The Comovement in Inventory Investments and in Sales: Higher and Higher

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Abstract

We re-examine changes in the cross-section correlation pattern of sales and inventories using Ng's (2006) "uniform spacing" method, which permits the estimation of the number of correlated pairs and focuses on the conditional correlations. In contrast to the literature, we find that the correlation of shocks across industries increased after the 'Great Moderation'.

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1 Introduction

Recent studies[1] of the great moderation have shown that the use of disaggregate data can provide new insights into the contribution of inventories and sales to the decline in U.S. output volatility. In particular, it has been shown that the reduction in volatility was more widespread among input than output inventories (Herrera and Pesavento, 2005), and that the comovents and persistence of inventories and sales have changed over time ((Irvine and Schuh, 2005b and Ramey and Vine, 2004 respectively). While Irvine and Schuh (2005b) use estimates of the unconditional covariances across industries to show that the decline in volatility came from the uncoupling of industries that once had moved together, Ramey and Vine (2004) conclude that a contributing factor is a reduction in the persistence of sales shocks. These findings suggest that a decline in the comovement across and within industries could have resulted from a reduction in the persistence of sales, a change in the comovement between the individual inventory and sales innovations, or both. To fully understand the forces behind the changes in the behavior of inventories and sales, and their impact in the recent changes in macro aggregates, it is therefore important to disentangle changes in the persistence of the series from changes in the covariance between the individual innovations.

This paper provides two main contributions. First, we re-examine the changes in the cross-section correlation of sales and inventories after netting out changes in dynamics. That is, we analyze *conditional* correlations instead of *unconditional* correlations between industries. Second, we use the "uniform" spacing method proposed by Ng (2006) to test the strength and prevalence of these correlations. While standard tests for no correlation or strong correlation amount to testing either zero or strong correlation, Ng's test allows us to explore situations where possibly some but not necessarily all the sectors are correlated. Additionally, this method permits the estimation of the number of correlated pairs and the quantification of the

[1] See for example Herrera and Pesavento, 2005, Irvine and Schuh, 2005a and 2005b, Ramey and Vine, 2004, Stock and Watson, 2002

extent of the correlation.

In contrast with the literature, we find an increase in the magnitude and prevalence of cross-section correlation after the "great moderation". This increase is mainly due to the higher correlation in inventory investment, particularly for input inventories.

The remainder of this paper is organized as follows. Section 2 describes the methodology, section 3 presents the results, and section 4 concludes.

2 Cross-Section Correlation Test

Our focus on the cross-section correlation is motivated by Ramey and Vine (2004) who argue that a key factor in the decline of U.S. output volatility is the smaller persistence of sales, especially in the automobile sector. Hence, a decline in the unconditional correlation between the sales process for two sectors can result from a reduction in the persistence of sales without any change in the covariance between the individual innovations.

To see this within a simpe model, consider a two industries model where sales follow AR(1) processes so that

$$y_{1t} = \rho_1 y_{1t-1} + \varepsilon_{1t} \quad \text{and} \quad y_{2t} = \rho_2 y_{1t-1} + \varepsilon_{2t}$$

with $COV(\varepsilon_{1t}, \varepsilon_{2\tau}) = \sigma_{12}$ for $t = \tau$ and 0 otherwise, and $COV(\varepsilon_{it}, \varepsilon_{i,t-j}) = 0$ for $j > 0$ and $i = 1, 2$. Even in this simple case it is easy to see that the unconditional covariance between sales in the two industries is given by

$$COV\left(y_{1t}, y_{2t}\right) = \frac{\sigma_{12}}{\left(1 - \rho_1 \rho_2\right)}$$

Changes in the persistent of the sales processes, ρ_1 and ρ_2 will results in changes in the covariance and correlations between sectors even if the conditional covariance σ_{12} has not changed. For example, using unconditional correlations, Irvine and Schuh (2005b) find a decoupling or decline in the covariance between sales, as well as inventory investment, for sectors with improved inventory holding and production techniques, especially for sectors linked through supply and distribution chains such as automobiles and related industries. This decoupling could have stemmed from a decline in the persistence of the sales process. In contrast, we focus on changes in the cross-section correlation net of changes in the dynamics. Thus, unlike Irvine and Schuh (2005a, 2005b), we analyze conditional correlations.

