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Sales Persistence and the Reductions in GDP Volatility

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Abstract:
A number of explanations for the observed decline in GDP volatility since the mid-1980s have been offered. Valerie Ramey and Daniel Vine (2003a, 2003b) in a couple of recent papers offer the hypothesis that a decline in the persistence of sales is an explanation for the decline in GDP volatility. Their models show that a decrease in sales persistence leads to a decline in the variance of production relative to the variance of sales. They provide econometric evidence that the persistence of unit automobile sales has declined at both the aggregate and model level. This paper explores reasons why sales persistence may have declined and then tests the Ramey-Vine hypothesis with monthly chain-weighted sales data from 2- and 3-digit manufacturing and trade industries. The estimates confirm the Ramey-Vine findings for motor vehicle retailers, wholesalers, and manufacturers. For a number of industries outside of motor vehicles, especially those in wholesaling and nondurable manufacturing, considerable evidence is found of declines in sales persistence. These declines seem to be consistent with changes in supply and distribution chains that have occurred as the result of the introduction of new information, inventory, and production control systems. However, in equations estimated for aggregate manufacturing, wholesaling, and retail sector sales, declines in sales persistence are not found.

JEL Classifications: E32, E22, E23

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1. Introduction

A substantial decline in the volatility of U.S. real GDP growth since the early 1980s, first observed by Kim and Nelson (1999), Blanchard and Simon (2001) and McConnell and Perez-Quiros(2000), has spawned a rapidly growing literature which attempts to explain the volatility reduction.[1] Generally these explanations fall into 3 categories: (1) Good Luck, (2) Better Policy, or (3) Structural Change. Ahmed, Levin, and Wilson (2004) attribute most of the reduction to "good luck" in the sense of smaller shocks hitting the economy; Stock and Watson (2003) also show a role for smaller shocks. Stock and Watson (2003) and Boivin and Giannnoni(2002, 2003) attribute most of the reduction in GDP volatility to improved monetary policy. The "Structural Change" explanation was first put forth by McConnell and Perez-Quiros (2000) and Blanchard and Simon (2001) who both agreed that the decline in volatility is linked to inventory investment.[2]

In positing the structural change hypothesis, Kahn, McConnell, and Perez-Quiros(2002) [hereafter, KMP] argued that the adoption of new inventory and production control systems allowed firms to respond more quickly and flexibly to changes in sales and hence reduce production volatility. As evidence for structural change, KMP point out that since 1984: (1) inventory to sales ratios have declined, (2) production variance declined more than sales variance, and (3) the covariance between sales and inventory investment has become more negative. Valerie Ramey and Daniel Vine (2003b) in their paper question the KMP explanation and offer a different "Sales Persistence" hypothesis[3]. They demonstrate in an inventory model involving non-convex costs that a decline in sales persistence leads to a decline in the variance of production relative to the variance of sales. Using monthly data (at the industry and plant level) from the U.S. automobile industry, they find that the persistence of motor vehicle sales indeed did decline in the post-1983 period relative to the pre-1984 period. They, in turn, argue that declines in the persistence of sales probably help account for the decline in GDP volatility.

It is the goal of this paper to explore further the Ramey-Vine hypothesis that decreases in sales persistence are an explanation for the decline in GDP volatility. In the next section we briefly review the Ramey-Vine theory. In section 3 we use monthly seasonally adjusted data for available two and three digit SIC Manufacturing and Trade industries from 1967:1 through 2001:3 to examine just how much (and in what industries) sales persistence has declined. Equations similar to those used by

[1] Blanchard and Simon (2001) suggest that GDP volatility has been declining continually since the 1950s.
[2] McConnell and Perez-Quiros(2000) conclude (p. 1474), "Clearly, some aspect of inventory investment in the United States has changed in such a way as to have markedly reduced the volatility of U.S. output fluctuations." Warnock and Warnock (2000) offer similar evidence based on employment, and also suggest a possible role for inventory management changes in reducing volatility. .
[3] Ramey and Vine (2003b) call the KMP structural change explanation the "Information Technology" hypothesis.

Ramey and Vine are estimated. At the aggregate level, there is not much evidence of declines in sales persistence. Results at the industry level confirm that sales persistence has declined in some industries and gone up in others. In section 4 we discuss possible causes of the declines in sales persistence in certain industries and relate these to the KMP structural change hypothesis. Section 5 concludes.

