) in section II by the Johansen (1991) method and invert it to the vector moving average model (the Wold representation).[7] We then follow King et al. (1991), who consider conditions to identify the common stochastic trend that is assumed to follow a random walk. Given the estimated cointegrating rank ($r = 1$), the fraction of forecast error variance for each series attributed to shocks to the common stochastic trend are computed (table 6). In figures 1 and 2 the estimated permanent component of inventory and sales series are plotted along with the actual series and simulated one-standard-error confidence intervals for each trade sector.[8]

Substantial forecast error variance in sales is associated with the common stochastic trend, while a little of uncertainty in inventory behaviour is explained by it. This is more the case in the retail trade than in the wholesale trade sector.

7 The order of vector moving average model is 36 (VMA(36)). We have also used VMA(48), and the results were almost the same.

8 The permanent component of each series is the sum of the initial value, time trend, and the common stochastic trend (see King et al. 1991, 838). Note that the values of initial observation and the slopes of the time trend are different in inventory and sales series. In computing Monte Carlo standard errors we used both the recursive bootstrap method and (conditional) normal approximation. As we have used the assumption of conditional normality throughout the paper, we report the results using only the latter. The bootstrap results however, may be available on request. We computed standard errors and quantiles as well, but the quantiles are not reported; they are also available from the authors.

TABLE 6
Forecast error variance decomposition

	Wholesale		Retail	
Horizon	ΔI	Δs	ΔI	Δs
1	0.322 (0.203)	0.757 (0.194)	0.024 (0.097)	0.911 (0.131)
6	0.339 (0.184)	0.736 (0.188)	0.129 (0.081)	0.870 (0.126)
12	0.343 (0.175)	0.734 (0.188)	0.158 (0.072)	0.870 (0.126)
24	0.343 (0.173)	0.734 (0.188)	0.165 (0.071)	0.870 (0.126)
36	0.343 (0.172)	0.734 (0.188)	0.166 (0.071)	0.870 (0.126)

NOTE: Approximate standard errors, shown in ( ), were computed by Monte Carlo simulation (normal approximation) using 500 replications. $k = 3$.

These results from the forecast error variance decomposition are also consistent with what we may observe from the estimated permanent components in figures 1 and 2. In both trade sectors the sales series move more closely with its permanent component than the inventory series. This is also more the case in the retail trade than in the wholesale trade sector.

As the common stochastic trend is more closely related to the sales than to the inventory series, the shocks to the common stochastic trend may be more likely to come from the demand side than from the supply side. In other words, the permanent shocks to the system of $(I_t s_t)$ consist of more demand shocks and fewer cost shocks. This situation is quite as expected for the trade sectors. As is also expected, this is even more the case in the retail trade than in the wholesale trade sector. Further studies comparing these results with the manufacturing sector might be interesting.

V. CONCLUDING REMARKS

We have studied uncertainty in sales and inventory behaviour in the U.S. trade sectors in two ways. First, in section III, using the VECM-GARCH-M model, we have seen that uncertainty measured by one-month-ahead forecast error variance in sales does not affect inventory behaviour in both trade sectors. Second, in section IV, using forecast error variance decomposition, we have seen that the uncertainty measured by one-to-thirty-six-months-ahead forecast errors may be attributed to demand shocks rather than to cost shocks.

The results indicate some differences between the wholesale and retail trade sectors. First, from the test of non-symmetric error correction it may be suggested that inventory holding cost is more important relative to stockout cost in the wholesale trade sector, whereas both motives are not significantly different for the retail trade sector. Secondly, the sales seem to be more exogenously determined in the retail trade than in the wholesale trade.

The results also indicate some similarities between the two sectors. First, while