Most tests for cross-section correlation evaluate the hypothesis that all the correlations in a panel of data with N cross-section units and T time series observations are zero, against an alternative that the correlation is non-zero for some unit. Hence, it is unclear if rejections of the null are due to a small or large number of units. In contrast, Ng (2006) proposes a method to test the correlation of units when possibly some, but not necessarily all, units are correlated. It also allows the estimation of the number of correlated pairs and the evaluation of the magnitude of the correlations. Following Ng's notation we use $\hat{\theta}$ to denote the fraction of correlation pairs that are not significantly different from zero. The $n = \frac{N(N-1)}{2}$ unique correlations are ordered and split into two groups, labeled S (small) and L (large) with $\hat{\theta} \in [0, 1]$ being the estimated fraction of the spacings in the small group S. The strength of the correlation in each subsample can be tested with the standardized variance-ratio test $SVR(\eta)$., which follows a standard normal distribution as the number of unique correlations goes to infinity[2]. We set $\eta = n$ to test the full sample, $\eta = \hat{\theta}n$ to test uniformity in S

[2] The reader is referred to Ng's (2006) original paper for details.

and $\eta = n - \hat{\theta}n$ to test uniformity in L. If the uniformity hypothesis is rejected in L but not in S, a fraction $\hat{\theta}$ of the correlation coefficients are not statistically different from 0.

3 Test Results

We use series on monthly manufacturing sales and inventories by stages of production from the BEA. The data are seasonally adjusted, measured in chained dollars of 1996, and cover January 1959 to March 2000. The series comprise 19 two-digit SIC sectors, and 2 three-digit SIC sectors (motor vehicles and other transportation equipment).

We apply the testing method to the residuals from a regression of each variable on a constant and 12 lags in order to isolate cross-section from serial correlation (Herrera and Pesavento, 2005). Three periods are examined: (1) January 1959 to March 2000, (2) January 1959 to October 1984, and (3) November 1984 to March 2000. October 1984 is used to separate the subsamples, since it is conventionally agreed on as the break date of U.S. output volatility.

TABLE 1 here

Table 1 reports the test results for all possible correlation pairs between sales and inventories across all industries. Because we have 21 sectors and 4 variables (sales, materials and supplies inventories, work in progress inventories, and finished goods inventories), we have a total of 3,486 correlation pairs. We find significant evidence of cross-section correlation; the SVR test for L with $q = 2$ is larger than 1.64 in absolute value. Yet, a change in the correlation pattern across subsamples is apparent. The proportion of pairs in the small group, $\widehat{\theta}$, equals 0.66 for 1959:1-1984:10 versus 0.10 for 1984:11-2000:3. Hence, 34% of pairs are large in the first subsample versus 90% in the second subsample.

TABLE 2 here

To probe deeper into the change in the correlation pattern, we run separate tests for each variable. Table 2 reports these disaggregated results. Three main conclusions can be derived. First, regardless of the sample period, there is significant evidence of cross-section correlation for manufacturing sales. The SVR test for L with $q = 2$ equals 7.19, 5.35, and -5.22 for 1959:1:2000:3, 1959:1-1984:10 and 1984:11-2000:3, respectively. The algorithm finds a value of $\widehat{\theta} = 0.17$ for the whole sample, 0.14 for the first subsample and 0.10 for the second subsample. Given the large number of pairs in L, the evidence against no correlation is quite compelling. However, the smaller value of $\widehat{\theta}$ for the second subsample suggests an increase in the cross-section correlation for sales. The largest increases occurred in durable-durable correlation pairs (unreported results).