2. Theoretical Considerations

Ramey and Vine propose models in two papers which show that a decline in the persistence of sales shocks decreases the variance of production relative to the variance of sales without any changes in the structure of the production scheduling, inventory control systems, or information systems. The basic insight is that if sales shocks are persistent, then when a shock occurs the firm must adjust production to lessen the costs of inventories being away from their target levels. When sales unexpectedly increase in a particular month, then the firm expects sales also to be higher than normal in the following months. Hence, the firm must increase production since not doing so would involve drawing down inventories well below their target levels (maybe to zero) and incurring the cost of insufficient inventories. Likewise, if the firm unexpectedly has sales fall, then the firm expects them to be low for several months and hence, the firm must cut production to avoid building up large excess inventories which are expensive to carry.

Ramey and Vine (2003a) present a standard-production smoothing model of a firm which seeks to minimize production and inventory costs given a particular process for sales:

(1) Minimize $$\mathbf{V = E_0 \sum_{t=0}^{\infty} \beta^t \left[\tfrac{1}{2}\, \alpha_1\, Y_t^2 \;+\; \tfrac{1}{2}\, \alpha_2\, (I_t - \alpha_3 S_{t+1})^2 \right]}$$

subject to $Y_t = S_t + I_t - I_{t-1}$

where E_0 denotes the expectation conditional on information in period 0, β is a discount factor between 0 and 1, Y_t is production during period t, I_t is the stock of inventories a the end of period t, and S_t is the sales during period t. In scheduling production, the firm considers two types of costs: increasing marginal costs of production and the cost of allowing inventories to deviate from the desired inventory to sales ratio. Under the assumption that sales are given by an AR(1) process

(2) $$\mathbf{S_t = \rho S_{t-1} + \epsilon_t \qquad 0 < \rho < 1 \qquad \epsilon_t \text{ i.i.d.}}$$

Ramey and Vine derive that the optimum rule for production is given by:

(3) $$\mathbf{Y_t = -(1-\lambda)\, I_{t-1} + \varphi S_t}$$

The parameter φ depends on the underlying parameters including ρ (the persistence parameter for sales). Hence, their model shows that the relative variance of production and sales and the covariance between production and inventory investment are dependent on ρ. For most parameter values, Ramey and Vine report that a decrease in ρ leads to a decrease in the variance of production relative to the variance of sales. Similarly, for "every parameter combination we studied"(Ramey & Vine(2003a, p5)), the covariance between sales and the change in inventories decreased with a decrease in ρ.

In Ramey and Vine (2003b), they use a cost function for an automobile assembly plant described by Bresnahan and Ramey (1994) and Hall(2000) which involves various non-convexities to analyze the response of production to changes in among other things the persistence of the sales process. To do this they perform a simulation of the firm's dynamic cost minimization problem solving for the firm's short-run production decisions with sales evolving as a first-order Markov process parameterized to mimic an AR(1) sales process. They find that "if a given change in the variance of sales stems from a reduction in the persistence of shocks to sales, this can lead to a large decline in the variance of output relative to sales"(Ramey and Vine, 2003b, p.23).

3. Empirical Results

To examine whether sales persistence declined, we utilize the same empirical specification used by Ramey and Vine (2003b) who estimated the following simple univariate model of monthly sales when they modeled the sales of new cars and trucks:

$$(4)\quad \mathbf{Sales}_t = \alpha_0 + \alpha_1\,\mathbf{Sales}_{t-1} + \alpha_2\,\mathbf{trend}_t + \beta_0\,\mathbf{D}_t + \beta_1\,\mathbf{D}_t\,\mathbf{Sales}_{t-1} + \beta_2\,\mathbf{D}_t\,\mathbf{trend}_t + \epsilon_t$$

$$\text{Where}\quad \epsilon_t \sim N(0, (\sigma^2 + \beta_3 D_t))$$

$$\text{and}\quad D_t = 0 \text{ for } t < 1984{:}1$$

$$D_t = 1 \text{ for } t \geq 1984{:}1$$

The break date at the beginning of 1984 conforms to generally accepted break date found initially for GDP by McConnell and Perez-Quiros(2000). The specification given by equation (4) allows all the parameters to change in 1984:1: the constant term, the coefficient on lagged sales, the trend term, and the variance of the residual. The AR(1) coefficient on lagged sales serves as the <u>measure of the persistence</u> in monthly shocks to sales. Hence, of particular interest to us is the estimate of β_1, the amount the coefficient on lagged sales changed in the post-1983 period. If this decreased, one can conclude that sales persistence decreased in the post-1983 period. We estimated equation (4) by maximum likelihood on the log of monthly chain-weighted real seasonally adjusted sales data[4]. This data is from the Bureau of Economic Analysis of the U.S. Commerce Department from 1967:1 through 2001:3 for many 2 and 3 digit SIC code industries[5].

