WORKING PAPER 198/2020

INVENTORY CYCLES AND BUSINESS CYCLES – HAS THE RELATIONSHIP LOST ITS IMPORTANCE OVER THE YEARS: A TIME-VARYING PARAMETER APPROACH USING U.S. DATA

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Price : Rs. 35

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Inventory Cycles and Business Cycles – Has the relationship lost its importance over the years: A Time-Varying Parameter Approach using U.S. Data

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Abstract

Despite widespread recognition that fluctuations in inventories are one of the primary drivers of business cycles and the introduction of Just-In-Time (JIT) Production system in the 1980s has resulted in declining inventory to sales ratio, suggesting that the role of inventories in generating business cycles may be diminishing, surprisingly very little empirical work has been done to investigate how this relationship has varied over the years.

In this study we use U.S. Business cycle and Inventory to sales ratio data from 1967 Q1 to 1996 Q4 and estimate their relationship in a Time-Varying Parameter framework.

We find that the importance of inventory cycles w.r.t business cycles has declined over the years, with multiple structural breaks observed in the 1970s and the 1980s. However, our estimates also show that despite the decline in the strength of the relationship, fluctuations in inventories are still an important factor in business cycles, particularly in recessions.

Key words: *Inventory to Sales Ratios; Inventory; Business Cycles; Trend Breaks*
JEL Codes: *E00, E32, E37*

Acknowledgement

This paper is part of the first author's Master's thesis submitted to the Madras School of Economics. The authors would like to thank Dr. Debojyoti Mazumder (Indian Institute of Management Indore) and Dr. Purna Banerjee for their useful comments and suggestions.

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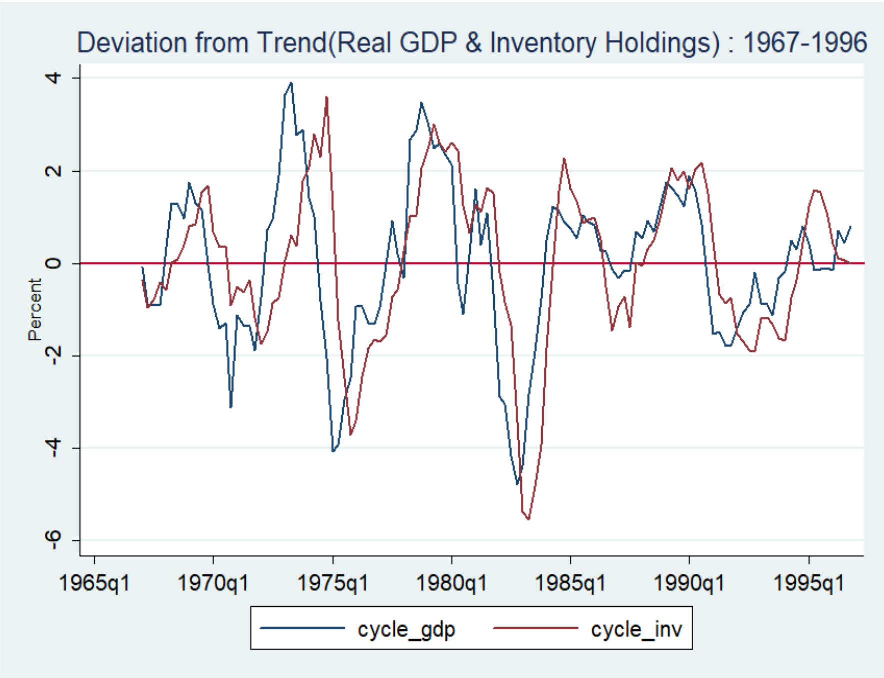
INTRODUCTION

Investments in inventories have traditionally drawn a lot of interests from policymakers and macroeconomists primarily because although investment in business inventories has averaged about 0.5 percent of real GDP in the U.S. over the post war period, changes in inventory investment constituted, on an average, more than 30 percent the size of quarterly changes in real GDP during the same time. More striking is perhaps the relationship between peak-to-trough decline in real GDP during postwar recessions and the fall in inventory investment. Blinder and Maccini (1991) suggests that "*the drop in inventory investment has accounted for 87 percent of the drop in GNP during the average postwar recession in the U.S*."

Movements in business inventory levels are also very closely related with movements in real GDP with the cyclical component of real GDP leading the cyclical component of inventory holdings slightly (Figure 1).

Figure 1: Deviation from Trend – Real GDP and Real Inventory Holdings



Source: Author's calculation using data from the U.S. Department of Commerce, BEA.

Quarterly Data Logged and De-Trended Using Hodrick-Prescott Filter (λ = 1600). Raw Data Are in Billions of Chained 1996 Dollars.

Table 1 shows the correlation between cyclical components of real inventory holdings and the cyclical component of real GDP (and its lags). Relationship: Pro cyclical.

Correlation between the cyclical components of Inventories and real GDP = 0.585 and peaks at 0.867 when output is lagged by two quarters.