Second, the degree of correlation between inventories varies across sample periods, with the number of large correlation pairs (L) being considerably greater in 1984:11-2001:3 than in 1959:1-1984:10. The value of $\widehat{\theta}$ declines for all types of inventories by at least 0.37. Most increases occurred in correlations of chemicals, rubber and plastics, electrical equipment and industrial machinery with other industries.

Finally, changes in the correlation pattern differ for input and output inventories. Evidence against no correlation in L is found only for materials and supplies (SVR for $L = 2.27$) during 1959:1-2000:3. Splitting the sample reveals changes in the correlation structure for work in progress and finished goods. For work in progress ($SVR = 0.02$ for L and 0.73 for S), we cannot reject the null of no correlation in 1959:1-1984:10. In contrast, with 90% of the sample in L ($\widehat{\theta} = 0.1$) and a corresponding SVR of 2.94, evidence against no correlation is quite strong in 1984:11-2000:3. For finished goods inventories, we reject the null in the first period (SVR for $L = 2.17$, $\widehat{\theta} = 0.67$) but not in the second (SVR for $L = -1.44$, $\widehat{\theta} = 0.10$).

Our results also have implications for the literature that estimates standard factor model to evaluate the role of common factors in explaining the relationship between the variance and the covariance in the industries. Because there are many zero correlation pairs in 1984:11-2000:3, and we cannot reject the null for L, a common factor structure is not a suitable characterization of output inventories (i.e., finished goods). In contrast, evidence of a common factor for input inventories is quite compelling in 1984:11-2000:3.

4 Conditional and Unconditional Correlations

In Section 2 we argue that looking at changes in the unconditional correlations can be missleading as they may represent changes in the persistence rather than changes in the covariances between sectors. To understand how focusing on the unconditional correlations can affect the results, we compute all the correlations pairs using unconditional covariances.. That is, we do the same calculations as above but now the estimates are obtained from regressions of each variable on a constant alone. The graphs in Figure 1 plot the ordered 210 correlations pairs pre and post 1984. It is clear, even from a simple visual inspection, that unconditional correlations (squares) would lead to the conclusions that the correlations have either not changed (sales) or decreased... Conditional correlations (triangulars) instead are all well above the 45 degrees line indicating a significant increase. Once again, differences in the behavior of input and output inventories, and sales are evident although less marked when looking at conditional values.

FIGURE 1 here

5 Conclusion

We find strong evidence of higher cross-section correlation among manufacturing inventories and sales over the period of the great moderation. At the disaggregate level, this change is particularly evident for input inventories. Our results, indicate that comovement across industries, measured by the conditional correlation, has increased. Conversely, a decoupling of industries that previously moved together (i.e. a decline in the unconditional correlation) cannot be explained by lower cross-sectional correlation among industries but by changes in the dynamics.

6 References

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Table 1: Sales and Inventories by Stages of Production

	N	n	T	$\hat{\theta}$	SVR for S	SVR for L
1959:1-2000:3	84	3486	495	0.70	0.53	7.08*
1959:1-1984:10	84	3486	310	0.66	-0.30	12.04*
1984:11-2000:3	84	3486	185	0.10	5.18	7.08*

Table 2: Disaggregate

	N	n	T	$\hat{\theta}$	SVR for S	SVR for L
Sales						
1959:1-2000:3	20	190	495	0.17	0.58	7.19*
1959:1-1984:10	20	190	310	0.14	-0.70	5.35*
1984:11-2000:3	20	190	185	0.10	1.49	-5.22*
Materials and Supplies						
1959:1-2000:3	20	190	495	0.67	0.33	2.27*
1959:1-1984:10	20	190	310	0.47	-1.45	2.98*
1984:11-2000:3	20	190	185	0.10	-0.61	6.26*
Work in Progress Inventories						
1959:1-2000:3	20	190	495	0.75	-1.32	-0.01
1959:1-1984:10	20	190	310	0.67	0.73	0.02
1984:11-2000:3	20	190	185	0.10	-0.152	2.94*
Finished Goods Inventories						
1959:1-2000:3	20	190	495	0.57	0.78	0.84
1959:1-1984:10	20	190	310	0.67	1.64	2.17*
1984:11-2000:3	20	190	185	0.10	1.76	-1.44

