"Inventory Investment and Output Volatility"

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PRELIMINARY – COMMENTS WELCOME

Abstract: This paper reports the results of a detailed examination of the hypothesis that improved inventory management and production techniques are responsible for the decline in the volatility of U.S. GDP growth. Our innovations are to look at the data at a finer level of disaggregation than previous studies, to exploit cross-sectional heterogeneity to obtain clearer identification of this hypothesis, and to provide a complete accounting of the change in GDP volatility. Almost half of the reduction in GDP volatility is associated directly with changes in inventory behavior. However, we discover that almost half of the reduction in GDP volatility is associated with reduced covariance (and correlation) among the output and sales of industries. Thus, there has been a significant uncoupling of industries that once exhibited substantial co-movement. Sales have become less correlated among industries, but inventory investment has become more correlated. These distinctive changes in co-movement suggest that development and management of supply chains are an indirect channel through which changes in inventory management and production techniques have influenced GDP volatility. Cross-section evidence from the manufacturing and trade sector show that reduced covariance among industries is not simply a byproduct of lower variance in an aggregate factor(s), but is associated with changes in supply and distribution chains among key industries, such as automobiles. The data provide cross-sectional evidence that inventory management techniques are associated with reductions in industry output volatility, especially the management of input inventories. However, reductions in output volatility across industries are not associated with the interest sensitivity of industries. This result, together with the importance of covariance reductions, pose difficulty for the hypothesis that better monetary policy, or changes in other aggregate factors, are primarily responsible for lower GDP volatility.

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1. Introduction

Two recent thought-provoking papers have documented a decline in the volatility of U.S. real GDP growth. McConnell and Perez-Quiros (1999) argue that the volatility of GDP growth experienced a one-time drop around 1984, with volatility since then being about half what it was before then, as can be seen in Figure 1 (vertical line at 1984:Q1). Blanchard and Simon (1999) also argue that the volatility of GDP growth has declined, but believe that it has been declining steadily since the 1950s. Although the two studies disagree on the nature and timing of the decline in volatility, they agree that the decline in volatility is linked to inventory investment.[1]

Other studies have also investigated the reduction in volatility but do not attribute it to inventory investment. Stock and Watson (2002) attribute most of the reduction to improved monetary policy, and Ahmed, Levin, and Wilson (2002) attribute most of the reduction to "good luck." Ramey and Vine (2001) argue that the apparent strong link between output volatility and inventory behavior is an indirect consequence of lower sales volatility. They demonstrate that a small reduction in sales volatility will induce a large decline in output and inventory volatility if there are non-convexities in the cost function, and provide evidence from U.S. auto plants. McCarthy and Zakrajsek (2002) also argue that reductions in sales volatility was more important than reductions in inventory investment volatility, but they do find that changes in inventory behavior have contributed to greater stabilization of production.

McConnell and Perez-Quiros report that output volatility declined primarily in inventory holding (goods producing) sectors, especially durable goods industries, and conclude (p. 1474), "Clearly, some aspect of inventory investment in the United States has changed in such a way as to have markedly reduced the volatility of U.S. output fluctuations." Kahn, McConnell and

Perez-Quiros (2002) further demonstrate that the decline in output and inventory volatility coincides with a decline in the ratio of inventories-to-sales (I/S ratio), which they assume reflects improved inventory management techniques. They further speculate that improvements in management techniques resulted from the installation of information technology capital.

Blanchard and Simon instead focus on the correlation of inventory investment with sales growth. They report that the correlation was positive (pro-cyclical inventory investment) until the mid-1980s, when it turned significantly negative (counter-cyclical). This change accounts for much of the reduction in output volatility and they conclude, "This fact…. *must* [emphasis added] have come from a change in the inventory management of firms."

In this paper, we conduct a more detailed investigation of the hypothesis that changes in inventory behavior are responsible for a reduction in output volatility. Although the existing evidence is intriguing, it is only suggestive thus far (as authors in the literature have pointed out). At fairly *aggregate* levels, it appears that volatility and inventory behavior may be correlated, but of course correlation does not imply causation. Even if the hypothesis is true, there is little understanding of exactly how or why it is true. Our innovation is to begin examining the cross-section evidence on inventory behavior and volatility change at the detailed industry level. In this introductory exploration, we take as given a one-time break (reduction) in GDP output volatility in 1984, as argued by McConnell and Perez-Quiros.

Examination of cross-section evidence offers several advantages over aggregate approaches. First, cross-section data offer greater opportunity to obtain clearer identifying restrictions on potential explanations for the reduction in aggregate volatility. For example, industries that exhibit greater improvements in inventory management should experience greater

[1] Warnock and Warnock (2000) offer similar evidence based on employment, and also suggest a possible role for inventory management changes in reducing volatility. Kim and Nelson (1999) also provide evidence of a break in

reductions in volatility. Second, detailed industry data can offer a clearer view of the mechanism by which inventory management works to reduce volatility through reference to specific developments in the industry. For example, widespread publicity has been given to just-in-time techniques adopted by the automotive industry. Third, an important innovation in inventory management has been the development of more sophisticated supply and distribution chains among firms and industries. Studying detailed industries allows us to examine the role of inventory management in these supply and distribution chains.