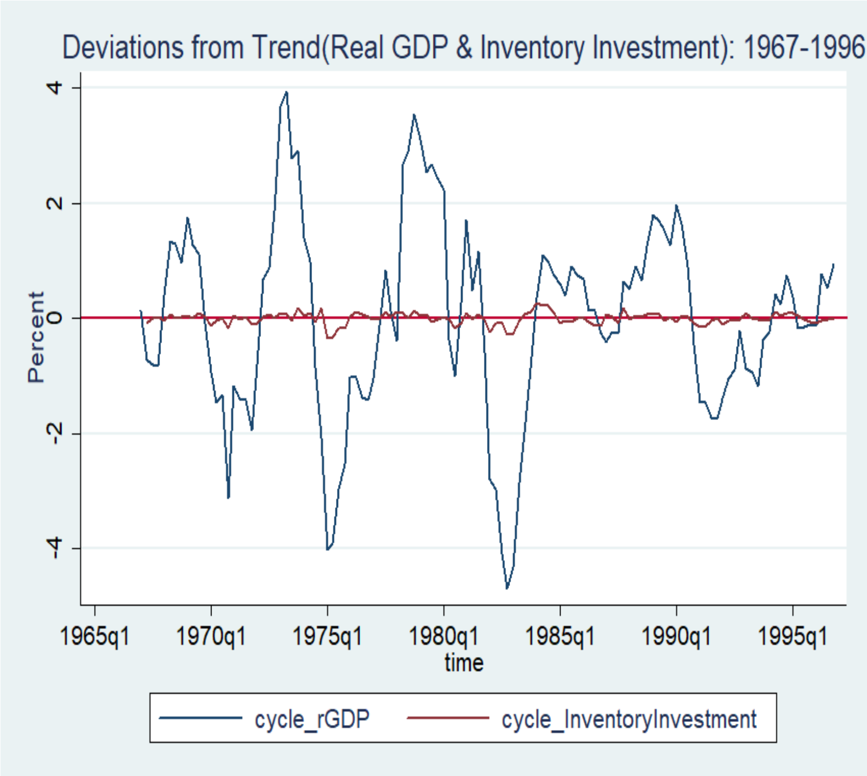
Table 1: Pairwise Correlation – Cyclical Components of Real Inventory Holdings and Real GDP and Its Lags

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) cycle_inv	**1.000**					
(2) cycle_gdp	**0.585**	1.000				
(3) L.cycle_gdp	**0.770**	0.871	1.000			
(4) L2.cycle_gdp	**0.867**	0.687	0.871	1.000		
(5) L3.cycle_gdp	**0.850**	0.467	0.686	0.871	1.000	
(6) L4.cycle_gdp	**0.747**	0.248	0.468	0.687	0.872	1.000

These observations about the behavior of inventories w.r.t to the business cycle (also see Figure 2, Table 2) have led many economists to speculate that inventory fluctuations hold the key to understanding the business cycle. In fact, it was Blinder (1990) who stated that "*business cycles are, to a surprisingly large degree, inventory cycles.*"

From Table 2, the relationship between real inventory investments and real GDP - pro cyclical & correlation between the cyclical components of Inventory investments and real GDP = 0.583 (peak obtained at the current quarter) and it declines and eventually reverses as output is lagged further.

Figure 2: Deviations from Trend – Real GDP and Real Inventory Investments.



Source: Author's calculation using data from the U.S. Department of Commerce, BEA.

Because inventory investment is sometimes negative, the levels of the quarterly data have been detrended using the Hodrick–Prescott filter (λ= 1,600), and both series are expressed as a percentage of the trend in GDP.

Raw data are in billions of chained 1996 dollars.

Table 2: Pairwise Correlation – Cyclical Components of Real Inventory Investments and Real GDP and Its Lags

Pairwise Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) v2	**1.000**					
(2) v1	**0.583**	1.000				
(3) L.v1	**0.419**	0.871	1.000			
(4) L2.v1	**0.227**	0.689	0.871	1.000		
(5) L3.v1	**-0.025**	0.471	0.688	0.871	1.000	
(6) L4.v1	**-0.214**	0.254	0.472	0.689	0.872	1.000

It was Abramovitz (1950) who first provided empirical evidence on the importance of inventories in business cycle fluctuations during the post WWII period. However, it was Metzler (1941) who proposed a model which showed that serial uncorrelated exogenous shocks, coupled with certain structure of business inventory investment could generate business cycles.

Since then, research has primarily been motivated by two overriding questions:

(1) Do business inventory investments play a key role in intensifying and in the transmission of exogenous shocks to the economy?
(2) Does inventory behavior provide any information on the source and the nature of shocks that lead to business cycle fluctuations?

Till the early 1980s, the Production Smoothing Model was considered the benchmark model of inventory behavior. However, with greater availability of quality data, economists found out that the empirical predictions of this model were not consistent with the key features of U.S. data dealing with production, sales and inventories.

This has led to a sizeable body of literature dealing with the augmented versions of the model to make it more consistent with the empirical observations. At the same time, economists have developed alternative models of inventory behavior which are also consistent with the data.

The Production Smoothing Model

The Production Smoothing Model has provided the microeconomic foundations on which most research on the relationship between inventory cycles and business cycles is based on.

The primary assumptions of this model are:

(1) Manufacturing firms face variable demands for their goods.
(2) The cost of production is a convex function.
(3) The manufactured goods are storable.

