The Decline in U.S. Output Volatility: Structural Changes and Inventory Investment

Ana María Herrera
Michigan State University

Elena Pesavento
Emory University

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Abstract

Explanations for the decline in US output volatility since the mid-1980s comprise: "better policy", "good luck", and technological change. Our multiple break estimates suggest that reductions in volatility since the mid-1980s extend not only to manufacturing inventories but also to sales. This finding, along with a concentration of the reduction in the volatility of inventories in material and supplies, and the lack of a significant break in the inventory-sales covariance, imply that new inventory technology cannot account for the majority of the decline in output volatility.

Key words: GDP variance, structural break.

Corresponding author: Elena Pesavento, Department of Economics, Emory University, Emory GA30322, USA. Phone: (404) 712-9297. E-mail: epesave@emory.edu..

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1 Introduction

In recent years, several papers have documented a decline in US output volatility since the mid-1980's. Using different econometric methods, both Kim and Nelson (1999), and McConnell and Perez-Quiros (2000) find evidence of a structural break in volatility at the beginning of 19 84.Various studies indicate that the reduction in volatility is not confined to aggregate output, but that it extends to other aggregate variables such as all the major components of GDP (McConnell, Mosser, and Perez-Quiros, 1999), aggregate unemployment (Warnock and Warnock, 2000), aggregate consumption and income (Chauvet and Potter, 2001), and wages and prices (Sensier and Van Djik, 2001; Stock and Watson, 2002). Only interest rates, exchange rates, stock prices, money and credit series have experienced an upward shift in volatility (Sensier and Van Djik, 2001; Stock and Watson, 2002).

These findings have bolstered a line of research that seeks to understand the causes of this shift in economic behavior. Three competing explanations are: better policy, better technology, and good luck. The proponents of the first hypothesis (Clarida, Gali and Gertler, 2000; Boivin and Giannoni, 2003) claim that a significant change in the monetary policy rule during the Volcker-Greenspan period was the main source of this break. A second explanation advanced by McConnell and Perez-Quiros (2000), and Kahn, McConnell and Perez-Quiros (2002), argues that the introduction of better inventory management technology is the key to understanding the break in the variability of production. Central to this hypothesis is the finding of a reduction in the ratio of inventory to sales volatility, which coincides roughly with the introduction of just-in-time inventory techniques, and the lack of a break in the variance of sales. Finally, Ahmed, Levin, and Wilson (2002) contend that the decline in volatility is just a result of "good luck", that is to say, a reduction in the shocks hitting the economy during the last two decades. They identify the contribution of "good luck" or smaller shocks with the high frequency component of the GDP spectrum, low frequency with technological change, and the medium range of the frequency domain with monetary policy. They conclude that most of the reduction in volatility was caused by a decrease in the size of the innovations, a behavior that could be consistent with both "good luck" as well as with "better policy" in the form of improved monetary policy that worked to reduce aggregate volatility.

We extend this work by studying inventories and sales at a more disaggregate level, using Bai and Perron (1998) test for multiple breaks instead of tests for single breaks. The motivation for the higher level of disaggregation is twofold. On one hand, cross-sectional aggregation can introduce changes in the time series properties of the data, possibly affecting the location of the break. Furthermore, a framework that does not treat input (i.e. materials and work-in-process) and output (i.e. finished goods) inventories separately, makes it impossible to distinguish among factors that affect the volatility of these variables in a different manner. Recent work by Humphreys, Maccini and Schuh (2001) suggests that the response of inventories to demand shocks differ across durable and nondurable industries, as well as by stages of production. The stylized facts they present indicate that input inventories are twice as large as output inventories, three times more volatile, and particularly important in the durable goods industries. According to their estimates, the response of output inventories to demand shocks would lag the response of input inventories, and it would be smaller in magnitude. Thus, in the pre-Volcker era, a combination of high oil prices and a monetary policy rule that allowed for increases in anticipated inflation could have led to high variability in inflation, sales, and inventories at all stages of production. Possibly, with a smaller increase in volatility for finished goods inventories.

On the other hand, the 1980's transformations in the manufacturing sector, such as reduction in production cycles and delivery times, could have acted to lower work-in-process and finished goods inventory levels (Milgrom and Roberts, 1990). As for the volatility of inventories, one could conjecture that given a fixed variability in the sales process, the introduction of new technologies could have resulted in faster and smaller adjustments in finished goods and work-in-process inventories, with little change in materials.

Our results show that the decline in the variance is a phenomena that extends not only to manufacturing inventories but also to sales. Furthermore, we show that materials and supplies, not finished goods, account for most of the reduction in the variance of total inventories in the 1980's. Our findings of (a) a break in sales, (b) no significant change in the inventory-sales covariance, and (c) a break in inventories that is mainly accounted by materials and supplies, lead us to conclude that the introduction of new inventory holding techniques is insufficient to explain the reduction in output volatility. These results suggests that future research on the behavior of output volatility should not only seek to explain the decline in the variance in the mid-1980's, but also the heightened volatility of the 1970's. Moreover, any theory linking better technology, in the form of better inventory management and production techniques, and reduced output volatility should focus on the role of input inventories.

The remaining content of this paper is organized as follows: section 2 describes the industry level data; section 3 reviews the test and estimation techniques for breaks of unknown timing, and presents the structural break estimates; section 4 discusses time aggregation issues and presents the results for monthly data; the last section provides concluding remarks.

2 The Data

The industry level data used in this paper are manufacturing and trade sales and total inventories series from the Bureau of Economic Analysis. Specifically we study manufacturing and trade sales, as well as inventories, and we disaggregate the latter by stages of production. The series are seasonally adjusted and measured in chained dollars of 1996, spanning January 1959 to March 2000. They comprise 19 two-digit SIC sectors, 2 three-digit SIC sectors (motor vehicles and other transportation equipment) and three aggregates (total manufacturing, durable and non-durable manufacturing).

Because we are interested in calculating the contribution of movements in sales and inventories to the variability of output, we transform the inventories and sales data in the following manner. Consider the standard inventory identity:

$$Y_{i,t} = S_{i,t} + \Delta FH_{i,t} \tag{1}$$

where

$Y_{i,t}$: output of sector i in period t

$S_{i,t}$: sales of sector i in period t

$FH_{i,t}$: final goods inventories of sector i at the end of period t.