Our central result is that substantially reduced covariance (and correlation) of output and sales among detailed industries is vital part of the explanation for the reduced variance of aggregate output since the early 1980s. Variance decompositions of the aggregate economy and the inventory-holding sector reveal that changes in inventory behavior – the variance of inventory investment and the covariance of sales with inventory investment – can account directly for almost half of the reduction in GDP volatility. However, we find that almost half of the reduction in GDP volatility also can be attributed to lower covariance of output and sales – both between the inventory-holding sector and other sectors, as well as among industries within the inventory-holding sector itself. Although most inventory-holding industries experienced lower sales volatility, the vast majority of the reduction in aggregate sales volatility can be attributed to lower covariance among industries' sales. Thus, there has been a significant uncoupling of industries that once exhibited substantial co-movement over the business cycle. At the same time, covariance of inventory investment among industries actually increased.

Exploring the detailed cross-sectional data for industries in the inventory-holding sector, we find that the reduction in covariance is widespread but also associated with industries linked by supply and distribution chains. Data from manufacturing and trade show that reduced

1984 using a nonlinear business cycle model, but they do not offer explanations for the break.

covariance among industries is not simply a byproduct of lower variance in an aggregate factor(s). Rather, the distinctive changes in sales and inventory investment co-movement suggest that development and management of supply and distribution chains are an indirect channel through which changes in inventory management and production techniques have influenced GDP volatility. The data also provide cross-sectional evidence that inventory management techniques are associated with reductions in industry output volatility, especially the management of input inventories. Reductions in output volatility and reductions in average inventory-to-sales ratios, which presumably reflect improved management techniques, are positively correlated across industries.

Overall, our results seem to lend support to the hypothesis that changes in inventory behavior helped reduce the volatility (variance) of aggregate output. However, to enhance our conclusions we also test the hypothesis that better monetary policy is responsible for the decline in output volatility. We find that reductions in output volatility across industries are not associated with the sensitivity of industries to monetary policy (interest rates). This result, together with the importance of covariance reductions, pose difficulties for the hypothesis that better monetary policy is primarily responsible for reducing GDP volatility. More generally, our results provide important facts that confront any theory or model purporting to explain the reduction in GDP volatility. Such theories and models should exhibit widespread declines in covariance among industries, especially those with supply and distribution chain linkages.

The paper contains five main sections. Section 2 describes our decomposition of the variance of GDP volatility among major sectors. Section 3 examines the behavior of production and inventory investment of industries within the inventory-holding sector, and provides a complete variance decomposition. Section 4 delves more deeply into the covariance properties of industries in the inventory-holding sector. Section 5 presents some simple cross-sectional evidence on inventory management and production volatility at the industry level. Section 6 provides some cross-sectional evidence on the sensitivity of industries in the inventory-holding sector to monetary policy. Conclusions follow in Section 7.

2. Aggregate Decomposition

Initial observations about inventory behavior and output volatility have been based on national income and product account (NIPA) data at high levels of aggregation. Output is real GDP growth, and inventories are total private business stocks. The total private business sector includes diverse industries such as farming, construction, manufacturing, and trade (wholesale and retail), as well as an "other" category. Inventories generally are not held by many other service-producing sectors, such as finance, insurance, and real estate (FIRE), transportation, services, and government.[2] Thus, the economy comprises two main sectors: one that holds inventories and one that does not.

This two-sector decomposition of the economy raises the first obvious question. Did output volatility change in both the inventory-holding sector and the sector without inventories? If output volatility declined in the sector without inventories as much as it did in the inventory-holding sector, one should question whether inventory management could be responsible for the decline in aggregate GDP volatility.

2.1 Methodological Approach

[2] Firms in these sectors may actually hold inventories, but inventory data are not collected for these sectors. Households also probably hold some inventories of goods, but these are not counted either.

To answer this question, we examine the output growth behavior of three main sectors of GDP and calculate how much of the change in volatility of real GDP growth is attributable to each sector.[3] The goods sector (G) is assumed to be the inventory-holding sector. The structures sector (ST) mainly produces to order and holds few, if any, inventory stocks.[4] The third sector, services (SV), does not hold inventories. In the NIPA, output (real GDP) of the goods sector is the sum of the levels of final sales of goods and total private sector inventory investment:

$$Y_t = S_t + \Delta I_t \ .$$

Because NIPA output is a value added concept, inventory investment includes all types of stocks (finished goods, work-in-process, and materials and supplies). Output (real GDP) in services and structures equals final sales of those sectors.

We must use growth rates of the data because they are expressed in chain-weighted 1996 dollars. The chain-weighting procedure of constructing real data has advantages with regard to growth rate calculations and price measurement, but it introduces severe difficulties with aggregating and manipulating data in levels. As a result, we focus on contributions to aggregate real growth, i.e., real growth rates weighted by shares of nominal data.[5] Only growth contributions of GDP components can be aggregated exactly to equal GDP growth. Raw growth rates can be aggregated approximately, but the error typically is too large to permit exact decompositions. Throughout the paper, lowercase characters denote growth rates (e.g., y_t) and an overhead tilde denotes growth contributions ($\tilde{y}_t$).

[3] Kahn, McConnell, and Perez-Quiros (2002) use the same disaggregation scheme and compute some, but not all, of the variance decomposition components that we report.
[4] Data on construction inventories are available only since 1997 as a result of the recent change in industrial classification scheme to NAICS from SIC.