These implies that a profit maximizing firm has an incentive to use inventories to smooth production across time as a response to fluctuating sales or demand.

We consider an individual firm that produces a single good. Let the total sales and price of the good at time t be denoted by S_t and p_t respectively. These variables are allowed to vary through time. At time t, the firm faces the following cost function:

$$C_t = \gamma_1 Y_t + \gamma_2 Y_t^2 + \gamma_3 I_t^2 \qquad (1)$$

Where, $\gamma_1, \gamma_2 > 0$, $\gamma_3 \geq 0$, Y_t is the production during period t and I_t is the stock of inventories at the end of period t.

γ_2 being strictly positive implies that the marginal costs of production are increasing in output. The last term which represents the cost of holding inventories is assumed to be an increasing function of the size of inventories.

The relationship between inventory holding, production and sales is given by:

$$I_t - I_{t-1} = Y_t - S_t \tag{2}$$

With inventory accumulation subject to the non-negativity constraint,

$$I_t \geq 0 \tag{3}$$

Given these constraints, a firm chooses its output and inventory holdings so as to maximize the expected discount value of its profits,

$$E_0\sum_{t=0}^{\infty} \beta^t(p_t S_t - C_t) \tag{4}$$

Where E_0 denotes the expectation, conditional on the information available at time t = 0 and β represents the discount factor related to the constant real rate of interest.

Given that sales vary through time, firms will hold inventories in order to lower the variance of output or smooth production, as long as the cost of holding inventories is not too large, the discount factor is not too small and the production cost is sufficiently convex.

This model predicts that the variance of sales exceeds the variance of output and inventory investment is counter cyclical.

Fitzgerald (1997) shows that the standard deviation of the cyclical components of real GDP during the postwar period is 1.81 percent compared to 1.44 percent for final sales; just the opposite of the what the model predicts.

Also as shown by Figure 2 and Table 2, inventory investment is pro cyclical.

These empirical findings cast a large shadow of doubt over the appropriateness of the Production Smoothing Model, a view expressed by the Blinder 1986 paper "*Can the Production Smoothing Model of Inventory Behavior Be Saved?*"

Given these discrepancies, economists have tried alternative models to explain inventory behavior.

(S,s) Model

The (S, s) model of inventory behavior focuses attention on the timing of deliveries rather than that of production. In this model, a firm's decision rule about inventory holding is based on the following assumption. The firm chooses a threshold *s*, below which it doesn't let the inventory level to fall. When inventory stocks go down to the threshold level, *s*, the firm orders a new batch, increasing the level of inventory holdings to optimally chosen level, *S*.

$S - s$ denotes the firm's optimal lot size. The primary assumption behind the (S,s) model of inventory behavior is that the cost of acquiring goods includes a fixed cost with a constant marginal cost.

The firm in a (S,s) model faces the following cost function:

$$C_t = \begin{cases} \gamma + \varphi[I_t - (I_{t-1} - S_t)] \\ \quad \text{if } I_t > I_{t-1} - S_t \\ \quad 0 \text{ if } I_t = I_{t-1} - S_t \end{cases} \qquad (5)$$

Where, γ represents the fixed cost of placing an order while φ represents the marginal cost and S_t is the current period sales. Thus cost is incurred only when new goods are acquired, i.e., end of period inventory holding, I_t exceeds the difference of the beginning of period inventories, I_{t-1} and the current period sales, S_t.

This model predicts that the variance of production (varies between zero and optimal lot size) can exceed the variance of sales, when sales are constant. Or when the variance of sales is not too large – a prediction which is consistent with the empirical findings.

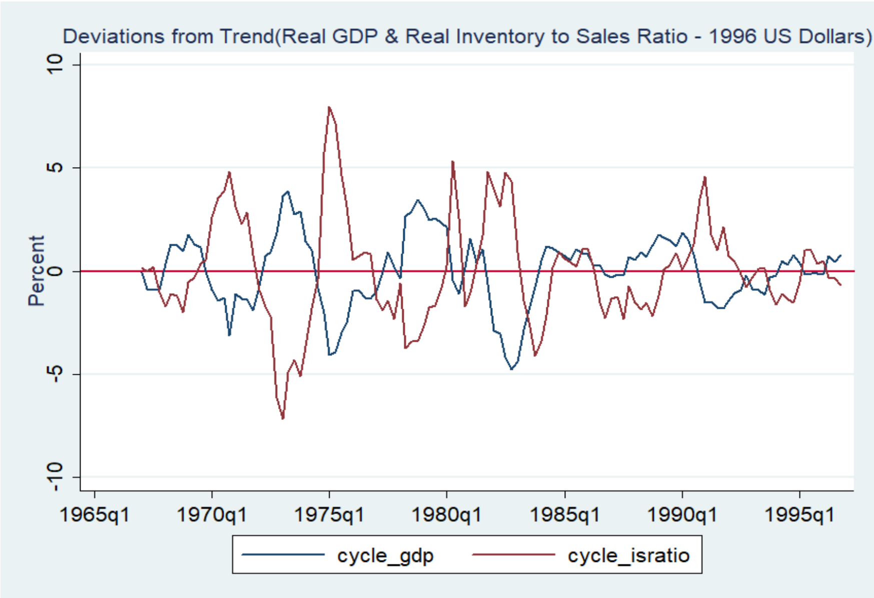
These two theories are not mutually exclusive, but applicable to different types of inventories; hence both of them, together, and not on their own, may be relevant for understanding of the overall inventory behavior.