Estimates of equation (4) for the sales of various segments of the motor vehicle industry are given in Table 1. The first column is for Retail Motor Vehicle Sales measured in thousands of units sold, which is the data utilized by Ramey and Vine (2003b)[6]. The other columns (and the rest of this paper) use the log of chain weighted sales for the respective SIC industry. These results confirm the Ramey and Vine findings. In all segments except Auto and Home Supply stores, the estimated first order autocorrelation of sales falls. The estimated $\boldsymbol{\beta_1}$ coefficients range from -.12 to -.14 and test by a two-tailed test at the 5 percent level to be different from zero. The $\boldsymbol{\beta_1}$ estimate in the first column estimated on units data is -.24 suggesting an even larger drop in sales persistence. Retail chain weighted sales of motor vehicle dealers (SIC 551) include sales of parts and services as well as new and used vehicles whereas the first column units sales is just new cars and light trucks. This difference in definition probably accounts for the smaller $\boldsymbol{\beta_1}$ estimates using chain weighted data. This is supported by the third column estimates which shows no reduction in the autocorrelation of sales of parts and other items sold by by Auto and Home Supply stores. So the estimates of Table 1 support the Ramey-Vine sales persistence hypothesis at least applied to the motor vehicle industry.

What about other industries? In Irvine and Schuh(2005a) we found through a variance decomposition that reductions in the volatility of the NIPA Goods sector output accounted for nearly two-thirds of the reduction in GDP volatility, the NIPA Structures accounted for 9% of GDP volatility reduction, while the NIPA Services sector accounted for basically none of the GDP volatility reduction. An additional 19% was accounted for by a reduction in the covariance between the Goods and Structures sectors. In this paper we use monthly data from the manufacturing and trade (M&T) sector which we believe is representative of the NIPA Good Sector[7]. Hence, if we find reductions in sales persistence for M&T sector sales, then that would imply that the Ramey-Vine hypothesis is an important part of the explanation for the decline in GDP volatility in the post-1983 period.

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[4] The RATs program from Estima was used to estimate equation (4). Robust Standard errors are reported.

[5] After 2001:3 data is only available from a new industrial classification scheme (NAICs). Our data are from HAVER.

[6] The dependent variable is the log of the of sum domestic retail auto sales and light truck sales, seasonally adjusted from 1967:2 through 2001:3. Ramey and Vine(2003b) used a slightly longer sample, 1967:2 through 2002:9.

[7] See our earlier discussion in Irvine and Schuh (2005). The variance properties of M&T gross production are very similar to those of NIPA goods value added, and the growth rates of the two aggregate measures have a correlation of about 0.7. Overall, M&T gross production varies less than the NIPA goods value added output, most likely because the M&T sector excludes relatively high variance sectors (e.g. agriculture and mining). However, the relative variance reduction from the pre-1984 period to the post-1984 period is virtually identical for the two output measures.

In Table 2 are the results of estimating equation (4) for the sales of the Total M&T sector (column one), and for the sales of the 3 major M&T sub-sectors: Manufacturing, Merchant Wholesalers, and Retailers. Examining the estimates of $\boldsymbol{\beta_1}$ we find no evidence that autocorrelation of sales has fallen from the early to the late period; in fact, all four $\boldsymbol{\beta_1}$ estimates are positively signed and statistically insignificant[8]. This is despite the fact that these M&T sales aggregates each contain motor vehicle sectors which we know from Table 1 did experience a reduction in sales persistence. Hence, on its own, it does not appear that the reduction in sales persistence accounts for much of the reduction in GDP volatility since 1984.

On the other hand, in Table 2 the estimated $\boldsymbol{\beta_3}$ coefficients show that there was a reduction in the innovation variance in Total M&T sales, Manufacturing sales, and Wholesaler sales. In contrast the innovation variance of Retail sales is not estimated to have declined (i.e. the estimated $\boldsymbol{\beta_3}$ is zero)[9].