Figure 2 plots real GDP growth contributions for the goods, services, and structures sectors plus the contribution of inventory investment since 1947. It is immediately apparent that the variance of goods output is lower in the period after the early 1980s (vertical lines at 1984:Q1), and that the variance of inventory investment is lower during this period as well.[6] The variance of structures output also appears to have dropped since the early 1980s. After declining early in the sample, the variance of services output has been fairly steady since around 1960, so the service sector does not exhibit the same kind of one-time drop in output volatility around 1984. Also, note that since the variances of goods output and inventory investment are much larger than the variances of structures and services output, declines in the variances of goods output and inventory investment have more scope for accounting for the decline in overall GDP volatility.

Table 1 provides a variance decomposition of quarterly GDP growth contributions for each of the three major sectors. We calculate the unconditional variances of output over the two periods identified by McConnell and Perez-Quiros (1999) – an early period, prior to 1984:Q1, and a late period, 1984:Q1 through 2001:Q4. The early period begins in 1959 to coincide with the sample period of the industry-level data available for the manufacturing and trade sectors used in the subsequent sections of the paper.

Looking down a particular column of Table 1 we find the components of the variance decomposition of real GDP growth,

$$\begin{aligned}&\mathrm{Var}(y) = \mathrm{Var}(\tilde{y}_G) + \mathrm{Var}(\tilde{y}_{SV}) + \mathrm{Var}(\tilde{y}_{ST}) \\ &+2\left[\mathrm{Cov}(\tilde{y}_G, \tilde{y}_{SV}) + \mathrm{Cov}(\tilde{y}_G, \tilde{y}_{ST}) + \mathrm{Cov}(\tilde{y}_{SV}, \tilde{y}_{ST})\right]\end{aligned},$$

[5] For more details about the proper procedures for working with chain-weighted data, see Landefeld and Parker (1997) and Whelan (2000). In particular, note that there is essentially no "clean" way to measure or control for changes in real shares across industries.

where "Var" and "Cov" stand for time series variance and covariance, respectively. The variance of goods output is decomposed further as follows:

$$\mathrm{Var}(\tilde{y}_G) = \mathrm{Var}(\tilde{s}_G) + \mathrm{Var}(\Delta\tilde{i}_G) + 2\mathrm{Cov}(\tilde{s}_G, \Delta\tilde{i}_G) \ .$$

Some of the information in the table is similar to that reported in Kahn, McConnell, and Perez-Quiros (2002). However, by including information they did not report or emphasize, the table offers a more complete understanding of the total change in GDP volatility. The first two columns report the variance or covariance in the early and late periods, and the third column reports their ratio (late/early). Ratios less than one indicate a decline in volatility. The last two columns report the percent shares of the changes in total GDP variance, $\Delta\mathrm{Var}(\tilde{y})$, accounted for by changes in each component of the decomposition, and the percent shares of the changes in the goods sector output variance, respectively. For example, the goods variance term 63.8 percent, is $100 \times [\Delta\mathrm{Var}(\tilde{y}_G) / \Delta\mathrm{Var}(\tilde{y})]$, and likewise for all other terms.

2.2 Decomposition Results

The results in Table 1 reveal that the 64 percent of the reduction in output volatility did indeed occur in the goods sector, and that much of this reduction involved changes in inventory investment behavior. However, the table also reveals clearly that the change in overall GDP volatility cannot be attributed simply to the goods sector or to inventory investment alone. Instead, the volatility reduction is more widespread and complex.[7]

Output volatility declined significantly in the goods and structures sectors but not in the services sector. Output variance fell by a factor of four (output standard deviation fell by a factor of two) in both the goods and structures sectors, as measured by the variance ratios. Because the

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[6] The variance of the growth contribution of final sales in the goods sector, not shown in Figure 2, is also lower after the early 1980s, as is apparent from Table 1 below.

structures sector does not hold officially measured inventories, a simple inventory management story cannot explain the volatility reduction in structures. However, because the construction sector does hold some stocks, and because the structures sector uses goods supplied by wholesalers, retailers, and manufacturers, the structures sector is closely linked to the goods sector. Smoother production of structures should affect inventory and production behavior in the goods sector, and more reliable production or inventory management in industries that produce construction goods should influence the structures sector production behavior. For example, fewer shortages of construction materials (in the goods sector) should reduce the variance of structure sector output.

In contrast to these sectors, output variance in services was about the same in both periods (variance ratio about 1). This lack of a discernable reduction in services output volatility raises doubts about explanations of reduced GDP volatility that depend on a reduction in aggregate shocks, or "good luck." Aggregate shocks seemingly would affect all sectors of the economy, unless there were some complicated feedback mechanism at work that offsets the aggregate effects on services. However, the stability of services output growth leaves room for explanations that rely on differential effects among sectors, where services are affected less than other sectors.

Because output volatility declined only in the goods and structures sectors, which either hold inventories or may be linked to inventory behavior, it is natural to suspect that changes in inventory management may be connected to the volatility decline.[8] So, the answer to our earlier question of whether output volatility changed by the same amount in the inventory-holding and non-inventory holding sectors is "no."

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[7] Kim, Nelson, and Piger (2001) also found the reductions in volatility to be widespread and point out that the volatility of aggregate final sales declined similarly to the volatility of GDP.