Recent Research

Since the early 1990s, researchers have started using a new measure for inventories – *The Real Inventory-Sales Ratios for Manufacturing and Trade*. This is primarily based on the assumption that firms target their inventory levels in relation to their expected sales (Ruth et al, 2011).

Figure 3 and Table 3 show that inventory-sales ratio, unlike inventory holdings and inventory investments exhibit countercyclical behavior. The reason being, during business cycle upswing, sales grow faster and the demand outpaces expectations leading to diminishing inventory stocks. Thus the inventory-sales ratio goes down. On the other hand, during business cycle downturn, lower sales result in increasing inventory holdings, leading to increasing inventory-sales ratio. However, Bils and Kahn (2000) suggests that inventory – sales ratio is too persistent to be generated by short run sales surprises. They opine that the augmented (S,s) Model provides a better explanation for the countercyclical behavior of the inventory-sales ratio.

Figure 3: Deviation from Trend – Real GDP and Real Inventory to Sales Ratio



Source: Author's calculation using data from the U.S. Department of Commerce, BEA.

Quarterly Data Logged and De-Trended Using Hodrick-Prescott Filter (λ = 1600).
Raw Data Are in Billions of Chained 1996 Dollars.

Table 3: Pairwise Correlation – Cyclical Components of Real Inventory – Sales Ratio and Real GDP and Its Lags

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) cycle_isratio	**1.000**					
(2) cycle_gdp	**-0.709**	1.000				
(3) L.cycle_gdp	**-0.468**	0.871	1.000			
(4) L2.cycle_gdp	**-0.229**	0.687	0.871	1.000		
(5) L3.cycle_gdp	**-0.021**	0.467	0.686	0.871	1.000	
(6) L4.cycle_gdp	**0.183**	0.248	0.468	0.687	0.872	1.000

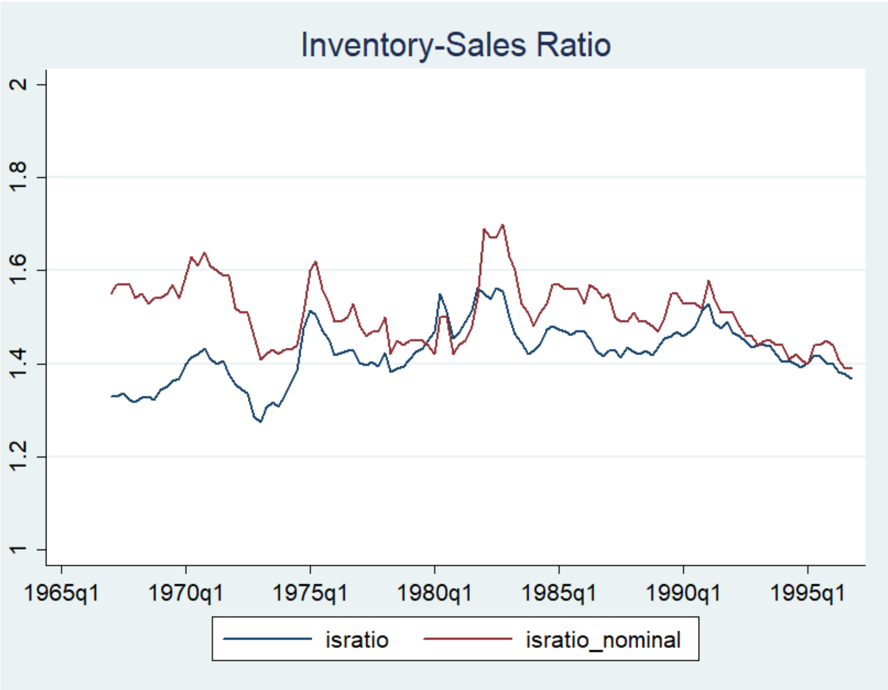
Relationship: Countercyclical.
Correlation between the cyclical components of Inventory to Sales Ratio and real GDP is -0.709 and it declines and eventually reverses as output is lagged further.

According to this model, firms maintain stocks to meet expected demand; countercyclical inventory-sales ratios are explained by the fact that it is relatively costly for the firm to hold inventories during the time of economic boom. As discussed, this model can also explain the observed positive correlation between sales and inventory holdings and the pro cyclicality of inventory itself. [Bils and Kahn (2000), Khan (2003), Khan and Thomas (2007) and Tsoukalas (2005)]. But most researchers are silent on the issue whether the use of chain weighted inventories to sales ratio or that at current prices is more appropriate.

However, "*Why Do Real and Nominal Inventory-Sales Ratios Have Different Trends?*" by Valerie A. Ramey and Daniel J. Vine suggests that since the trend in the nominal ratio can be impacted by relative price changes (in inventories and sales), comparisons of inventory-sales ratio across time can lead to spurious results.