To further test the sales persistence hypothesis, we estimated equation (4) on sales series from detailed two and three-digit M&T industries. The results for industries dealing with durable goods are reported in Table 3. For retailers and manufacturers, sales persistence declined (see the coefficients on Δ AR(1)) mainly in industries associated with motor vehicles. None of the estimated $\boldsymbol{\beta_1}$ coefficients for non-auto retailers are negative. Among the 9 two-digit durable manufacturers outside of transportation, the estimated $\boldsymbol{\beta_1}$ coefficients are only negatively signed four times with only Instruments having a statistically significant decrease. However, among wholesalers, 4 of the 8 non-automotive wholesalers are estimated to have had a statistically significant decrease in sales persistence. In contrast, across all the durable goods industries, most of them are estimated to have experienced a reduction in innovation variance with the a majority of these negatively signed $\boldsymbol{\beta_3}$ coefficients testing to be statistically significant. So the evidence suggests that while sales variance decreased for most durables goods industries, outside of motor vehicle related industries, this reduction in variance came mainly through channels other than a reduction in sales persistence.

The results of estimating equation (4) for industries dealing with nondurable goods are reported in Table 4. Looking first at the innovation variance we see that the estimated $\boldsymbol{\beta_3}$ coefficients

[8] As a check on these results, sales were alternatively modeled as an AR(2) or AR(3) process. This required that sales for periods t-2 and t-3 be added to equation (4). Here the measure of persistence was the sum of coefficients on lagged sales. There were no significant estimated decreases in the sum of these coefficients. Hence, these alternative specifications provided no evidence of a decrease in sales persistence for the aggregate sectors reported in Table 2.

[9] This is consistent with the results of Stock and Watson (2003) who examined 168 macro series and found that two-thirds of the series had breaks in their conditional variances with most of the estimated break dates being in the 1980s. Their estimated break dates for M&T total sales and M&T Manufacturing sector sales was the fourth quarter of 1983; for M&T Wholesalers their estimated break date was 1982 Q3. They estimated no break in the conditional variances of Retailers. See Table A-1 in Appendix A of Stock and Watson (2003).

are negatively signed and statistically significant in most nondurable industries. All the nondurable retailer estimates of $\boldsymbol{\beta_3}$ are negative and show large statistically significant reductions in innovation variance. For example, the aggregate Nondurable Retail equation estimate suggests innovation variance fell 50.62%. Innovation variance is also estimated to have decreased on average by 54.17% for wholesalers with the estimates showing that $\boldsymbol{\beta_3}$ decreased in a statistically significant way for 6 of the 9 nondurable wholesalers. Similarly, the $\boldsymbol{\beta_3}$ coefficient estimate in the aggregate Nondurable Manufacturing sales equation suggests innovation variance fell 37.86%. The individual sales equations show that innovation variance fell in 7 of the 10 nondurable manufacturers.

Turning to sales persistence, we find a very interesting pattern. Among nondurable goods retailers, sales persistence is estimated to have increased! The estimated $\boldsymbol{\beta_1}$ coefficients are all positive and all but one test to be statistically significant. In contrast, 7 of the 9 estimated $\boldsymbol{\beta_1}$ for wholesaler sales are negatively signed indicating a decrease in sales persistence; 2 of these test to be statistically significant. Moreover, sales persistence decreased even more for manufacturers of nondurables. The aggregate Nondurable Manufacturing sales equation shows a relatively large statistically significant decrease in $\boldsymbol{\beta_1}$. Across the 10 manufacturers of nondurable goods, 9 of the $\boldsymbol{\beta_1}$ estimates are negative with 4 testing to be statistically significant and another two having p-values less than 0.07.

So for nondurable industries, how can it be that sales persistence is estimated to have increased significantly at the retail level, but decreased at the wholesaler and especially the manufacturing level? One possible answer is that the decrease in sales persistence is coming from structural changes related to the adoption of information technology as KMP posited.

4. Possible Causes of the observed Declines in Sales Persistence

Why should the persistence of sales decline? Ramey and Vine (2003b) offer two hypotheses for the motor vehicle industry: (1) the vehicle manufacturers changed their pricing policy after 1983 offering more rebates and other incentives to smooth out their sales and (2) improved monetary policy operating through interest rates stabilized sales of interest sensitive sectors like automobiles. They report some reduced form empirical evidence supporting the second hypothesis but not the first.

Declines in sales persistence would also seem to result from some of the changes cited by KMP in describing structural changes within and between industries. These changes can be classified as (1) Information technology allowing better monitoring of each firm's own sales and inventory levels, (2) Better monitoring of downstream firms sales by suppliers (facilitated by the introduction of better information technology), and (3) The adoption of just-in-time production systems which requires deliveries (sales) of suppliers to adjust to the changing production needs of downstream firms.