The variance decomposition for the goods sector in Table 1 supports a role for inventory management changes in the reduction of GDP volatility. The variance of goods inventory investment declined by 60 percent, from the early period to the late period, and the covariance between inventory investment and sales declined, becoming much more negative in the latter period, as was observed first by Blanchard and Simon (1999). However, the variance of final goods sales also declined by more than half.

Interestingly, the covariance among the three aggregate sectors also declined considerably from the early period to the late period. Qualitatively, the most notable change was that services became uncoupled from the rest of the economy. Services sector output, which had been positively correlated with output in the goods and structures sectors during the early period, became uncorrelated with the other sectors in the later period. The change was particularly marked for the covariance between goods and services, which actually declined so much that it turned slightly negative in the later period. The covariance between goods output and structures output also became much smaller.

The last two columns of Table 1, which show how much each component contributed to the reduction in GDP volatility, reinforces the points observed earlier. Reductions in the variances of output in the three primary sectors account for 73 percent of the decline in GDP volatility, and declines in the covariance among the three sectors' output accounts for the remaining 27 percent. Among variance terms, note that the service sector – which accounts for more than 50 percent of nominal GDP – accounted for essentially none of the reduction in variance. Reduction in the variance of output in the structures sector – which accounts for nearly 10 percent of nominal GDP – accounted for more than 9 percent of the decline in GDP volatility, i.e., proportional to its size. Thus, the reduction in variance of the goods sector –

[8] Kahn, McConnell, and Perez-Quiros (2002) also make this point.

which accounts for a little more than one-third of nominal GDP – accounted for a disproportionately large 64 percent share of the reduction in GDP volatility.

Within the goods sector, changes in inventory behavior are responsible for most of the change in goods output volatility. Reductions in the variance of inventory investment and reductions in the covariance between inventory investment and sales of goods together account for 69 percent of the reduction in goods output variance and hence 44 percent of the reduction in GDP variance. However, the reduction in the variance of goods sales is substantial, accounting for the remaining 31 percent of the decline in goods output variance and thus nearly one-fifth of the decline in GDP volatility.[9] This fact appears to support the argument of Ramey and Vine (2001) at the aggregate level. However, we show later that the vast majority of this change in aggregate sales volatility is attributable to reduced covariance of sales among industries.

2.3 Some Implications of the Decomposition Results

The direct effects of changes in inventory behavior – i.e., reductions in the variance of goods inventory investment and in the covariance of goods sales and inventory investment – can account for about half of the decline in GDP volatility. The remaining half of the decline in GDP volatility occurred through reductions in the variance of the sales of the goods sector (19.6 percent) and of the structures sector (9.4 percent) and through reductions in covariance. These reductions may be explained by non-inventory related factors but it is also possible that changes in inventory behavior may have indirect effects that help account for this remaining half of the reduction in GDP volatility. Changes in inventory management techniques should theoretically affect the sales behavior of supplier firms. So some of the reduction of the variance of sales of the goods sector could be an indirect influence on the supply chain of the adoption of new inventory and production management techniques. The reduction in the covariance of goods and structures is estimated to account for 19 percent of the reduction in GDP volatility. This too may partially reflect the adoption of inventory and production control methods by goods suppliers who supply construction materials to the structures sector.

If a key factor behind changes in inventory behavior involves changing supply chain relationships between firms and industries, then inventory management changes in one firm or industry should affect the sales behavior of an upstream firm or industry. Furthermore, inventory innovations occurring through supply chain management likely would change the covariance between firms and industries. The importance of changes in covariance is reinforced when we look further inside the goods sector, which we turn to next.

3. Inventory Sector Decomposition

To investigate the cross-section evidence on the link between inventory behavior and output volatility, we examine the inventory and production behavior of industries within the goods, or inventory-holding, sector. This section reports the results of three basic calculations. First, we look at the industry-level distributions of changes in volatility to see whether volatility declined uniformly across industries or not. Second, we check to see whether changes in output volatility across industries were related to the size of industries. Finally, we decompose the variance of the goods sector to gain a better understanding of the potential role of industry-level covariance reductions.

3.1 Data and Methodological Issues

[9] Kahn, McConnell, and Perez-Quiros (2002) emphasize that the reduction in sales volatility is much smaller in durable goods industries where I/S ratios have declined more. Nevertheless, the fact remains that a substantial fraction of total GDP volatility reduction is coming through reductions in sales volatility.

In this part of the investigation, we used quarterly data from the Bureau of Economic Analysis for the manufacturing and trade (M&T) sector during the period 1967 through 2002:Q1. For this analysis, we divided the sector into 2-digit SIC manufacturing industries and 3-digit SIC retail and merchant wholesale trade industries. NIPA data are not available at this level of industry detail and frequency.

Three important differences arise between the NIPA and the M&T data. First, the M&T sector represents only a subset of the NIPA goods sector, which includes other sectors such as mining and agriculture. Second, the M&T sales data do not exclude input materials costs, and thus M&T output is gross production rather than value added. This means that there is double counting of sales (especially within manufacturing) when one firm's or industry's sales are another's inputs. If production is Cobb-Douglas with constant returns in all factors with separable input materials, the variance of gross production is

$$\mathrm{Var}(y) = \mathrm{Var}[(1-\alpha)v] + \mathrm{Var}(\alpha m) - 2\mathrm{Cov}[(1-\alpha)v, \alpha m] \ ,$$

where v denotes value added, m denotes input materials usage, and α denotes materials' share. Thus, the variance of gross production can be larger or smaller than the variance of value added, depending on the magnitudes of the variance of materials usage and its covariance with value added (which presumably is positive).[10] We recognize the importance of using value added, as emphasized by Humphreys, Maccini, and Schuh (2001), but the use of gross production is common in inventory studies, and high-frequency data on value added for detailed industries are unavailable. In calculating production, we used total inventory stocks, as in the NIPA.