The rate of output growth can be written as

$$\overset{\bullet}{y}_{i,t} = \overset{\bullet}{s}_{i,t} + \Delta \overset{\bullet}{fh}_{i,t} \tag{2}$$

where

$$\overset{\bullet}{y}_{it} = \frac{\Delta Y_{it}}{Y_{i,t-1}}, \quad \overset{\bullet}{s}_{i,t} = \frac{\Delta S_{i,t}}{Y_{i,t-1}}, \quad \text{and} \quad \Delta \overset{\bullet}{fh}_{i,t} = \frac{\Delta^2 FH_{i,t}}{Y_{i,t-1}}, \tag{3}$$

and the variance in the rate of growth of output is given by:

$$VAR\left(\overset{\bullet}{y}_{i,t}\right) = VAR\left(\overset{\bullet}{s}_{i,t}\right) + VAR\left(\Delta \overset{\bullet}{f}h_{i,t}\right) + 2COV\left(\overset{\bullet}{s}_{i,t}, \Delta \overset{\bullet}{f}h_{i,t}\right) \tag{4}$$

Typically the inventory identity (1) does not include inventory investment in production inputs such as materials and supplies or work-in-process. However, input inventories have been historically larger and more volatile than output inventories (Humphreys, Maccini and Schuh., 2001) and, along with output inventories, they are included in the computation of GDP. In order to evaluate their contribution to reduction in overall inventory volatility, we maintain the definition of output as in (1), but compute a measure of materials (or work-in-process) inventories relative to the production of the sector as follows:

$$\Delta \overset{\bullet}{i}h_{i,t} = \frac{\Delta^2 IH_{i,t}}{Y_{i,t-1}} \tag{5}$$

where $IH_{i,t}$ is the level of raw materials or work-in-process inventories in sector i at the end of period t, and Y_{t-1} is the production of sector i in period t computed as the sum of manufacturing sales and the change in final goods inventories. We use the same normalization for total inventories, as well as for the wholesale and retail trade series.

Our data and computation methods differ from McConnell and Perez-Quiros (2000) and Kahn McConnell and Perez-Quiros (2002) in the following manner. First, we use the BEA data on manufacturing and trade, while the above mentioned papers use goods sector data from the national income and product accounts (NIPA). An advantage of using the NIPA is that they contain data on sectors that hold inventories, but are not included in the manufacturing and trade data (i.e., agriculture and mining). Nevertheless, the high level of aggregation of the NIPA series makes it difficult to evaluate the contribution of improved inventory management and production techniques to the decline in U.S. output volatility, and especially to the change in the volatility of inventories at different stages of production.

Second, the NIPA contain data on output, while the manufacturing and trade data do not. We therefore use the inventory identity to compute output. Due to the use of chain-weigthed data, our computation of the contribution to growth is an approximation to the real contribution (Whelan, 2000). This is also the case in McConnell and Perez-Quiros (2000).

Finally, while output in the NIPA includes investment in total inventories, we only include finished goods inventories in our calculation of output, as it is commonly done in inventory studies. Yet, estimation results - not reported in the paper- using total inventories to compute output, are essentially the same.

3 Structural Breaks

In cases where the date of the break is known, testing for a structural change can be easily done using a Wald test. However, when the date of the shift is unknown, the problem is complicated by the fact that the break date becomes a nuisance parameter that is present only under the alternative hypothesis but not under the null of no structural break. When this is the case, the standard asymptotic optimality properties of the Wald test do not hold.

While tests for a single break have been commonly used in applied research, modeling a shift in the variance as a one-time change has a drawback in finite samples: the low power of the test in the presence of multiple breaks (Bai, 1997 and Bai and Perron, 2003.) This might well be the case for a series with two breaks in the variance such that the volatility increases in the second period with respect to the first period, but returns to its initial value after the second break. Bai and Perron (1998) have proposed several tests for multiple breaks. We use the procedure propose by Bai and Perron (2003) and sequentially test the hypothesis of l breaks versus l+1 breaks using a $\sup F_T(l+1|l)$ statistics, where the supremum is taken over all possible partitions of the data for the number of breaks tested.

Let $x_{i,t}$ denote the sales, $\overset{\bullet}{s}_{i,t}$, and inventory, $\Delta\overset{\bullet}{h}_{i,t}$, variables defined in expressions (4) and (5). As in Stock and Watson (2002), we test for structural breaks in the parameters of the AR model

$$x_{i,t} = \mu_{i,1} + D_{i,t}\mu_{i,2} + \rho_{i,1}(L)\,x_{i,t-1} + D_{i,t}\rho_2(L)\,x_{i,t-1} + \varepsilon_{i,t} \qquad (6)$$

where $D_{i,t} = \left\{ \begin{array}{ll} 1 & if\ t < k \\ 0 & if\ t \geq k \end{array} \right\}, \quad var(\varepsilon_t) = \left\{ \begin{array}{l} \sigma_1^2,\ t < \tau \\ \sigma_2^2,\ t \geq \tau \end{array} \right\},$

k is the date of the break in the conditional mean, and τ is the date of the break in the conditional variance. The number of lags in the AR model is selected using the BIC, with a maximum of 4 quarters. The number selected is usually 2 or 3 for total inventories series and 1 or 2 for sales. This formulation allows for the conditional mean and variance to possibly experience breaks at different dates. We test for parameter constancy in the conditional mean of the absolute value of the residuals in (6):

$$|\widehat{\varepsilon}_{i,t}| = \alpha_{1,i} + D_{it}\alpha_{2,i} + \nu_{it}. \qquad (7)$$

Since when we test for a change in the covariance between inventories and sales we are interested in sign changes, we use $\widehat{\varepsilon}_{i,t}^h\widehat{\varepsilon}_{i,t}^s$, as an estimate of the conditional covariance, where $\widehat{\varepsilon}_{i,t}^h$ is the residual for inventories and $\widehat{\varepsilon}_{i,t}^s$ is the residual for sales from (6)

If the null of no break is rejected at a 10% significance level, we proceed to estimate the break date using least squares, divide the sample in two subsamples, according to the estimated break date, and perform a test of parameter-constancy for both sub-samples. This process is repeated by increasing l sequentially until we fail to reject the hypothesis of no additional structural change. The estimated break dates are refined by repartition as suggested by Bai (1997) and Bai and Perron (1998). To impose the minimum structure on the data we allow for different distribution of both the regressors and the error terms in the different subsamples, as well as for heterogeneity and serial correlation in the residuals.

There are a few cases in which the sequential procedure breaks down. For example, if two breaks of equal magnitude but opposite sign were present, the procedure would stop at the first step and would wrongly point in the direction of no breaks. We carefully made sure that failure to find any break was not due to breaks of opposite sign. When this was the case, and all the tests indicate the presence two breaks, we side-step the first step of the sequential procedure and proceed with the estimation of two breaks.

Given the asymptotic distribution of the break dates (see Bai and Perron, 1998), we calculate the corresponding 90% confidence intervals imposing a minimum structure on the regressors and the error terms in the different regimes. Because we allow for different variances in the error in equation (6), the reported confidence intervals are asymmetric, showing greater uncertainty in the regime in which the variance is larger.