The authors say that *"For many purposes, such as studying the historical effects of information technology on inventory holdings or the connection between inventory-sales trends and business cycle volatility, the chain-weighted ratio is the correct ratio to use. On the other hand, the nominal ratio may be more appropriate for some studies of credit and working capital requirements for financing the dollar value of inventories."*

Figure 4: Inventory-Sales Ratio: Nominal and Real (Us 1996 Dollars)

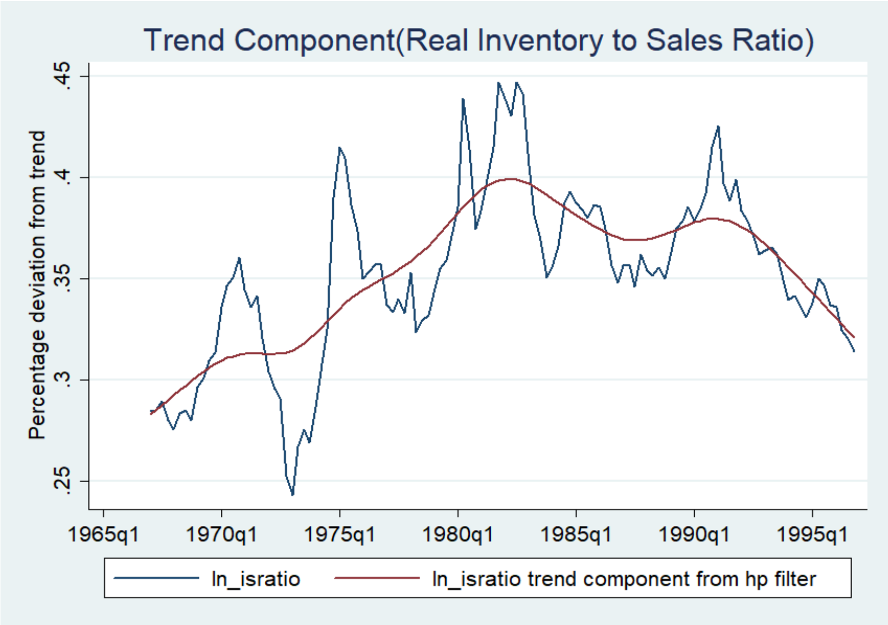


Source: Author's calculation using data from the U.S. Department of Commerce, BEA.

Given the significant improvements in inventory management since the 1980s, it is quite reasonable to expect to observe a downward trend in the long term U.S. inventory-sales ratio. Blinder, Maccini (1991), Hirsch (1996), albeit using data from the 1980s only, disagrees. In fact, Blinder, Maccini (1991) observes "*Furthermore, contrary to popular belief, inventories are not leaner than they were decades ago.*"

Figure 5 (it includes the 1990s) seems to suggest otherwise.

Figure 5: Trend Component – Real Inventory Sales Ratio



Source: Author's calculation using data from the U.S. Department of Commerce, BEA

Irvine (2003), by using aggregate fixed weight inventory-sales ratio, shows that the aggregate manufacturing inventory-sales ratio has steadily declined since the early 1980s. More strikingly, the fixed weight manufacturing and trade inventory-sales ratio has declined from 1.55 in the mid-1980s to 1.31 in 1999. But why did it peak in 1981-82? Surely any technological progress would imply a strictly downward trend in the inventory-sales ratio.

He attributes this to the composition of sales moving increasingly towards durable goods, which was in turn driven by a shift in the mix of consumer expenditure towards durables. Since the manufacturers, whole-sellers and retailers dealing with durable goods have historically higher inventory-sales ratio as compared to those dealing with non – durables, as sales mix moved towards durable goods, the subsector dealing with durables weighed more in the BEA aggregate inventory-sales ratio leading to it reaching the peak in the early 1980s. In 1967, the inventory-sales ratio for the durable sub-sector was, on an average, 1.91 while that for the non-durable sub-sector was 1.81.

Irvine (2003) also find that the fixed weight durable inventory-sales ratio after fluctuating around 2.1 in the early years, has declined steadily since 1983, reaching 1.4 in 1999. This decline has caused the overall fixed weight aggregate manufacturing inventory-sales ratio to be on the downward trend since 1983. Similar trends were observed in case of retail and merchant whole-sale sectors. This can be attributed to firms dealing with durable goods were more eager to adopt inventory control methods, given their historically high inventory-sales ratio.

Irvine (2005) shows that the aggregate inventory-sales ratio trended upwards at an average rate of 0.76 percent per year till 1985 Q3 and has trended downwards at a rate of 1.29 percent per year since then. All the pre-1990s reduction in the inventory-sales ratio occurred in industries dealing with durable goods. He also found that 19 out of the 25 inventory-sales ratio trend breaks in industrial sub-sectors occurred in the years 1972-75 and 1980-84 – years of or years around deep recessions in the U.S.

He says, "*Trends in the inventory-sales ratios presumably reflect long term changes in the determinants of the target industries.*
Decrease in the inventory-sales ratio have to be the result of changes in factors which allow (make it more cost efficient) for firms to lower target stock levels relative to sales over long term….