A third empirical difference between the NIPA and the M&T data is that M&T output data are not published, but rather must be constructed from sales and inventory investment data.

[10] We thank Susanto Basu for reminding us of this point.

Furthermore, growth contributions are not published for the chain-weighted M&T data. Consequently, we derive industry (subscript j) output growth rates from sales growth rates and inventory investment growth rates using lagged nominal weights:

$$y_{jt} = \theta^{s}_{j,t-1} s_{jt} + \theta^{i}_{j,t-1} \Delta i_{jt} \ ,$$

where $s_{jt} = (\Delta S_{jt} / S_{j,t-1})$ is the growth rate of real sales, $\Delta i_{jt} = (\Delta^2 I_{jt} / \Delta I_{j,t-1})$ is the growth rate of real inventory investment, and $\theta^{s}_{j,t-1} = (\hat{S}_{j,t-1} / \hat{Y}_{j,t-1})$ and $\theta^{i}_{j,t-1} = (\Delta \hat{I}_{j,t-1} / \hat{Y}_{j,t-1})$ are lagged *nominal* (denoted by ^) output shares that sum to 1. Nominal output shares must be used because real shares cannot be constructed with chain-weighted real data in levels (see Whelan 2000 for details).

To obtain an approximately correct variance decomposition, we must also construct aggregate M&T output growth using an approximation to the chain aggregate rather than using the actual growth rate of the chain aggregate. We use the Tornqvist formula recommended by Whelan (2000, equation 2, page 10),

$$y_t = \sum_{j=1}^{J} \theta^{y}_{jt} y_{jt} \ ,$$

where $\theta^{y}_{jt} = (1/2)\sum_{\tau=0}^{1} (\hat{Y}_{j,t-\tau} / \hat{Y}_{t-\tau})$ are industry nominal output shares. Henceforth, we use the weighted growth rates as described above but suppress the weights in all notation. Note that the derived industry output growth rates and the Tornqvist aggregate growth rate both involve approximation error.[11]

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[11] Thus, the aggregate M&T output growth rate is not exactly the same as the output growth rate that would be calculated from an output measure obtained by adding the reported level of sales to the reported change in inventory investment.

To gauge the magnitude and nature of the difference between the reported NIPA goods sector output growth rate and the M&T gross output growth rate (with output calculated by the Tornqvist formula), see Figure 3. The two most obvious and important conclusions to draw from the figure are that the output growth rate measures are positively correlated (about 0.7) and that both exhibit a notable reduction in variance beginning around 1984. Overall, M&T gross production varies less than NIPA value added output, most likely because the M&T sector excludes relatively high-variance sectors (e.g., agriculture) but possibly for reasons related to materials usage, as explained above. However, the relative variance of output in the late and early periods is virtually the same between the two measures (see Table 2).

3.2 Industry-Level Volatility Change

The first question we ask is whether all industries in the goods sector experienced similar reductions in output and inventory investment volatility. For each M&T industry, we calculated volatility ratios for y_{jt}, s_{jt}, and Δi_{jt}. Figure 4 plots the unweighted frequency distributions of these ratios; the right-hand tail includes all ratios greater than 3. Although the growth of inventory investment, Δi_{jt}, is the relevant component of the growth of output, y_{jt}, it is much more volatile than the other growth rates and somewhat unfamiliar. Consequently, we also show the distribution of volatility ratios for scaled absolute inventory investment, $\left|\Delta I_{jt}\right| / S_{j,t-1}$, a measure used commonly in the recent literature.

Nearly all industries in M&T experienced dramatic reductions in output volatility, as can be seen from the upper left panel of Figure 4. The vast majority of industries experienced output variance reductions of more than one-half, and many experienced reductions of more than one-fourth. Most industries also experienced sizable reductions in sales volatility (upper right panel), but the median reduction in volatility was clearly smaller for sales than for production.

Interestingly, a small but nontrivial portion of industries actually saw their sales variance increase by as much as 50 percent. The substantial difference between volatility reductions in production and volatility reductions in sales implies that inventory investment volatility changes must have been quite heterogeneous.

Indeed, not all industries experienced reductions in the volatility of inventory investment growth (lower left panel). In fact, about half of all industries experienced reductions in the variance of the rate of growth of inventory investment, Δi_{jt}, but the other half saw increases in the variance – some industries' late period variance was more than three times larger than the early period variance. Scaled absolute inventory investment, $|\Delta I_t| / S_{t-1}$, did become less volatile for most industries (lower right panel). But the growth of inventory investment, Δi_{jt}, exhibited more heterogeneous changes in volatility, actually becoming more volatile – ratios greater than 1 – for a substantial fraction of industries.

Although virtually all industries experienced reductions in output volatility, the extensive heterogeneity in the volatility of sales and inventory investment growth should provide sufficient scope for cross-section identification of the effects of inventory behavior on output volatility. First, however, we examine the importance of heterogeneity in industry size and the covariance among industries in the determination of aggregate output volatility.