3.1 Total Inventories and Sales

Table 1 reports break estimates with the corresponding confidence intervals for the volatility of manufacturing sales and total inventories by sectors. Results for higher levels of aggregation, such as durables and nondurables, comprising manufacturing, wholesale, and retail trade are reported in Table 2. For all the series where tests indicate that the null of no break can be rejected at a 10% significance level, we estimate the date of the breaks using the sequential procedure described in the previous section. Given the lack of precision of the tests and the size distortions at the end of the sample, we test for breaks only in the central 70% fraction of the data.

There are only a few industries for which we estimate two breaks, and none with more than two break points. We estimate a structural change in the mid-1980's for half of the 2-digit series and all of the manufacturing aggregates. For all other industries the break dates are located in the late 1970's or in the early 1990's. Estimated breaks in the 1970's correspond to an increase in the volatility, while those in the 1980's represent a pronounced drop in the variance, often by as much as 50%. In all of the cases where more than one break is identified, the volatility increased in the second period and subsequently reverted to a lower volatility similar to that of the first period. In fact, for the majority of the series where two breaks are estimated, one is located in the early 1970's and the other in the mid-1980's. The first period estimated mean variance of non-durable inventories is 0.0027, after the second quarter of 1973 it almost doubles to 0.0044, and then it falls again to a value of 0.0021 in 1987. This result agrees with Blanchard and Simon (2001), who contend that the observed decline in volatility is due not to a one time break in the 1980's but to a return to the lower volatility of the 1960s.

For the majority of series, the break date is estimated with a low degree of precision, namely the confidence intervals cover a large number of years. Nevertheless, in a few sales series (i.e., rubber and plastics, fabricated metals products, other durables, and non-durable manufactures), and few inventories series (i.e., textiles, leather, primary metals products, and motor vehicles) the multiple breaks procedure enables us to obtain estimates that are more precise with corresponding confidence intervals that span three to five years.

Our finding of a structural change in sales differs from McConnell and Perez-Quiros (2000), but agrees with Ahmed, Levin and Wilson (2002). Differences in the date break estimates stem from two sources. First, while our data spans the period between the first quarter of 1959 and the first quarter of 2001, other researchers have analyzed data beginning in 1967. Difference in the sample period can be of significant importance in identifying the break date since tests and estimates of an unknown shift point are particularly sensitive to the sample period. Because both tests and estimators are a function of the break parameter k, a possible break date that was ignored in the smaller sample can be taken into consideration when the sample is extended. Figure 1 in the Appendix illustrates how this is the case for the variance of finished goods inventories of non-durable goods. The date that minimizes the sum of square residuals for the 1959-2000 sample is located in the mid-1980's; yet if this test had been conducted at the beginning of the 1990's, the late 1980's data would have been eliminated by the trimming and the break would have been estimated in the early 1970's.

A second source of divergence is related to the use of different estimation methodologies. McConnell and Perez-Quiros (2000) estimate the break as the date associated with the maximum of the Wald test for a single break. Instead we follow the Bai and Perron (1998) sequential testing method for multiple breaks and estimate the break date using their proposed LS estimator. Both estimates of a single break are only equivalent when the estimated relationship is linear and the residuals are homoskedastic (see Hansen, 2001). In addition, Bai and Perron (1998) show that in the presence of multiple breaks, the least squares estimator will converge to a global minimum coinciding with the dominating break. A good illustration of these two sources of divergence is provided by Figure 1 in the Appendix, where from two possible shift points, the LS estimator selects the more pronounced one.

3.2 Inventory-Sales Covariance

Our findings of a break in the variance of manufacturing sales casts some doubts on the "technological change" hypothesis proposed by McConnell and Perez-Quiros (2000) and Kahn, McConnell and Perez-Quiros (2002), who argue that the decline in the volatility of GDP coincides with the development of new information technology and its application to inventory management in the durables sector. They present two key pieces of evidence in support of the “better inventory management techniques” proposition: the differential decrease in the volatility of durables sales and production, and the sign change in the covariance between inventories and sales. These two observations are consistent with the traditional version of the production-smoothing model where inventories act as a buffer stock to unexpected changes in sales. Yet, we find that at the 2-digit industry level, not only has the variance of inventories decreased, but also that of sales, thus blurring the evidence regarding the differential decrease in the volatility of sales and production. Therefore, the remaining question is whether a change in the sign of the inventory-sale covariance can account for the decline in output volatility? The answer we derive from our results is no.

Results reported in Tables 4 and 5 suggest that there has been a break in the conditional inventory-sales covariance in only a few 2-digit manufacturing industries. This shift stems from changes in the generating process for sales and inventories that took place in the 1970’s and 1980’s. Results not reported in this paper, but available from the authors by request, show that sectors for which the inventory volatility increased in the 1970’s also experienced a simultaneous rise in the covariance, and industries where inventory volatility fell in the 1980's experienced a decrease in the covariance. It is worth noting that, although the break in the covariance coincides with a decrease in inventory volatility, in almost all sectors it reflects a reduction in its magnitude but not a sign change. The only exceptions are the covariance between finished goods inventories and sales of lumber, and between work-in-process inventories and sales of textiles. In other words, at a 2-digit industry level, we find no significant evidence that a change in the covariance, and thus the correlation, between inventories and sales contributed to stabilize output. Our results contradict Golob (2000) findings who, using tests for equality of the unconditional correlation across the pre-1983:4 and post-1983:4 sub-samples, finds that inventory investment for trade and one-digit manufacturing industries has become negatively correlated with sales.

Summarizing, we estimate a decline in the volatility of inventories in the mid-1980's only for half of the series, and find significant evidence of a break in the variance of manufacturing sales. In addition, we find little evidence of a change in the sign of the covariance between inventories and sales. These results cast some doubts on the hypothesis that attributes the decline in output volatility to the introduction of better inventory holding techniques and suggest that other factors must have also played an important role.

Since aggregating inventories across different stages of production might underscore the role of technology in explaining the reduction in the volatility of inventories and output, we examine input and output inventories separately in the following section.

3.3 Input and Output Inventories

There seems to be ample anecdotal evidence regarding the transformation that manufacturing underwent in the late twentieth century (Milgrom and Roberts, 1990; Mosser, McConnell and Perez-Quiros, 1999). Flexible machine tools and computerized multi-task equipment replaced specialized single-task machinery allowing firms to produce a variety of output in small batches. As a result, production cycles shortened and inventory holdings of work-in-process and finished goods dropped. Shorter production cycles lead to faster order processing, reduced product-developement times, and speedier production of goods. Consequently, firms were able to increase the pace of their response to fluctuating demand and to reduce the size of the back orders. Theoretical work by Milgrom and Roberts (1990) suggests that the adoption of the new technologies should have resulted in "more frequent setup and smaller batch sizes, with correspondingly lower levels of finished-goods and work-in-process inventories and back orders per unit of demand". Kahn, McConnell and Perez-Quiros (2002), among others, provide empirical evidence of a decline in the real manufacturing inventories-sales ratios since the mid-1980's, which followed a buildup in the 1970's. However, there is little said in the literature about the implications of adopting the new technology for the second moment of inventories at different stages of production. Kahn, McConnell and Perez-Quiros (2002), for example, present a model in which information technology can account for a reduction in the volatility of total inventories and output, but not sales. While developing a theoretical model that can account for the effect of technological innovation on inventory volatility is beyond the scope of this paper, we make an effort to decompose the change in inventory volatility by stages of production.