The adoption of JIT and other production control system allows holding of less inventory per unit of sales…

The durable manufacturers (especially auto) adopted JIT in the early 1980s. The timing of the downward trend breaks in the early 1980s in six durable industries is consistent with the adoption of these systems."

Just-in-Time Production System

The Just-In-Time (JIT) Production System or the Toyota Production System was introduced by Shigeo Shingo and Taichi Ohno at the Toyota motor plant in the mid-1970s.

Biggart, Gargeya (2002) writes "*Firms implementing JIT seek to minimize the need for raw materials, work-in-process(WIP) and finished goods inventory by focusing on reducing the set-up times, coordinating of JIT deliveries from suppliers with production needs, balancing productive capacities of internal processes and, above all, maintaining a continuing commitment to achieving the highest level of quality at all stages of the business transactions…*

As such, JIT can be viewed as a long term strategy, one that promotes excellence and eliminates wastes throughout the company."

Their study on 74 U.S. firms (and 15 different industries) which adopted the JIT production system in the years 1975-1995 finds that post JIT adoption, total inventory-sales ratio declined from 0.1781 to 0.1474 (statistically significant at 0.01 level).

Morgan (1991) notes that the possible reasons why inventory-sales ratio declined in the 1980s are record high interest rate in the early 1980s and declining inflation after 1982 (these increased the cost of holding inventories), fierce competition from the Japanese firms (who adopted JIT production system in the late 1970s) in the 1980s; in fact, analysts attribute the success of the Japanese firms in the U.S. market in part to the adoption of JIT. This reduced the operating cost of the Japanese firms which helped them undersell the U.S. firms.

On the 1991 recession, he says, "*While recessions in the past were often foreshadowed by a rising inventory-sales ratio, the current recession was not. In fact, inventory-sales ratio has declined noticeably since the last recession ended in 1982.*"

He opines that the adoption of inventory management techniques by about 15 percent of the U.S. firms in the 1980s may have been responsible for this.

Literature Review

Filardo (1995) was the one of firsts of many to empirically test for the relationship between inventory cycles and business cycles. For the first part of the study he examined three broad trends in the data – sectoral inventory to sales ratio, the direct contribution of inventory holdings to real GDP and the behavior of inventory investments in different phases of the business cycle, with special attention being paid to the recession of 1990-91 and the recovery that followed thereafter.

For the sectoral inventory-sales ratio he used MITS manufacturing and trade inventory to sales ratio (source – *Census Bureau's Survey of Manufacturing and Trade Inventories and Sales*) instead of the BEA's NIPA (National Income and Product Accounts) data primarily used by researchers studying inventory behavior. He found significant decline in the inventory-sales ratio only after 1990.

He further found that the after the new inventory management measures were implemented, the volatility of inventory investment has increased (from 1970-80, the standard deviation of aggregate inventory investment from mean was 18. From 1980 to the 1994 Q4 it increased to 26) rather than decreased.

Also, the during the 1990-91 recessions, the declining inventory investment contributed 59 percent to the drop in real GDP, very similar to the post war average. These observations alone provide little evidence that the business cycle has become more muted post adoption of inventory management practices.

For the second part of the study, he used two regression models to measure the links between inventory investment and business cycles. For the first model, he used atheoretical regression analysis or Vector Autoregression (VAR) analysis. In this method, the growth rate of GDP and the change in inventory investment were modeled as separate equations in a VAR. He estimated such a VAR using data from 1959 - 1994 and three tests (one measuring the stability of the regression parameter, another measuring the stability of the response of inventory investments and the third measuring the forecast accuracy) were run to search for a change in the link between inventory investment and real GDP. All the three tests failed to reveal such a change.

The second model, partially based on the 1992 Bechter, Stanley model of inventory investment suggested that the new inventory management systems have not substantially influenced the inventory cycles. Kahn *et. al.* 2002, however, finds that the improvements in inventory management, particularly aided by the progress in Information Technology (I.T.) have played a direct role in reducing real GDP volatility. Their structural model incorporating both inventories and I.T. showed that improved information about demand leads to lower output volatility without a comparable decrease in the volatility of sales.

Also, in this study, they extracted a smooth trend for the inventory –sales ratio (durable sector) using Kalman Filter. This smooth trend was interpreted as the target or the desired inventory –sales ratio and any movement away from the trend was treated as deviations from the target. They found 1) that the measure of the target declined steadily after the early 1980s and 2) there were significant decline in the deviations from the target after the early 1980s. They attribute these results to the fact that firms might be making smaller mistakes with time, something that is plausibly linked with improvements in I.T.

Last but definitely not the least, Irvine, Schuh (2005) found in a two-part study that improved inventory management is loosely associated with lower volatility of output at the industry level.

The first part of the study which was based on the complete decomposition of the variance of GDP growth using NIPA data showed that most of the reduction in the variance of GDP growth was associated with the goods sector, which holds inventories and not with the services sector, which doesn't hold inventories. Direct effects of the changes in inventory behavior – variance of inventory investment and covariance of sales and inventory investments – accounted for little less than 50 percent of the total reduction in real GDP volatility.

In the second part of the study which investigated the cross-section evidence on the link between inventory behavior and output volatility, they used quarterly data from the Bureau of Economic Analysis for the manufacturing and trade (M and T) sector during the period 1959: Q1 through 2002: Ql. - they found that virtually all industries experienced decline in output volatility post adoption of inventory management practices.