3.3 Industry Size and Volatility Change

Hypothetically, the reduction in output variance in the goods sector could have resulted from compositional shifts among industries within the sector. Industries with relatively low variance in the early period may have increased in size relative to industries with relatively high variance, leading to a reduction in aggregate volatility but without much change in industry volatility. The results portrayed in Figure 4, which show virtually all industries declining in volatility, seem to rule out compositional shifts as the primary explanation. More detailed examination of the data also has not revealed evidence of a significant secondary effect of compositional change.

However, one systematic compositional effect does stand out, as illustrated by Figure 5. Larger industries, measured in terms of nominal output shares, tended to experience larger relative declines in their production volatility. This tendency, indicated by the regression line in the figure, is significant but fairly modest, at least in linear terms.[12] An increase of 1 percentage point in aggregate share is associated with a decrease of 0.04 in the volatility ratio.

3.4 Inventory Sector Decomposition

In the decomposition of GDP variance done in Section 2, we found that reductions in goods output volatility accounted for nearly two-thirds of the change in GDP volatility. Here we report the results of an analogous decomposition of M&T aggregate output variance. This M&T variance decomposition provides a complete accounting of the changes in aggregate variances of y_t, s_t, and Δi_t in terms of the changes in industry variances of y_{jt}, s_{jt}, and Δi_{jt}, as well as all covariance terms among industries and variables.

Table 2 reports the decomposition of change in the variance of M&T output growth. The first three rows pertain to the components of the cross-section output variance decomposition,

$$\mathrm{Var}(y) = \sum_{j=1}^{\mathrm{J}} \mathrm{Var}(y_j) + 2\sum_{\mathrm{j}\neq\mathrm{k}} \mathrm{Cov}(y_j, y_k) \ .$$

The remaining rows pertain to the cross-section decomposition of the sales and inventory investment components of output growth,

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[12] The data points in Figure 5 (and subsequent similar figures) are industries' SIC number. A glance at Figure 5 suggests the true relationship may be nonlinear, but we have not explored this possibility.

$$\mathrm{Var}(y) = \sum_{j=1}^{J}\left[\mathrm{Var}(s_j) + \mathrm{Var}(\Delta i_j)\right] + 2\sum_{j \neq k}\left[\mathrm{Cov}(s_j, s_k) + 2\mathrm{Cov}(s_j, \Delta i_k) + \mathrm{Cov}(\Delta i_j, \Delta i_k)\right] .$$

The table includes the variance and covariance terms in the early and late periods (first two columns), their ratio (third column), and the share of aggregate (M&T) output variance change (fourth column). The last column reports the shares of industry variance and covariance terms within each aggregate variable type.[13]

In general, volatility in the M&T sector declined similarly to the volatility decline of the overall NIPA goods sector, as can be seen by comparing the first three columns of Table 2 with the same columns in Table 1. The output volatility ratio is nearly identical: 0.24 in M&T versus 0.26 in the NIPA goods sector. However, the volatility of M&T sales and inventory investment declined more than in the goods sector, falling about 80 percent compared with 60 percent or less. In contrast, the covariance between sales and inventory investment did not decline as much in M&T as it did in the NIPA goods sector.[14]

The shares of aggregate M&T volatility change accounted for by the aggregate components of output are also broadly similar to those in the goods sector, as can be seen by comparing the last two columns of Tables 1 and 2. Reductions in the volatility of sales and inventory investment accounted for 42 percent and 51 percent, respectively, of the decline in M&T output volatility, compared with 31 percent and 49 percent, respectively, for the goods sector. The relatively larger contribution of M&T sales volatility change is offset by a relatively

[13] Note that the approximation errors from using nominal weights and the Tornqvist formula prevent the variance decomposition from adding up exactly. The cumulative approximation error typically is less than 3 percentage points for any particular category.

[14] Note that the first three columns of Table 2 are based on published chain weighted data on M&T sales and inventory investment with M&T production simply the sum these. The last two columns of Table 2 use M&T production growth rate series calculated by the Tornqvist formula discussed in section 3.1.

smaller contribution of the sales-inventory investment covariance change (7 percent versus 20 percent).

Thus far, the aggregate M&T results generally affirm the conclusions drawn from the NIPA goods sector, suggesting that the difference between gross production and value added may not be important for understanding the change in output volatility. The reduction in volatility of inventory investment accounts for about half of the decline in output volatility. The reduction in the volatility of sales is also quite important, and a reduction in the covariance between sales and inventory-investment is nontrivial. Together, the direct effects of changes in inventory behavior account for more than half of the decline in M&T output volatility.

However, the industry-level decomposition of M&T output volatility brings to light an important and intriguing role for changes in the covariance structure among industries in explaining the reduction of GDP volatility. In particular, note that the cumulative covariance among industry output growth rates accounts for 28 percent of the reduction in M&T output volatility. Because the reduction in goods sector output volatility accounted for about 64 percent of the decline in GDP volatility, this result suggests that this reduction in covariance among industry output growth accounts for nearly one-fifth (about 18 percent) of the decline in GDP volatility. Put differently, a significant portion of the explanation for lower GDP volatility lies in an uncoupling of the well-known cyclical co-movement of output of industries in the economy.