Historically firms conducted a count of physical inventory once or twice a year. In between they estimated stock levels by keeping track of dollar sales volume. When sales slowed, they were often slow to recognize this and respond and hence accumulated excess inventory. Eventually orders to suppliers would be cut (to a level below sales) and kept at a lower level for an extended period of time while the firm sold off the excess inventory. Hence, negative sales surprises resulted in excess inventories and in turn, prolonged cuts in orders to suppliers (and hence sales of suppliers). This process created many of the classic "inventory liquidation cycles": typically around recessions, excess inventories would develop first at the retail and wholesale level which would lead eventually to cuts in orders to upstream manufacturers. The opposite would happen in response to positive sales surprises: stocks would be run down below target levels causing firms to raise orders above normal levels for lengthy periods. These extended periods of order cuts or order increases certainly raised the persistence of the sales of their suppliers.

Today, when sales decrease, most medium and large firms observe this information almost immediately since sales and physical inventory stocks are tracked item by item by bar codes. This real time information allows firms to respond much more quickly to sales surprises. When sales decrease unexpectedly, orders to suppliers are cut more quickly which in turn means less excess inventories build-up[10]. Since there are less excess stocks to liquidate, firms can return to normal order levels to suppliers much more quickly than before. Hence, for a given stochastic sales process, this adoption of inventory control systems using modern information technology, should have reduced the orders or sales persistence observed by the firms' suppliers.

Of course, many wholesalers and manufacturers now monitor the sales of their customers. The automobile manufacturers were one of the first to monitor the sale of every car by their franchised retail dealers. However, many manufacturers have since arranged to monitor the sales by wholesalers and retailers of items they supply to these firms. This information sharing is often part of a shared inventory re-order system in which the manufacturer takes some of the responsibility for keeping the distributor adequately stocked. This sharing of information by for example, downstream firms (e.g. retailers) with their upstream (wholesaler) suppliers allows the upstream suppliers to adjust their production levels (and adjust their orders to their suppliers, e.g. manufacturers) in anticipation of an order level change by the downstream (retail) firm. Such adjustments by upstream firms should in turn reduce any inventory disequilibrium (excess inventory build-up or shortage) at the upstream firm.

[10] The firm might also respond more quickly to sales declines by cutting prices to sell the excess stocks (see Irvine(1981)) and in turn further decrease the need to cut orders to suppliers for an extended period of time.

Smaller deviations of inventory from their target levels, should in turn lead to a smoother order flows and hence, less observed persistence in sales following a shock to sales.

Some firms have gone beyond monitoring of downstream firm sales. Many have teamed with their suppliers to adopt just-in-time production systems where for example, automobile suppliers continuously monitor the assembly of cars and deliver car seats and other parts just in time to be put onto the assembly line. These JIT systems have been widely adopted; e.g., a large U.S. retailer's (J.C. Penney) individual stores are supplied with men's dress shirts on a JIT basis from a manufacturer in China. Under such systems supplier sales vary with the production levels of their downstream customers; hence, the only sales surprises faced by suppliers should be those faced by their customers.

In Table 4 for Nondurable Goods industries we observed that despite the fact that sales persistence increased for retail firms, it decreased for wholesalers and especially manufacturers. This result can be explained by the adoption of new information technology, inventory, and production control systems by these firms. Retailers, which experienced smaller innovation variances, were able to smooth their orders to their suppliers, the wholesalers and manufacturers. Similarly, wholesalers experienced smaller sales innovation variances (partly as a result of smoother orders from retailers) and hence were able to reduce the persistence of their orders to manufacturers. These results suggest the reduction in sales persistence that is observed among these nondurable good firms is coming from structural changes among industries, not directly from monetary policy or other aggregate shocks.

5. Conclusions and further research directions

As Table 2 estimates of aggregate M&T sales indicated, there appears to be no indication of a decline in sales persistence that has influenced the sales of the main goods sectors of the economy: Manufacturing, Wholesaling, and Retailing. In this sense, the Ramey-Vine hypothesis that declines in sales persistence are a major separate explanation of the decline in GDP volatility seems incorrect. This said, we found a considerable amount of evidence that sales persistence has declined for a number of industries (outside of motor vehicles) especially those in wholesaling and nondurable manufacturing. These observed declines in sales persistence seem to be consistent with the structural changes that have occurred due to the introduction of new information technology and the new relationships between upstream and downstream firms in supply chains and distribution chains. To show that structural change is a reason for the decline in GDP volatility, much further detailed modeling of the interaction between industries needs to be done. Declines in sales persistence will probably be part of that story.