FIGURE 1a Inventory: wholesale trade

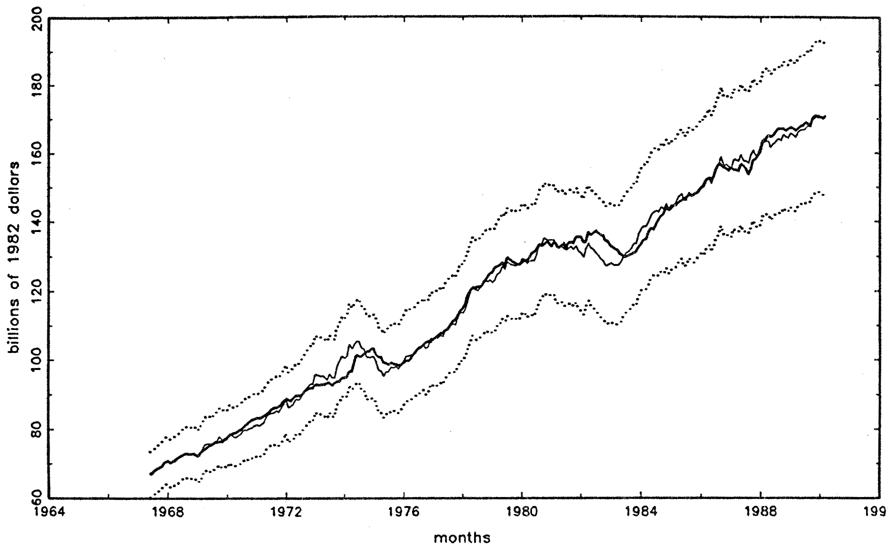

FIGURE 1b Sales: wholesale trade

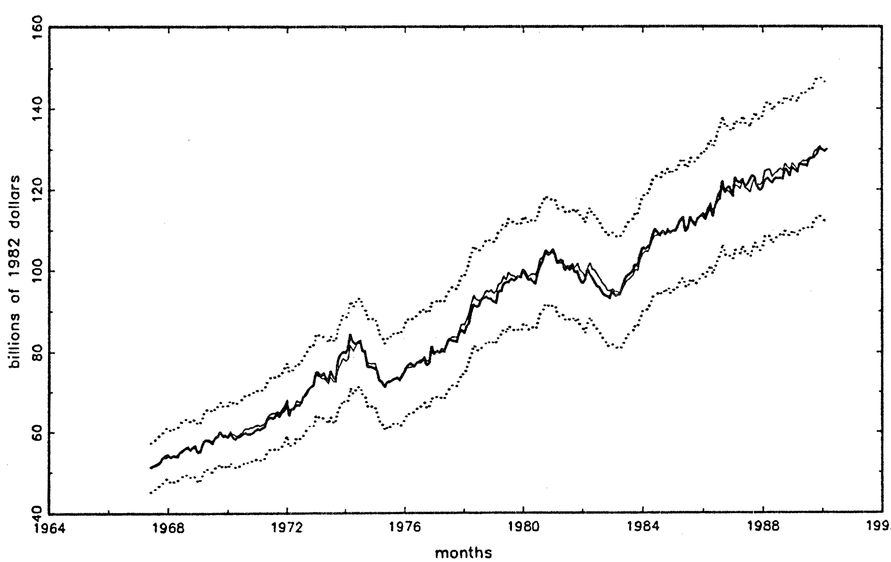

FIGURE 1 Stocastic trends (wholesale trade)
NOTE: Actual series (bold solid line), estimates of stochastic trends (thin solid line), and one standard deviation confidence interval (dotted lines). The empirical standard deviations were computed by Monte Carlo simulation (normal approximation) using 500 replications.

FIGURE 2a Inventory: retail trade

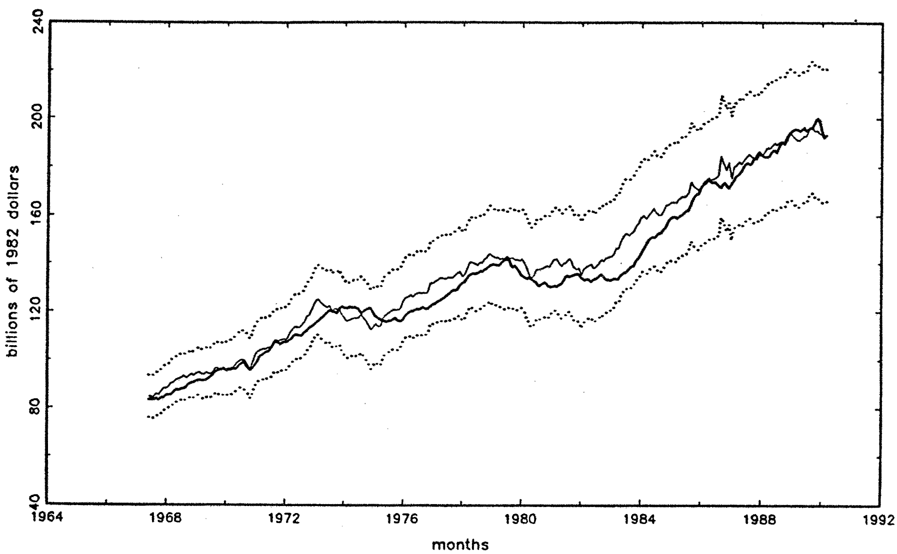

FIGURE 2b Sales: retail trade

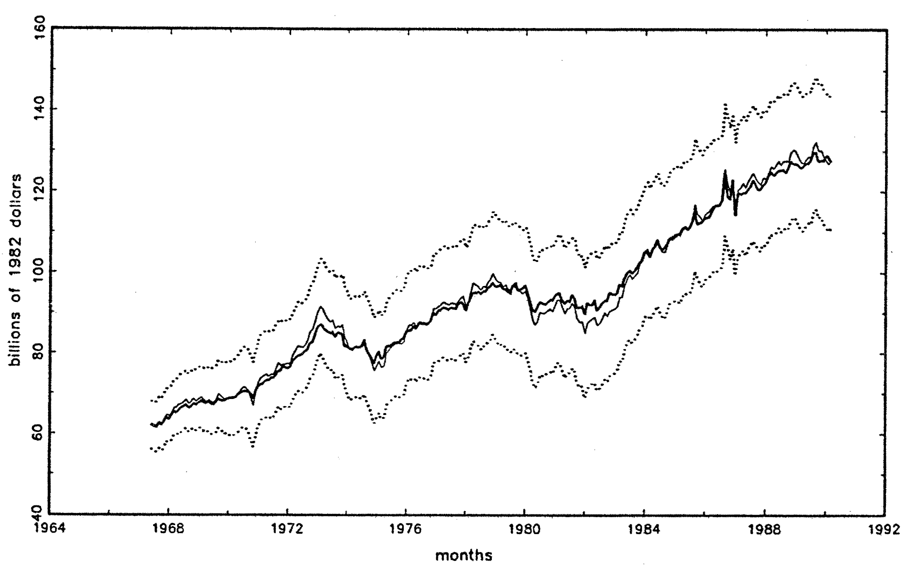

FIGURE 2 Stochastic trends (retail trade)
NOTE: Actual series (bold solid line), estimates of stochastic trends (thin solid line), and one standard deviation confidence interval (dotted lines). The empirical standard deviations were computed by Monte Carlo simulation (normal approximation) using 500 replications.

inventory holding costs and stockout costs have a significant effect on inventory behaviour, neither uncertainty in sales nor uncertainty in inventories has a significant impact on sales and inventory behaviour. Second, more forecast error variance in sales than in inventories is attributed to the permanent shocks, implying that the permanent shocks consist more of demand shocks than of cost shocks in both trade sectors.

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