Recall that the break date estimates for total inventories (see Table 1) suggests that a reduction in volatility took place mainly in the 1980's. These results are confirmed for the manufacturing aggregates (see Table 2), with the exception of inventories of work-in-progress for manufacturing and durable goods and inventories of finished goods for durable manufactures. Yet, at a 2-digit SIC level (see Table 3), we estimate a break in finished goods or work-in-progress inventories in the mid-1980's only in a few cases. For most industries, the shift is located in the 1970's or the 1990's; for other industries, there is no evidence of a break in work-in-progress inventories. On the other hand, we estimate a break in the 1980's for roughly half of the materials and supplies series. We derive two conclusions from the results by stages of production. First, materials and supplies account for most of the reduction in the volatility of total inventories during the 1980's. Furthermore, since it is only the input inventory-sales ratio that has decreased since the 1980's, if information technology played a role in reducing the volatility of output, it appears to have done so by allowing firms to reduce the variation in input inventories. Second, aggregation across industries and stages of production can lead one to make a stronger statement regarding the location of the break in inventories in the 1980's than one would by looking at disaggregated data. In fact, for half of the 2-digit series if there is a break, it is not located in the decade of the eighties. This widespread reduction in volatility across stages of production and years suggests a reduced role of information technology in explaining the moderation of output volatility of the 1980's.

3.4 Identifying the Break Date and the Source of the Break

One element that makes it particularly difficult to identify the source of the shift is the low degree of certainty with which one can date the structural break. The 90% confidence intervals around the break can be so wide as to encompass as many as twenty years. This seems to be the case not only for inventories and sales, but for a variety of macroeconomic series. In recent work, Stock and Watson (2002) reject the hypothesis of a constant residual variance in 80% of 166 macroeconomic series. In the majority of the cases, they estimate a break in the mid-1980's; however they also find that the 90% confidence intervals suggest break estimates that are imprecise. They argue that these confidence intervals are not very informative in the case of date break estimates which have a highly non normal distribution, thus they report tighter 65% confidence intervals.

Even though there are several cases where the 90% confidence intervals are wide in our analysis, there are series for which the interval spans only three years, allowing us to identify the date of the break with increased precision. Hence, we report 90% confidence intervals instead of the 65% ones reported by Stock and Watson (2002). Given the large degree of uncertainty reflected in the wide confidence intervals, we believe the estimates of the break dates should be regarded with caution, even more in trying to identify changes in technology, policy or shocks that coincided with the time of the reduction in output volatility.

4 Effects of time-aggregation

In order to make our results comparable to previous literature, we transformed the monthly data into quarterly data by aggregating monthly sales and using end of quarter inventories. However, time-aggregation may modify the time series properties of the data as the magnitude of the variance decreases. Thus, we replicate our estimations using the original monthly data.

Tables 6 to 10 report the structural break estimates and the corresponding confidence intervals for the monthly series. A comparison of these results with those for the quarterly data suggests only a few differences. First, no break is estimated during the 1980's for manufacturing, non durable and durable finished goods inventories (see Table 7). However, estimates at the industry level suggest a higher number of breaks in that decade than the quarterly estimates (see Table 9). While these differences appear to be larger at a first sight, a careful inspection of Tables 3 and 8 reveals that there are the same number of industries for which the confidence intervals cover the mid-1980's at both frequencies.

Second, while the maximum number of breaks we estimate with the quarterly data is 2, using monthly data we do estimate 3 breaks for total inventories of motor vehicles and inventories of materials for petroleum products. Furthermore, there are a few series for which the number of estimated breaks increases from 1 to 2. We believe this result is due to the heightened variance that results from the use of higher frequency data.

Our main findings remain unchanged. We find evidence of (a) decrease in the variance of both manufacturing inventories and sales during the 1980's; (b) a decrease in the variance of total inventories during the 1980's; (c) no structural break in the inventory-sales covariance (Table 10); and (d) diminished volatility in inventories by stages of production, particularly in materials and, to a lesser degree, in work in process and finished goods.

Is a higher frequency data more appropriate for estimating and identifying the source of the structural breaks? The answer is not clear. On one hand, it allows us to identify some additional breaks that might have been smoothed out by the time-aggregation. On the other hand, the degree of precision of the estimates does not improve significantly: the confidence intervals continue to be large for various series.

5 Final Remarks

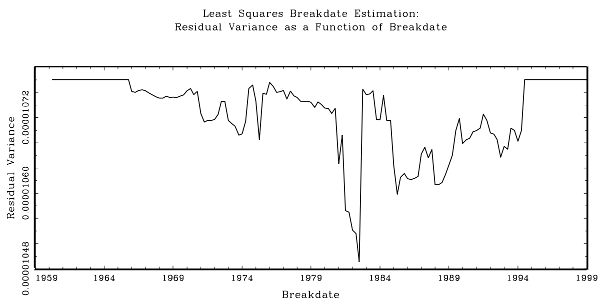
We have analyzed an event that has been documented and studied in recent macroeconomic literature: the decline in US output volatility. Although we confirm McConnell and Perez-Quiros (2000) finding of a decline in the volatility of total and durable goods in the 1980's, we find evidence of multiple breaks, which suggests that the structural change in the variance might not be a one time phenomena. There are a number of inventory and sales series for which the decline in the variance seems to be a return to a less volatile state experienced before the volatile 1970's.

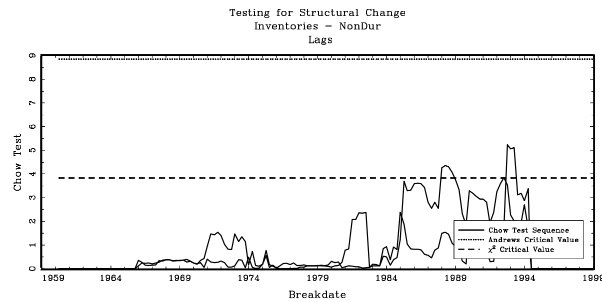
In agreement with Ahmed, Levin and Wilson (2002), we find that the decline in the variance is a phenomena that extends not only to manufacturing inventory series but also to sales. In addition, we find that the decline in the volatility of manufacturing inventories is mainly accounted by a decline in that of materials and supplies. These findings suggest that the introduction of better inventory tracking technology only partly explains the decline in output volatility. We agree with Stock and Watson's (2002) conclusion that better monetary policy can account for some of the moderation in the volatility of output. We can expect that at least some of the lower volatility might continue if the monetary rule is maintained.