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TABLE 1

Estimates of Motor Vehicle Industry Sales Processes

$$\text{Sales}_t = \alpha_0 + \alpha_1 \text{Sales}_{t-1} + \alpha_2 \text{trend}_t + \beta_0 D_t + \beta_1 D_t \text{Sales}_{t-1} + \beta_2 D_t \text{trend}_t + \epsilon_t$$

$$\epsilon_t \sim N(0, (\sigma^2 + \beta_3 D_t))$$

and $D_t = 0$ for $t < 1984{:}1$
$D_t = 1$ for $t \geq 1984{:}1$

		Domestic Unit Retail Sales Motor Vehicles	RETAIL FIRMS Motor Vehicle Dealers	Auto & Home Supply Stores	Wholesalers Motor Vehicles	Manufacturers Motor Vehicles
SIC CODE:			551	553	501	371
COEFFICIENT						
α_0	(constant)	0.7783 *	0.6255 *	0.7279 *	0.4087 *	0.9351 *
		(.2171)	(0.2335)	(0.1816)	(0.1624)	(0.2392)
β_0	(Δ constant)	1.512 *	1.311 *	-0.1626	1.1252 *	1.0907 *
		(0.332)	(0.431)	(0.2670)	(0.4015)	(0.3741)
α_1	(AR(1))	0.8849 *	0.9385 *	0.8946 *	0.9532 *	0.9019 *
		(.0328)	(0.0242)	(0.0265)	(0.0191)	(0.0257)
β_1	(Δ AR(1))	-,2383 *	-0.1396 *	0.0277	-0.1177 *	-0.1225 *
		(0.0488)	(0.0440)	(0.0378)	(0.0436)	(0.0409)
α_2	(time trend)	-0.00005	0.00015	0.00043 *	0.00017	0.00011
		(0.00009)	(.00008)	(.00011)	(0.00010)	(0.00012)
β_2	(Δ time trend)	0.00055 *	0.00061 *	-0.00025	0.00002	0.00055 *
		(0.00014)	(.00015)	(0.00013)	(0.00011)	(0.00018)
σ^2	(innov. Variance)	0.00663 *	0.00192 *	0.00066 *	0.00107 *	0.00659 *
		(0.00047)	(0.00016)	(.00005)	(0.00010)	(0.00039)
β_3	(Δ innov. Variance)	-0.0014 *	0.00001	-0.000413 *	-0.00011	-0.00302 *
		(0.00057)	(0.00018)	(.000055)	(0.00013)	(0.00043)
Log likelihood		848.03	1079.12	1396.67	1209.55	888.09
% Decrease in Innov. \ Var.		21.1	0.5	62.7	10.6	45.8

Notes: Sample 1967:2 thru 2001:3 Estimated by Maximum Likelihood with robust standard errors, which are reported in parentheses.
* Denotes coefficient tests to be statistically significant at the 5% level by a two-tailed t-test.

Table 2

Estimates of Aggregate Manufacturing & Trade Sales Processes

$$\textbf{Sales}_t = \alpha_0 + \alpha_1\,\textbf{Sales}_{t-1} + \alpha_2\,\textbf{trend}_t + \beta_0\,\textbf{D}_t + \beta_1\,\textbf{D}_t\,\textbf{Sales}_{t-1} + \beta_2\,\textbf{D}_t\,\textbf{trend}_t + \epsilon_t$$

Where $\epsilon_t \sim N(0, (\sigma^2 + \beta_3 D_t))$

and $D_t = 0$ for $t < 1984{:}1$
$D_t = 1$ for $t \geq 1984{:}1$

COEFFICIENT		Total Manufacturing & Trade	Manfacturing Sector	Merchant Wholesalers	Retailers
α_0	(constant)	0.6427 *	0.7457 *	0.7649 *	0.5202 *
		(0.1721)	(0.2091)	(0.1943)	(0.2048)
β_0	(Δ constant)	-0.4542	-0.1791	-0.1604	-0.1232
		(0.3065)	(0.3301)	(0.3370)	(0.3599)
α_1	(AR(1))	0.9495	0.9382 *	0.9319 *	0.9589 *
		(0.0136)	(.0160)	(0.0175)	(0.0180)
β_1	(Δ AR(1))	.0356	0.0139	0.0139	0.01
		(0.0244)	(0.0278)	(0.0305)	(0.0317)
α_2	(time trend)	0.0001 *	0.00009 *	0.00023 *	0.0001 *
		(0.00003)	(0.00003)	(0.00006)	(0.00005)
β_2	(Δ time trend)	-0.000001	0.00003	-0.00003	0.00002
		(0.000001)	(0.00007)	(0.00010)	(0.00008)
σ^2	(innov. Variance)	0.000114 *	0.00022 *	0.00025 *	0.00015 *
		(0.000009)	(.00002)	(0.00002)	(.00001)
β_3	(Δ innov. Variance)	-0.000029 *	-0.00006 *	-0.00012 *	0.00000
		(0.000012)	(0.00002)	(.00002)	(0.00002)
Log likelihood			1550.21	1564.08	1601.17
Percent Reduction in Innovation Variance		25.4	27.3	48	0

Note: Sample 1967:2 thru 2001:3 Estimated by Maximum Likelihood with robust standard errors, which are reported in parentheses.