Data and Methodology

Data

(1) *Real Inventory-Sales Ratios for Manufacturing and Trade, Seasonally Adjusted [Based on chained 1996 dollars, 1967-96, SIC]* – the data is available from 1967 onwards. Also, post 1997, the move to NAICS system of classification from the SIC system resulted in significant shift of measured activities across sectors, primarily between the manufacturing and the services sectors. Because of this re-classification it's difficult to compare data pre and post 1997; hence our study focuses on the years between 1967 and 1996.

(2) *Real Manufacturing and Trade Inventories, Seasonally Adjusted, End of Period [Chained 1996 dollars, 1967-96, SIC]*

(3) *Real GDP, Seasonally Adjusted [Chained 1996 dollars, 1967-96, SIC]*

Sources: Bureau of Economic Analysis (BEA), StatCAN Archive, NBER.

The cyclic components of the real GDP and real inventory-sales ratio were obtained using Hodrick-Prescott (HP) Filter.

HP Filter is built on the idea that if log-linearized actual output (y_t) can be expressed as the sum of the potential output or the trend component (g_t) and cyclical component or deviations from trend (c_t), then,

$$y_t = g_t + c_t \tag{6}$$

The HP filter generates the trend components $\{g_t\}_{t=1}^{T}$ by the following minimization:

$$\{g_t\}_{t=1}^{T} = \arg\min \left[\sum_{t=1}^{T}(y_t - g_t)^2 + \lambda\sum_{t=1}^{T}[(g_t - g_{t-1}) - (g_{t-1} - g_{t-2})]^2\right] \tag{7}$$

Where λ is the smoothing parameter, whose value governs the ratio of variation in the cyclical components w.r.t the variation in the trend components. Hodrick and Prescott suggested a value of 1600 for the smoothing parameter for quarterly data.

Model

We estimate the following Time-varying Parameter model:

$$y_t = \alpha + \beta_t(y_{t-1}) + \gamma_t(cycle\_isratio) + \varphi_t \tag{8}$$

$$\beta_t = \beta_{t-1} + \eta_t \tag{9}$$

$$\gamma_t = \gamma_{t-1} + \rho_t \tag{10}$$

where, y_t is the output gap,

cycle_isratio is the cyclic component of the real inventory-sales ratio,

β_t is the time varying output-gap persistence parameter,

γ_t is the time varying slope coefficient which measures the relationship between business cycles and inventory cycles.

The error terms φ_t, η_t and ρ_t are serially uncorrelated disturbances with zero mean and constant variances and are assumed to be uncorrelated with each other in all time periods.

Our empirical strategy is to estimate the path of the time varying slope coefficient γ_t. In this model we treat output gap as the observable variable and the output gap persistence parameter and the slope coefficient γ_t as unobserved time-varying state variables.

Equation (8) represents the measurement equation while equations (9) and (10) represent the transition equations. These equations represent a state space form, in which the unknown parameters β_t, γ_t and the error variances are estimated using M.L.E techniques. Post estimation, Kalman Filter recursions is applied to yield optimal estimates of the state variable sequence.

Due to absence of theoretical priors, we had no idea about the true nature of the intercept coefficient, α. So we tested for both the scenarios, one where α is time invariant and the other, where the intercept coefficient varies with time. Our estimations suggested that the intercept coefficient is time invariant.

Post estimation we tested the Kalman Filter smoothed estimates of γ for the existence of trend breaks using the Bai, Perron (2003) test for the detection of multiple structural breaks.

The primary reason for using Time Varying Parameter models over traditional estimation methods is that when one is dealing with historical time series data, it is quite possible that any abrupt changes, such as structural breaks or transition periods may alter the relationship under study in such a way, that any estimations using traditional methods where the underlying structure is assumed to be fixed over the full sample may yield spurious results.