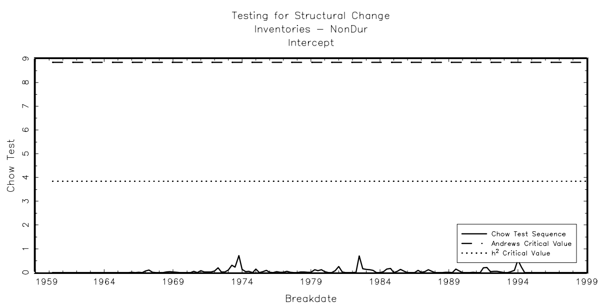
Thus, two relevant features of our results are: (a) inventories of materials and supplies played an important role in accounting for the decline in inventory, and output volatility; and (b) breaks in the variance of inventories and sales are not a one time phenomena. These two features of the data should be taken into account by business cycle theorists, as well as by researchers seeking to explain the decrease in U.S. output volatility.

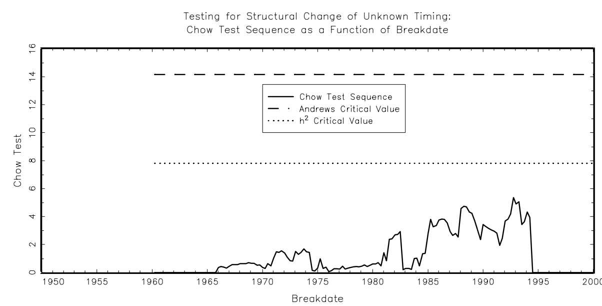
6 Appendix

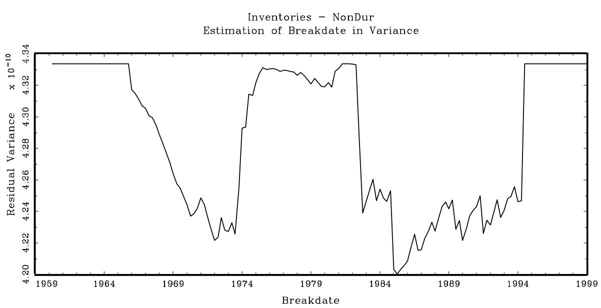
6.1 Wald test for break testing

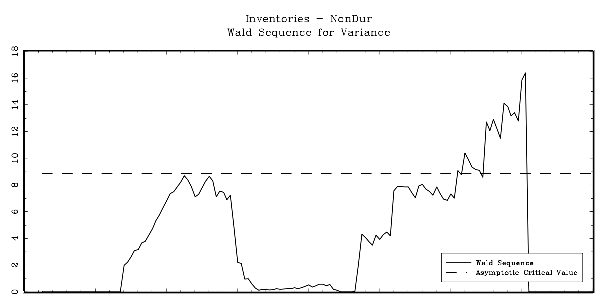












6.2 Legend for Tables

Sector	Abbreviation
Food	Food
Tobacco	Tobacco
Textiles	Textiles
Apparel	Apparel
Paper	Paper
Printing & Publishing	Pri&Pub
Petroleum Products	PetProd
Chemicals	Chemical
Rubber & Plastics	Rub&Pla
Leather	Leather
Lumber	Lumber
Furniture & Fixtures	Fur&Fix
Stone, Clay & Glass Prods.	StClGl
Primary Metals Products	PriMet
Fabricated Metals Products	FabMet
Industrial Machinery	IndMac
Electrical Machinery	EleMac
Motor Vehicles	MotVeh
Other Transportation Equip.	OthTran
Instruments	Instru
Other Durable Manufactures	OthDur
Manufacturing	Manufac
Non Durables	NonDur
Durables	Durabl

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Table 1:Estimates and CI for a multiple breaks date in the conditional variance for Total Inventories and Manufacturing Salest.

Sector	Breaks	90%CI		Breaks	90%CI	
		Inventories			*Sales*	
Food	1977:4	[1976:3,	1983:1]	1976:2	[1974:4,	1985:2]
Tobacco	-			1975:3	[1971:1,	1976:4]
Textiles	1972:4	[1966:4,	1976:3]	1991:3	[1988:4,	2002:1]
	1989:2	[1988:2,	1992:2]			
Apparel	1966:4	[1955:3,	1969:4]	1982:2	[1980:4,	1993:1]
Paper	–			1983:2	[1979:3,	1995:1]
Pri&Pub	1969:4	[1965:4,	1978:4]	1978:4	[1976:1,	1989:1]
PetProd	1974:3	[1969:3,	1975:1]	1984:1	[1983:1,	1993:2]
	1987:1	[1985:3,	1992:2]			
Chemical	1981:4	[1976:2,	1983:4]	1973:2	[1965:4,	1976:1]
	1990:1	[1989:1,	1994:1]			
Rub&Pla	1984:4	[1983:2,	1995:2]	1967:3	[1962:3,	1969:2]
				1983:4	[1982:4,	1986:3]
Leather	1968:2	[1964:3,	1968:3]	1970:3	[1961:2,	1974:4]
Lumber	1983:1	[1981:1,	1991:2]	1991:2	[1990:2,	1999:4]
Fur&Fix	1994:2	[1991:3,	2006:3]	1983:4	[1982:1,	1990:2]
StClGl	1981:4	[1980:1,	2002:2]	1993:1	[1989:2,	1997:2]
PriMet	1974:2	[1971:1,	1974:4]	1984:1	[1983:2,	1988:1]
	1987:4	[1987:2,	1990:1]			
FabMet	1983:3	[1982:4,	1991:1]	1974:1	[1969:4,	1977:1]
				1983:4	[1982:4,	1986:1]
IndMac	1983:2	[1981:1,	1992:1]	1991:2	[1990:1,	1999:3]
EleMac	1987:1	[1984:3,	1993:3]	-		
MotVeh	1983:4	[1983:2,	1986:3]	1983:4	[1981:1,	1991:4]
OthTran	1969:3	[1957:1,	1970:2]	–		
Instru	1969:4	[1960:3,	1973:1]	1984:2	[1982:3,	1989:1]
OthDur	1971:1	[1960:2,	1976:4]	1971:4	[1966:4,	1972:3]
				1981:2	[1980:1,	1985:2]
Manufac	1985:1	[1982:3,	2000:2]	1983:4	[1982:3,	1990:4]
NonDur	1973:2	[1965:4,	1974:1]	1971:3	[1968:2,	1972:2]
	1986:4	[1986:2,	1991:1]	1983:2	[1982:3,	1985:3]
Durabl	1985:1	[1984:2,	1990:1]	1983:4	[1982:4,	1989:2]
GDP	1983:4	[1982:3,	1988:4]			

Table 2: Multiple break test for conditional variance for aggregates at different stages of production.