* Denotes coefficient tests to be statistically significant at the 5% level by a two-tailed t-test.

TABLE 3 Durable Goods Industries

	SIC Code	Coefficient on: AR(1) "α_1"	Δ AR(1) "β_1"	P-value of change	Innovation Variance: Pre-1984	"β_3", Chg. Post-1984	P-value of change	% Change in variance
Durable Goods Retailers	**52-59n**	**0.9401**	**-0.0128**	**0.7306**	**0.000774**	**-0.000079**	**0.2932**	**-10.21%**
Automotives	55	0.9194	-0.1094	0.0137 *	0.001827	-0.000176	0.2919	-9.63%
Motor Vehicle Dealers	551	0.9361	-0.1396	0.0015 *	0.001919	0.000009	0.9610	0.47%
Auto & Home Supply Stores	553	0.8946	0.0277	0.4634	0.000659	-0.000413	0.0000	-62.67%
Lumber & Building Materials	521	0.9568	0.0087	0.7482	0.000590	-0.000164	0.0065	-27.80%
Furniture & Home Furnishings	571	0.9329	0.0596	0.0074	0.000359	-0.000191	0.0000	-53.20%
Other Durable Good Stores	579	0.9298	0.0135	0.6585	0.000638	-0.000360	0.0000	-56.43%
Durable Wholesalers	**50**	**0.9591**	**-0.0048**	**0.8590**	**0.000319**	**-0.000107**	**0.0006**	**-33.54%**
Motor Vehicles	501	0.9532	-0.1177	0.0069 *	0.001067	-0.000113	0.3723	-10.59%
Furniture & Home Furnishings	502	0.8899	-0.1295	0.0194 *	0.000890	0.000342	0.0058	38.43%
Lumber & Construction Mat.	503	0.9094	0.0096	0.8174	0.001169	-0.000271	0.0122	-23.18%
Prof. & Commercial Equipment	504	0.7811	0.1821	0.0002 *	0.000765	0.000039	0.6984	5.10%
Metals & Minerals (ex. Petrol.)	505	0.9569	-0.3236	0.0000 *	0.002034	-0.001051	0.0000	-51.67%
Electrical Goods	506	0.9538	0.0218	0.4256	0.000652	-0.000228	0.0011	-34.97%
Hardware & Plumbing	507	0.9457	-0.1011	0.0267 *	0.000612	-0.000010	0.8950	-1.63%
Machinery,Equipment,Supplies	508	0.9673	-0.0467	0.2006	0.001002	-0.000427	0.0000	-42.61%
Other Durable Goods	509	0.8837	-0.1290	0.0229 *	0.002109	-0.000413	0.0624	-19.58%
Durable Manufacturers		**0.9278**	**0.0324**	**0.2327**	**0.000488**	**-0.000179**	**0.0002**	**-36.68%**
Lumber & Wood Products	24	0.9154	-0.0749	0.0618	0.001247	-0.000300	0.0276	-24.06%
Furniture & Fixtures	25	0.8843	0.0074	0.8518	0.001173	-0.000625	0.0000	-53.28%
Stone, Clay,& Glass Products	32	0.9409	-0.0032	0.9246	0.000814	-0.000211	0.0145	-25.92%
Primary Metals	33	0.9186	-0.0620	0.1136	0.002280	-0.001819	0.0000	-79.78%
Fabricated Metals	34	0.8778	0.0675	0.0673	0.000681	-0.000367	0.0000	-53.89%
Industrial Machinery	35	0.9698	0.0180	0.3675	0.000426	0.000000	0.9954	0.00%
Electronic Machinery	36	0.9518	0.0298	0.2025	0.000405	-0.000020	0.7108	-4.94%
Instruments	38	0.9265	-0.1010	0.0297 *	0.000404	0.000052	0.3908	12.87%
Misc. Durable Manufacturing	39	0.9068	-0.0547	0.2561	0.001350	-0.000409	0.0076	-30.30%
Transportation Equipment	37	0.8728	-0.1699	0.0008 *	0.002935	-0.001031	0.0001	-35.13%
Motor Vehicles	371	0.9011	-0.1225	0.0027 *	0.006588	-0.003017	0.0000	-45.80%
Transp. Excl. Motor Veh.	37x	0.8953	-0.0399	0.4253	0.002199	0.000974	0.0025	44.29%