The importance and richness of the change in covariance structure is even more apparent when we look at the decomposition of M&T output into its sales and inventory investment components. As we saw earlier in Figure 4, the majority of industries experienced significant declines in the volatility of their sales growth. Despite this, the decomposition in Table 2 indicates that for aggregate M&T sales, the vast bulk of the reduction in sales volatility (87.6

percent) occurred through reductions in covariance among industry sales rather than through reductions in the variance of each industry's sales. This result indicates that although individual industries may have experienced significant reductions in sales volatility, this reduced volatility alone does not account for much of the aggregate change in GDP volatility.

In stark contrast, for M&T inventory investment growth, the reduction in aggregate inventory investment volatility was more than accounted for (126 percent) by reductions in the variances at the industry level. In fact, the total covariance between industries' inventory investment growth actually increased – that is, became either more positive or less negative. This increase in covariance increased aggregate M&T output volatility, and thus contributed negatively (-23 percent) to the actual decline in M&T output volatility.

Changes in inventory behavior explain about half of the reduction in output volatility directly through reductions in inventory investment volatility. It is likely that improved inventory management techniques are responsible for this change. However, Table 2 suggests that changes in the covariance structure among industries that hold inventories play a roughly equal role in explaining reduced output volatility. We suspect that changes in the industry covariance structure point toward a more sophisticated indirect channel through which inventory behavior has influenced output volatility.

Specifically, the reduced co-movement of industry sales and increased co-movement of inventory investment among industries seem to suggest that changes in so-called supply chain relationships among M&T industries may have altered the covariance structure. Development and management of supply chains has played a pivotal role in the implementation of inventory management techniques such as just-in-time production. Supply chains have also been affected by the evolution of information technology, which has increased real time sharing of information on final demand between supplier and customer, increased outsourcing by manufacturing firms, and encouraged the adoption of flexible manufacturing techniques.

4. Covariance among Industries: A Deeper Look

The variance decomposition in the previous section shows that reduced covariance among industries is an important factor in the decline in aggregate production variance since the mid-1980s. In this section, we begin to explore how the covariance structure has changed by focusing first on changes in the covariance of sales growth among M&T industries.[15] Our preliminary investigation tackles three basic questions. First, was the decline in covariance spread evenly among industries or did some industries exhibit disproportionately large changes in covariance? Second, what is the relationship between the change in variance and covariance at the industry level? In particular, can we rule out a simple explanation where industries exhibit some fixed covariance that declines simply because a common (aggregate) variance declined? Finally, is there any direct evidence that changes in covariance are related to the existence of supply chains among industries?

Overall, we find that covariance reductions generally were widespread across industries and not closely linked to variance reductions. Therefore, it seems unlikely that simple explanations of a reduction in aggregate variance can explain the decline in output volatility. However, we also find evidence that covariance reductions are linked to distribution chains – the relationships between manufacturing, wholesale trade, and retail trade – as well as input-output relationships within manufacturing.

4.1 Industry-Level Changes in Covariance

Most industries experienced large reductions in the covariance of their sales with the sales of other industries, as can be seen from Figures 6a and 6b.[16] Like Figure 4, these figures plot distributions of unweighted volatility ratios for the covariance of output, sales, and inventory growth plus scaled inventory investment across industries (e.g., $\mathrm{Cov}(y_i, y_j)\ \forall\ i \neq j$). The difference here is that the volatility ratio is the change in covariance relative to industry variance, e.g., $\left[\Delta\mathrm{Cov}(y_i, y_j)/\mathrm{Var}(y_i^E)\right]$, where E denotes the early (pre) period and Δ indicates the change from the early to late (post) period. We scale by industry variance to avoid confusions arising from sign changes in the numerator versus denominator. A negative covariance volatility ratio thus indicates an unambiguous decline in covariance. Figure 6a plots all pairs of changes in covariance; Figure 6b plots the sum across all other industries of covariance terms, thus showing the total change in covariance with all other industries (almost 50 covariances).

Most sales (and output) covariances declined after 1983, and the declines were significant. Figure 6a shows that nearly 9 in 10 covariances declined, and the mean reduction in covariance between two industries amounted to about 20 percent of industry variance. Figure 6b shows that virtually every industry experienced a decline in the total covariance with all other industries. These declines were about seven times industry variance, on average, and most amounted to more than double the industry variance. These results portray a broad-based uncoupling of industries – the long-standing business cycle fact of comovement among industries weakened significantly in the later period. In contrast to output and sales, changes in

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[15] Change in the covariance structure of inventory investment growth among industries is an important and related piece of the puzzle and merits further examination too, which we plan to do later.

[16] We have done the same calculations for correlation, rather than covariance, and the results are qualitatively similar – the correlations decline for virtually all industries. Because the focus of this paper is to account for the total change in aggregate variance, we focus on covariances.

the covariances among industry inventory investment were much smaller in absolute value and more evenly distributed around zero. This result indicates that some industries became more synchronized in terms of inventory investment.

4.2 Industry Size and Changes in Covariance

Although virtually every pair and industry-level covariance declined, it is possible that certain very large or highly volatile industries accounted for most of the decline in aggregate covariance. Figure 10 provides evidence on the importance of industry size by plotting the shares of aggregate M&T nominal sales (size) in the early period against the contributions to the decline in aggregate covariance from the early to late period. Most industries tend lie along the solid 45-degree line, indicating that they contributed to the decline in aggregate covariance roughly in proportion to their size.