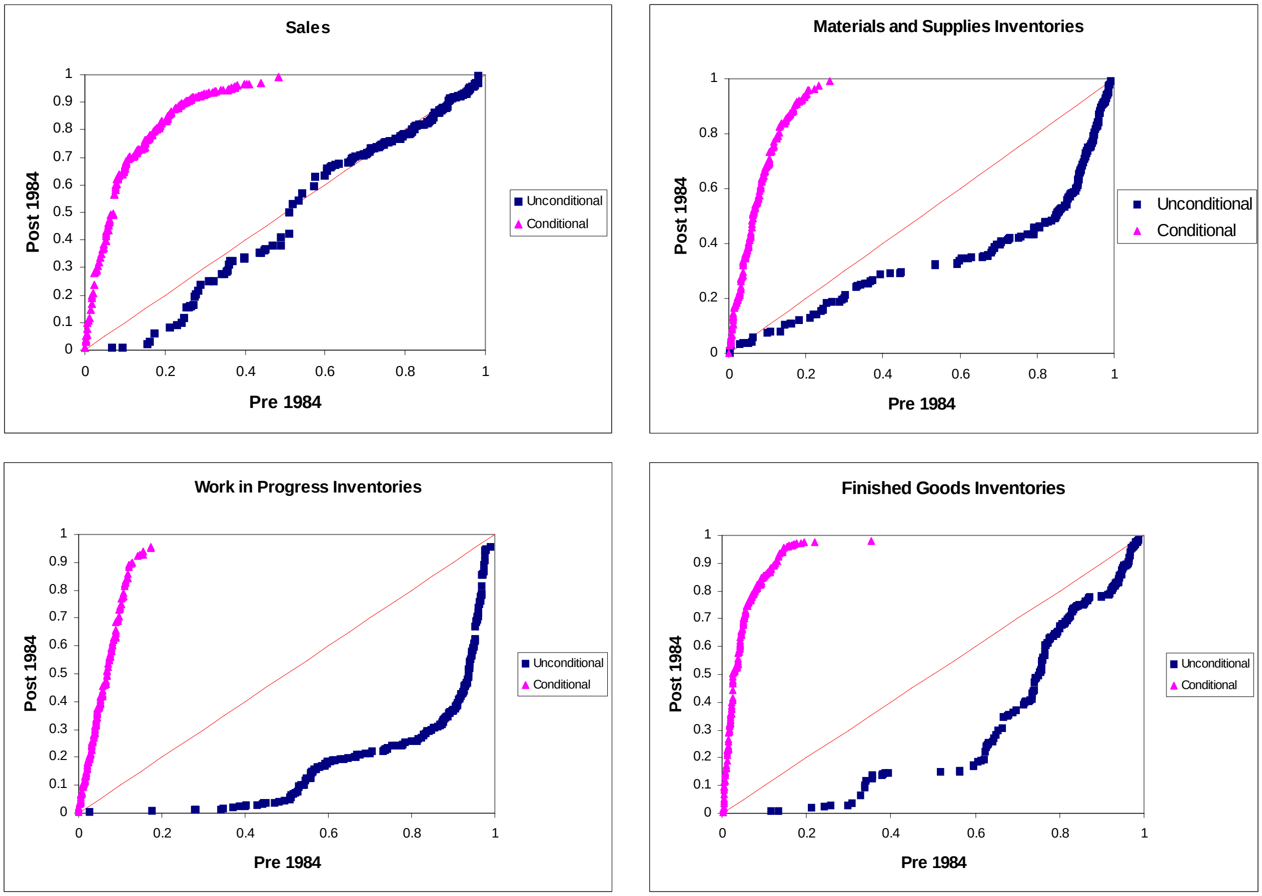

Figure 1: Ordered correlation pairs pre and post 1984