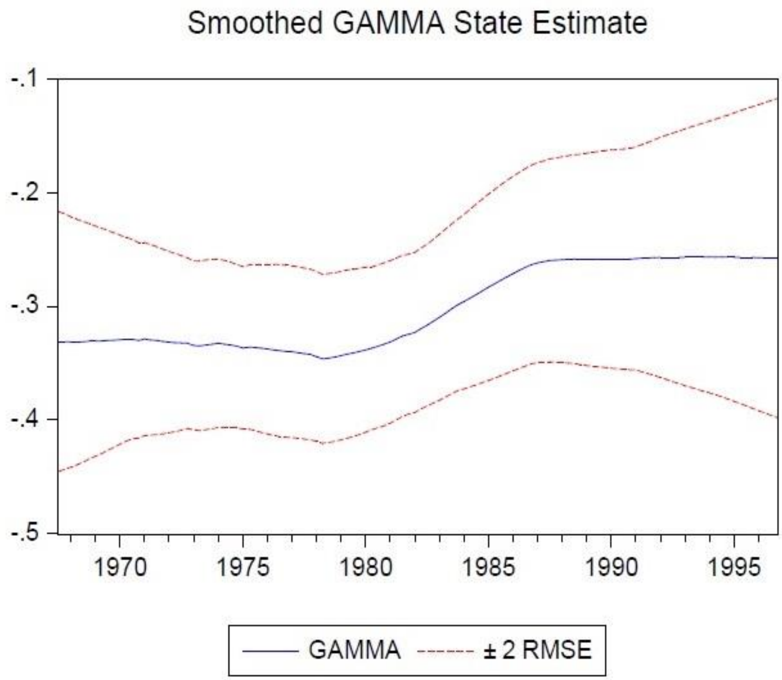
Estimation Results and Interpretation

The Estimation Results

Table 4: Estimation Results

Parameters	Final State	Z-Statistics	Probability
$\hat{\gamma}$	**-0.257422**	**-3.611404**	**0.0003**
$\hat{\beta}$	**0.748914**	**3.934582**	**0.0001**

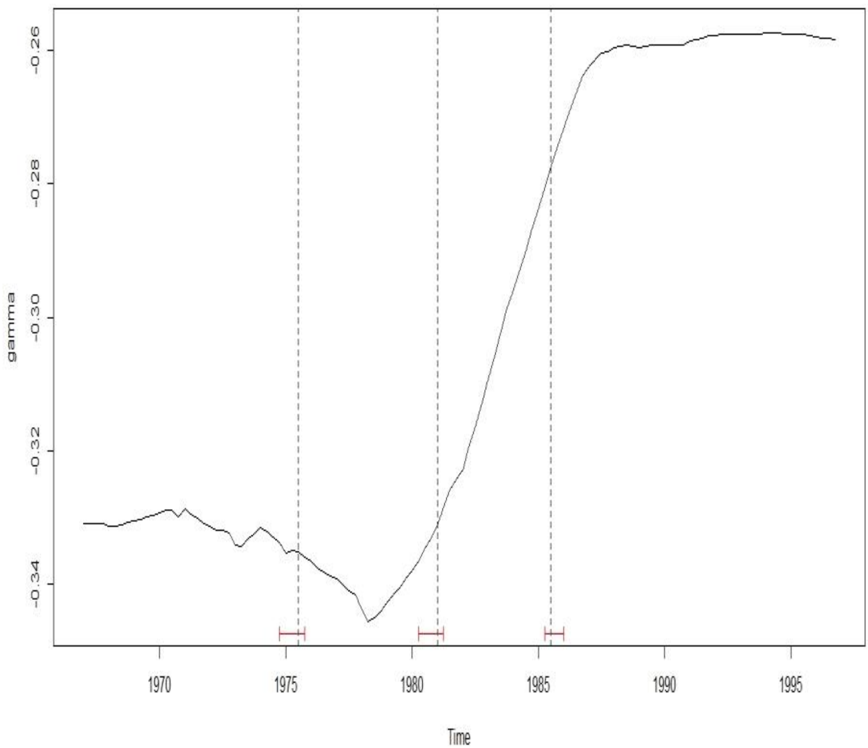
Figure 6: Kalman Filter Smoothed Estimate of γ with Standard Error Bands



Interpretations
Given that the real inventory-sales ratios are counter-cyclical in nature, the results obtained in Table 4 are as per expectations.

As we move to Figure 6, things get a bit more interesting. The smoothed estimates show that inventory cycles have indeed lost some of their significance vis-à-vis business cycles. However, the decline in its importance has primarily happened in the 1980s, when firms started embracing inventory management systems like JIT production system. 1990 onwards, things seemed to have leveled off.

Figure 7: Result of the Bai Perron Test for the Detection of Multiple Trend Breaks.



This may be explained by the fact that the 1980s were probably the transition period; by 1990 firms may have been able to adjust their production process as per the new economic conditions.

Moving on, Figure 7 suggests the existence of three trend breaks – 1975 Q2, 1981 Q1 and 1985 Q2.

These results are in agreement with the findings of Irvine (2005) who suggested that 19 out of 25 sectoral trend breaks in the inventory-sales ratio occurred during or around the time of deep recessions: 1972-75 or 1980-1984. And the trend breaks for the aggregate manufacturing and trade inventory – sales ratio was observed in 1985; since then the aggregate inventory – sales ratio has trended downwards at a rate of 1.29 percent per year.

In our case, the first two breaks occurred during the deep recessions while the third coincided with the trend break in aggregate inventory – sales ratio. One possible explanation for this might be that given the country was going through economic turmoil and at the same time, the domestic firms were facing tremendous competition from the Japanese firms with superior inventory management systems, the U.S. industries were being constantly forced to restructure for their very survival.

CONCLUSIONS

This study is one of the first, albeit a rather simplistic attempt at quantitatively estimating the relationship between inventory cycles and business cycles and how it has changed over the years. We find that the inventory cycles have indeed lost some of their significance w.r.t business cycles, primarily due to adoption of superior inventory management techniques by the U.S. firms in the 1980s.

However, since 1990, the relationship has held steady suggesting the possible presence of different forces at play. We also find that despite the loss in significance, inventory behavior still has a major role to play in generating business cycles. As such, the use of manufacturing and trade real inventory sales ratio as a lagging index is thoroughly justified. For future research work, we would like to use sectoral inventory data to get a better picture of what exactly transpired in the 1990s.

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