Aggregation	Sector	Breaks	90%CI		Breaks	90%CI	
			Inventories			*Sales*	
Materials	Manuf	1986:2	[1985:1,	1993:2]			
	NonDur	1987:2	[1985:3,	1994:2]			
	Durabl	1985:1	[1983:2,	1992:1]			
Work in Progress	Manuf	–					
	NonDur	1979:3	[1974:1,	1982:3]			
		1987:3	[1985:3,	1989:3]			
	Durabl	–					
Finished Goods	Manuf	1972:1*	[1965:2,	1974:3]			
		1985:1	[1982:3,	1992:2]			
	NonDur	1971:4	[1964:3,	1972:3]			
		1982:3	[1981:2,	1991:1]			
	Durabl	–					
Wholesale Trade	Manufac	1972:3	[1965:2,	1974:1]	1973:1	[1958:4,	1975:2]
		1983:3	[1982:3,	1989:2]			
	NonDur	1992:2	[1989:1,	2010:1]	1972:1	[1955:2,	1977:4]
	Durabl	1981:4	[1977:4,	2007:3]	1974:3	[1965:3,	1977:2]
Retail Trade	Manuf	1992:1	[1990:3,	1997:3]	–		
	NonDur	1968:1	[1966:1,	1973:3]	1973:2	[1962:2,	1975:2]
	Durabl	1970:3	[1965:3,	1972:3]	1979:2	[1973:3,	1984:4]
		1988:3	[1987:3,	1992:2]	1991:1	[1990:2,	1994:2]

* Indicates cases in which the Sup-F(0 vs 1) test failed to reject while the Sup-F(0 vs 2) did not. All other tests (Umax, Dmax, Sup-F(2|1), see Bai and Perron (1998)) also point in the direction of 2 breaks. In this case the estimated breaks come from the global optimization. For a discussion on when the sequential procedure breaks down see Bai and Perron (2003).

Breaks in the conditional variance are computed taking into account breaks in the conditional mean.

Table 3:Estimates and CI for a multiple breaks date in the conditional variance for different stages of production.

Sector	Breaks	90%CI		Breaks	90%CI		Breaks	90%CI	
		Materials			*Work in Progress*			*Finished goods*	
Food	1983:4	[1982:3,	1996:3]	1975:1	[1972:3,	1975:3]	1976:4	[1975:2,	1983:3]
				1983:1	[1981:3,	1985:3]			
Tobacco	–			1966:3	[1960:1,	1967:2]	1991:3	[1986:1,	1998:4]
Textiles	1987:1	[1986:2,	1991:3]	1993:1	[1992:3,	1999:2]	1976:2	[1972:2,	1988:3]
Apparel	–			1991:2	[1990:3,	2002:1]	1969:3	[1963:1,	1972:1]
Paper	1986:2	[1983:2,	1997:1]	1966:2	[1960:4,	1966:4]	–		
				1978:3	[1977:2,	1985:3]			
Pri&Pub	–			–			1977:3*	[1976:3,	1985:1]
							1992:1	[1988:1,	1992:3]
PetProd	1973:3	[1965:2,	1975:2]	1968:4	[1951:4,	1970:4]	1973:2	[1964:3,	1974:3]
	1988:2	[1985:4,	1993:3]						
Chemical	1981:2	[1972:2,	1986:2]	–			1978:3	[1971:4,	1981:4]
							1990:1	[1988:3,	1993:4]
Rub&Pla	1985:4	[1984:4,	1990:3]	1987:4	[1987:2,	1994:3]	1977:1	[1975:4,	1998:4]
							1993:1	[1991:4,	1997:1]
Leather	1972:1	[1964:3,	1974:1]	1977:4	[1970:4,	1978:4]	1972:3	[1969:2,	1973:1]
							1992:2	[1987:4,	1999:4]
Lumber	–			1971:4	[1969:1,	1979:4]	1986:2	[1983:3,	1991:1]
				1991:1	[1989:4,	1998:2]			
Fur&Fix	1983:4	[1980:2,	1995:1]	–			1974:2	[1962:1,	1976:1]
StClGl	1985:2	[1983:1,	1993:1]	–			–		
PriMet	1974:1	[1971:2,	1975:2]	1993:4	[1993:2,	1999:2]	1970:4	[1961:1,	1972:4]
	1986:4	[1986:2,	1988:4]				1987:3	[1986:1,	1995:4]
FabMet	1977:4	[1976:3,	1986:1]	1986:2	[1985:1,	1991:2]	–		
IndMac	1976:1	[1973:1,	1988:3]	–			1989:1	[1986:4,	1997:4]
EleMac	1987:3	[1984:4,	1993:3]	1986:1	[1984:3,	1992:1]	–		
MotVeh	1982:4	[1982:2,	1985:2]	–			1980:4	[1978:3,	1989:4]
OthTran	–			–			–		
Instru	–			–			1966:2	[1954:2,	1967:4]
OthDur	–			1979:3	[1971:3,	1981:3]	–		
				1989:4	[1988:3,	1995:1]			

Table 4: Estimates and CI for a multiple breaks date in the conditional covariance for Total Inventories and Finished Goods Inventories with Manufacturing Sales.

Sector	Breaks	90%CI		Breaks	90%CI	
		Total			*Finished Goods*	
Food	–			–		
Tobacco	1983:1	[1977:1,	1995:3]	–		
Textiles	–			–		
Apparel	–			–		
Paper	–			–		
Pri&Pub	–			–		
PetProd	–			–		
Chemical	1983:2	[1981:4,	2001:1]	1983:2	[1981:1,	2006:3]
Rub&Pla	–			1987:2	[1986:4,	2003:4]
Leather	–			–		
Lumber	–			–		
Fur&Fix	–			–		
StClGl	–			–		
PriMet	–			–		
FabMet	–			–		
IndMac	–			–		
EleMac	1985:3	[1981:2,	1994:3]	–		
MotVeh	–			–		
OthTran	1982:2	[1973:1,	1988:3]	–		
Instru	–			–		
OthDur	–			–		
Manufac	1983:4	[1982:4,	2006:4]	–		
NonDur	–			–		
Durabl	1975:1	[1960:4,	2029:4]	–		
	1992:1	[1991:4,	1998:1]	–		

The covariance is computed as the products of the residuals from equation (9) for inventories and manufacturing sales after accounting for possible breaks in the conditional means. The regressions are estimated with the same number of lags, which is chosen by BIC for the regression for total inventories.