Data: Log of chain weighted Monthly Seas. Adjusted Sales 1967:02--2001:03; * Denotes statistical significance at 5% level (two-tailed test)

TABLE 4 Nondurable Goods Industries

	SIC Code	Coefficient on: AR(1) "α_1"	Δ AR(1) "β_1"	P-value of change	Innovation Variance Pre-1984	"β_3", Chg. Post-1983	P-value of change	% Change in variance
Nondurable Retailers	**52-59d**	**0.8857**	**0.1177**	**0.0000 ***	**0.000081**	**-0.000041**	**0.0000**	**-50.62%**
Food Stores	54	0.6781	0.2177	0.0000 *	0.000270	-0.000221	0.0000	-81.85%
Apparel Stores	56	0.7572	0.1241	0.0191 *	0.000442	-0.000162	0.0019	-36.65%
Department Stores	531	0.8025	0.1698	0.0001 *	0.000406	-0.000250	0.0000	-61.58%
Other General Merchandise	539	0.8844	0.0195	0.6251	0.000587	-0.000192	0.0001	-32.71%
Misc. Nondur Retail Stores	59	0.9525	0.0449	0.0184 *	0.000007	-0.000002	0.0012	-28.57%
Nondurable Wholesalers	**51**	**0.8748**	**0.0174**	**0.6822**	**0.000469**	**-0.000254**	**0.0000**	**-54.16%**
Paper Products	511	0.9355	-0.0868	0.0264 *	0.000599	-0.000216	0.0001	-36.06%
Drugs and Sundries	512	0.8311	0.0708	0.1073	0.000742	-0.000332	0.0000	-44.74%
Apparel and Piece Goods	513	0.8463	-0.0673	0.2155	0.001523	0.000199	0.2914	13.07%
Groceries	514	0.7734	0.0035	0.9460	0.000580	-0.000228	0.0000	-39.31%
Farm Products	515	0.9188	-0.0672	0.0920	0.004131	-0.001527	0.0004	-36.96%
Chemicals and Allied Prod.	516	0.9140	-0.0214	0.6433	0.002810	-0.001954	0.0000	-69.54%
Petroleum Products	517	0.8666	-0.0011	0.9820	0.003006	-0.000947	0.0000	-31.50%
Alcoholic Beverages	518	0.8364	-0.2075	0.0003 *	0.000541	0.000587	0.0000	108.50%
Other Nondurable Goods	519	0.8270	-0.0668	0.1534	0.001387	-0.000001	0.9942	-0.07%
Nondurable Manufacturers		**0.7250**	**-0.0989**	**0.0351 ***	**0.000140**	**-0.000053**	**0.0000**	**-37.86%**
Food and Kindred Products	20	0.7718	-0.0791	0.2574	0.000374	-0.000220	0.0000	-58.82%
Tobacco Products	21	0.5362	-0.1222	0.0697	0.004515	0.004123	0.0000	91.32%
Textile Mill Products	22	0.9177	0.0188	0.6510	0.000642	-0.000274	0.0000	-42.68%
Apparel and other Products	23	0.8213	-0.2250	0.0008 *	0.001049	-0.000382	0.0000	-36.42%
Paper and Allied Products	26	0.8666	-0.0002	0.9970	0.000362	-0.000140	0.0003	-38.67%
Printing and Publishing	27	0.9165	-0.0863	0.0625	0.000589	-0.000310	0.0000	-52.63%
Chemicals and Allied Products	28	0.9492	-0.1332	0.0051 *	0.000485	-0.000247	0.0000	-50.93%
Petroleum Products	29	0.9276	-0.2201	0.0000 *	0.000722	0.000376	0.0007	52.08%
Rubber and Plastic Products	30	0.9438	-0.1361	0.0039 *	0.000785	-0.000391	0.0000	-49.81%
Leather and Leather Products	31	0.7575	-0.0866	0.1857	0.001568	0.000469	0.0159	29.91%

Data: Log of chain weighted Monthly Seas. Adjusted Sales 1967:02--2001:03; * Denotes statistical significance at 5% level (two-tailed test)