Table 5:Estimates and CI for a multiple breaks date in the conditional covariance for Materials Inventories and Work In Progress Inventories with Manufacturing Sales.

Sector	Breaks	90%CI		Breaks	90%CI	
		Materials			*Work in Progress*	
Food	1972:2	[1966:1,	1978:1]	–		
Tobacco	–			–		
Textiles	–			1980:1	[1974:1,	1983:1]
				1991:3	[1991:1,	1997:1]
Apparel	–			–		
Paper	–			–		
Pri&Pub	1980:3	[1972:1,	1988:4]	–		
PetProd	1986:1	[1984:4,	2006:3]	–		
Chemical	–			–		
Rub&Pla	–			1983:4	[1983:2,	1994:4]
Leather	–			1985:3	[1976:1,	1996:1]
Lumber	–			–		
Fur&Fix	1983:4	[1983:3,	1992:4]	–		
StClGl	–			–		
PriMet	1975:1	[1970:1,	1987:3]	–		
FabMet	–			–		
IndMac	–			–		
EleMac	–			1968:4	[1963:1,	1969:2]
				1976:4	[1975:2,	1981:1]
MotVeh	–			–		
OthTran	–			1982:2	[1971:2,	1988:2]
Instru	–			–		
OthDur	–			–		
Manufac	–			1991:4	[1990:4,	2001:1]
NonDur	–			–		
Durabl	–			1991:1	[1990:3,	2002:2]

Table 6: Estimates and CI for a multiple breaks date in the conditional variance for Total Inventories and Manufacturing Sales. Monthly Data.

Sector	Breaks	90%CI		Breaks	90%CI	
		Inventories			*Sales*	
Food	1978:3	[1976:10,	1984:7]	1982:12	[1981:4,	1987:8]
	1992:5	[1990:11,	1996:4]			
Tobacco	1980:11	[1975:5,	1982:3]	1978:5	[1976:5,	1978:7]
				1994:2	[1993:4,	1997:1]
Textiles	1989:5	[1989:1,	1992:7]	–		
Apparel	1977:5	[1974:6,	1983:8]	1985:10	[1982:12,	1994:7]
Paper	–			1981:2	[1975:4,	1992:8]
Pri&Pub	1965:12	[1964:2,	1971:9]	1978:10	[1975:11,	1987:3]
				1993:12	[1991:4,	2000:2]
PetProd	1971:10	[1962:4,	1974:8]	1971:11	[1968:10,	1972:4]
				1981:2	[1980:6,	1984:2]
Chemical	1980:9	[1978:2,	1981:2]	1979:2	[1975:6,	1981:1]
	1986:9	[1985:3,	1991:5]			
Rub&Pla	1987:10	[1987:6,	1990:8]	1991:4	[1990:9,	1994:10]
Leather	1968:7	[1965:10,	1968:12]	1970:6	[1961:8,	1974:1]
Lumber	1975:4	[1973:10,	1980:12]	1989:8	[1988:10,	1994:1]
	1993:9	[1991:4,	1998:1]			
Fur&Fix	1993:3	[1992:10,	1995:8]	1980:9	[1976:5,	1987:10]
StClGl	1987:3	[1986:5,	1993:12]	1966:2	[1962:10,	1972:11]
PriMet	1987:4	[1987:1,	1994:8]	1965:9	[1964:12,	1982:12]
				1992:1	[1991:10,	1996:1]
FabMet	1975:6	[1972:2,	1982:8]	1982:10	[1981:11,	1986:7]
	1992:3	[1991:1,	1997:10]			
IndMac	1987:10	[1986:2,	1993:5]	1987:9	[1984:7,	1994:10]
EleMac	1985:12	[1984:7,	1993:9]	–		
MotVeh	1970:10	[1970:4,	1977:3]	1971:8	[1968:8,	1987:10]
	1981:1	[1980:8,	1983:10]	1991:12	[1991:4,	1998:7]
	1993:8	[1992:11,	1997:3]			
OthTran	1993:7	[1987:10,	1998:3]	1993:6	[1998:12,	1995:8]
Instru	1969:4	[1962:12,	1970:2]	–		
OthDur	–			1973:8	[1970:3,	1974:5]
				1985:1	[1983:9,	1988:7]
Manufac	1985:2	[1983:2,	1993:10]	1980:11	[1978:10,	1989:10]
NonDur	1986:12	[1982:7,	1998:1]	1972:5	[1967:5,	1975:8]
				1983:6	[1982:3,	1987:3]
Durabl	1984:4	[1983:6,	1990:6]	1980:10	[1979:1,	1989:1]

Table 7: Multiple break test for conditional variance for aggregates at different stages of production. Monthly Data.

Aggregation	Sector	Breaks	90%CI		Breaks	90%CI	
			Inventories			*Sales*	
Materials	Manuf	1986:1	[1985:8,	1989:9]			
	NonDur	1987:1	[1986:2,	1992:2]			
	Durabl	1983:8	[1983:4,	1988:6]			
Work in Progress	Manuf	–					
	NonDur	1979:8*	[1975:6,	1980:9]			
		1987:9	[1986:9,	1991:9]			
	Durabl	1991:11	[1989:1,	2003:8]			
Finished Goods	Manuf	1991:12	[1988:7,	2001:4]			
	NonDur	1993:2	[1990:6,	1998:10]			
	Durabl	–					
Wholesale Trade	Manufac	1971:12	[1968:2	1973:6]	1974:2	[1969:3,	1975:10]
		1987:2	[1984:2,	1993:2]			
	NonDur	1971:9	[1968:3,	1973:2]	1972:5	[1967:11,	1974:12]
		1983:6	[1982:3,	1988:2]			
	Durabl	1973:8	[1969:12,	1975:3]	1974:11	[1972:2,	1975:8]
					1992:11	[1990:11,	1997:1]
Retail Trade	Manuf	1973:3	[1963:3,	1974:12]	–		
		1987:10	[1987:1,	1992:10]			
	NonDur	1980:4	[1978:5,	1984:6]	1973:6	[1968:3,	1976:9]
	Durabl	1974:7	[1966:6,	1975:5]	1993:9	[1992:4,	2008:8]
		1987:10	[1987:4,	1994:4]			

* Indicates cases in which the Sup-F(0 vs 1) test failed to reject while the Sup-F(0 vs 2) did not. All other tests (Umax, Dmax, Sup-F(2|1), see Bai and Perron (1998)) also point in the direction of 2 breaks. In this case the estimated breaks come from the global optimization. For a discussion on when the sequential procedure breaks down see Bai and Perron (2003).

Breaks in the conditional variance are computed taking into account breaks in the conditional mean.

Table 8:Estimates and CI for a multiple breaks date in the conditional variance for different stages of production. Monthly Data.

Sector	Breaks	90%CI		Breaks	90%CI		Breaks	90%CI	
		Materials			*Work in Progress*			*Finished goods*	
Food	1984:6	[1983:1,	1987:11]	1972:11	[1967:1,	1976:3]	1974:9	[1971:6,	1983:8]
							1982:9	[1980:6,	1987:4]
Tobacco	–			1978:7	[1975:12,	1979:9]	1965:11	[1965:5,	1969:8]
				1984:12	[1983:8,	1989:8]	1986:8	[1984:4,	1989:9]
							1994:3	[1994:1,	1998:8]
Textiles	1987:10	[1987:2,	1993:9]	1982:11	[1978:8,	1983:8]	1975:5	[1975:3,	1980:5]
				1988:11	[1988:9,	1991:1]	1984:1	[1980:6,	1984:11]
							1994:2	[1992:8,	1998:11]
Apparel	1971:10	[1965:8,	1972:6]	1991:3	[1989:8,	1996:5]	1990:5	[1988:6,	1998:8]
	1979:10	[1979:7,	1983:8]						
Paper	1985:11	[1984:12,	1991:4]	1983:7	[1982:5,	1991:3]	–		
Pri&Pub	–			1972:7	[1969:4,	1977:5]	1975:3*	[1974:3,	1978:9]
							1984:5	[1978:11,	1985:12]
PetProd	1973:6	[1971:6,	1974:11]	1969:1	[1964:8,	1969:4]	1974:7	[1970:10,	1975:8]
	1980:8	[1978:3,	1983:9]				1987:7	[1982:2,	1992:9]
	1988:7	[1986:8,	1994:2]						
Chemical	1973:5	[1968:2,	1976:4]	–			1980:6*	[1977:9,	1981:2]
	1981:11	[1972:9,	1984:7]				1987:9	[1986:10,	1990:4]
Rub&Pla	1979:3	[1974:7,	1981:12]	1991:12	[1991:9,	1995:7]	1985:8	[1985:3,	1989:5]
	1985:12	[1985:9,	1987:4]						
Leather	1972:7	[1968:10,	1973:1]	1978:8	[1973:3,	1979:7]	1968:6	[1966:5,	1968:10]
Lumber	1980:8	[1977:1,	1987:4]	1973:4	[1971:10,	1981:10]	1986:10	[1983:12,	1992:4]
				1992:1	[1991:9,	1994:4]			
Fur&Fix	1987:1	[1985:10,	1992:3]	1986:8	[1985:3,	1990:12]	1974:10	[1972:6,	1975:11]
							1981:4	[1980:4,	1984:10]
StClGl	1985:11	[1985:2,	1990:1]	1988:12	[1985:5,	2003:7]	1981:10	[1979:2,	1989:10]
PriMet	1974:10	[1971:9,	1977:5]	1993:11	[1993:6,	1998:4]	1987:5	[1986:7,	2005:4]
	1986:10	[1986:7,	1989:1]						
FabMet	1976:2	[1975:4,	1988:4]	1977:9	[1976:1,	1990:4]	–		
	1994:1	[1993:3,	1997:4]	1994:2	[1993:6,	1996:9]			
IndMac	1976:1	[1972:1,	1989:4]	–			–		
EleMac	1983:9	[1979:4,	1999:5]	1986:1	[1984:1,	1990:9]	1974:9	[1970:4,	1976:1]
							1982:3	[1981:4,	1985:9]
MotVeh	1975:3	[1974:8,	1981:6]	1983:5	[1983:1,	1986:6]	1970:10	[1969:10,	1975:6]
	1983:5	[1983:3,	1985:5]	1989:6	[1986,6,	1989:12]	1982:12	[1981:10,	1988:1]
OthTran	1976:11	[1971:6,	1980:12]	1969:6	[1959:8,	1972:5]	1973:4	[1969:4,	1980:6]
				1993:7	[1990:6,	1997:1]	1993:5	[1991:3,	1993:7]
Instru	1979:1	[1976:1,	1979:10]	1987:8	[1978:11,	1990:11]	–		
	1985:2	[1983:9,	1988:5]						
OthDur	—			–			–		

Table 9:Estimates and CI for a multiple breaks date in the conditional covariance for Total Inventories and Finished Goods Inventories with Manufacturing Sales. Monthly Data.

Sector	Breaks	90%CI		Breaks	90%CI	
		Total			*Finished Goods*	
Food	–			–		
Tobacco	1990:7	[1981:5,	1990:11]	1990:7	[1990:6,	1990:7]
Textiles	–			–		
Apparel	–			–		
Paper	–			–		
Pri&Pub	–			–		
PetProd	1974:7	[1960:3,	1981:3]	–		
Chemical	–			–		
Rub&Pla	–			–		
Leather	–			–		
Lumber	–			–		
Fur&Fix	–			–		
StClGl	–			1969:9	[1966:10,	1976:5]
PriMet	–			–		
FabMet	–			–		
IndMac	1980:7	[1972:10,	1991:3]	–		
EleMac	1984:4	[1981:4,	1990:12]	–		
MotVeh	–			–		
OthTran	1971:3	[1961:9,	1978:12]	–		
Instru	–			–		
OthDur	–			–		
Manufac	–			–		
NonDur	1974:5	[1965:3,	1985:9]	–		
Durabl	–			–		

The covariance is computed as the products of the residuals from equation (9) for inventories and manufacturing sales after accounting for possible breaks in the conditional means. The regressions are estimated with the same number of lags, which is chosen by BIC for the regression for total inventories.

Table 10: Estimates and CI for a multiple breaks date in the conditional covariance for Materials Inventories and Work In Progress Inventories with Manufacturing Sales. Monthly Data.

Sector	Breaks	90%CI		Breaks	90%CI	
		Materials			*Work in Progress*	
Food	–			–		
Tobacco	–			–		
Textiles	–			–		
Apparel	–			–		
Paper	1967:11	[1960:8,	1974:8]	1968:5	[1961:3,	1972:11]
Pri&Pub	–			–		
PetProd	1980:10	[1976:8,	1991:3]	–		
Chemical	–			–		
Rub&Pla	–			1984:10	[1982:7,	1997:9]
Leather	–			–		
Lumber	–			–		
Fur&Fix	–			–		
StClGl	–			–		
PriMet	–			–		
FabMet	–			–		
IndMac	–			–		
EleMac	–			1982:4	[1980:1,	1989:7]
MotVeh	–			–		
OthTran	–			1975:7	[1966:3,	1986:2]
Instru	–			–		
OthDur	–			–		
Manufac	–			–		
NonDur	–			–		
Durabl	–			–		