However, two groups of larger industries (3 percent or greater sales share) stand out as notable exceptions in Figure 7. One group – the auto industry (SIC industries 371, 551) along with some of its main suppliers (SIC 33, 34, and 30) plus the chemical industry (SIC 28) – accounted for disproportionately *large* shares of the decline in aggregate covariance (i.e., above the line). The other group – the food industry (SIC 20, 514, and 54) plus a residual of retail industries – accounted for a disproportionately *small* share of the decline in aggregate covariance (i.e., below the line).

The result in Figure 7 suggests a potentially important role for supply and distribution chains in explaining the covariance results. The relatively large contribution of auto manufacturers and their major suppliers reinforces the need to look at supply chains of input materials as a way of understanding the reductions in covariance across M&T industries.

Similarly, the relatively large contribution of motor vehicle dealers suggests looking at distribution chains.

4.3 Relationship between Changes in Variance and Covariance

Before looking at supply and distribution chains, we want to investigate whether the reductions in covariance might have occurred simply because aggregate variance declined for some reason. This result could emerge from an aggregate model that assumes a constant correlation between industry and aggregate activity and abstracts from economic explanations for correlation among industries such as supply or distribution chains (or assumes a fixed correlation among industries). This conjecture would predict a close link between reductions in variance and covariance across all industries.

To check this conjecture, we constructed the scatter plot of variance and covariance volatility ratios in Figure 8. Here covariance is measured by the sum of each industry's sales covariance across all other industries, and the volatility ratio is measured analogously to the variance volatility ratio (late period, or post-1983, relative to early period, or pre-1984) to be able to construct a 45-degree line.

Figure 8 provides strong evidence against the conjecture that the decline in covariance is simply a byproduct of the decline in (aggregate) variance. Sales covariance declined by at least 60 percent in essentially every industry (two outliers are omitted), and for most industries the decline in covariance was much greater in proportion than the decline in variance (i.e., the observations lie well below the 45-degree line). Perhaps more convincingly, covariance declined significantly even in the nine industries where sales variance actually increased. Together these facts reveal little relationship between the declines in sale variance and covariance for an industry.[17] Thus the decline in sales covariance among industries, this uncoupling of industry sales growth rates, is not easily explained or understood by simple reductions in aggregate variance.

4.4 Evidence from Distribution Chains

In this section, we look for direct evidence of systematic reductions in covariance among industries that are likely to be linked by distribution chain and supply chain relationships. For distribution chains, we selected 11 manufacturing industries for which we can identify counterpart industries in the wholesale (W) and retail (R) trade sectors. Table 3 lists the industries in these distribution chains, five of which span all three sectors.

Because manufacturers tend to sell their products to wholesalers, and wholesalers tend to sell these same products to retailers, these distribution chains are linked by a common final demand for their product.[18] Thus, these chains allow us to isolate one type of aggregate influence – product demand shocks – that may be exerted across distribution chains. Of course, these distribution chain industries also may share a common supply factor if they have become linked by production and/or inventory management techniques. Changes in supply factors also may have reduced these industries' variances and covariances. Theoretically, a firm that can reduce the covariance of its sales with its customer's sales should able to smooth its sales fluctuation, i.e., reduce the variance of its sales.

Intuitively, then, we expect to see a closer link between variance reductions and covariance reductions among these distribution chain industries than among all industries in

[17] There is actually a very mild positive correlation of about 0.1 but it is far from a one-for-one relationship.
[18] Note that the distribution chains are not exact relationships. Manufacturers may be able to bypass wholesalers and sell directly to retailers (or even consumers) in some chains, and wholesalers may be able to bypass domestic manufacturers by importing goods. In addition, the grouping of more detailed 4-digit SIC industries within the 2-digit and 3-digit industries of each sector can be different and reduce the distribution linkage. Ultimately, the relationships really form among firms within these industries.

general. Figure 9, which is similar to Figure 8 except that it isolates only the covariances among the distribution chain industries (and flips the axes), confirms this intuition. The figure reveals a much tighter positive relationship between the relative decline in variance of a manufacturing industry's sales and the relative decline in the covariance of its sales with the sales of an associated wholesale or retail distributor.[19] Thus, within distribution chains there does seem to be a connection between variance and covariance reductions, at least for sales.

The exact cause of the joint decline in variance and covariance of sales among distribution chain industries remains to be investigated. An important part of the explanation probably lies in the covariance structure of inventory investment among these industries. We plan to examine this potential link, as well as the adoption of new information technology and inventory or production control systems, in future research.

4.5 Evidence from the Automobile Industry

In addition to restructuring distribution relationships with wholesalers and retailers, some manufacturers have restructured their supply chains with other manufacturers (and some wholesalers) by outsourcing production and adopting inventory and production control systems such as "just-in-time." Presumably the reduction in covariance between the sales of different manufacturing industries is at least partially a result of these restructured supply chains. The most prominent of these manufacturers is the automobile industry and its supply chain, which still accounts for a substantial portion of overall goods production.

To get a first look at the effects of the well-known restructuring in the auto industry, we used the 1992 Input-Output table direct requirements matrix to classify other 2-digit SIC manufacturing industries as either major suppliers, minor suppliers, or non-suppliers. Figure 10

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[19] With the axes reversed, as in Figure 11, it is very clear that these industries lie along a line virtually parallel to the 45-degree line (slope coefficient of .98 and highly significant).

plots the volatility ratio (post-1983 over pre-1984) for the sales covariance of auto manufacturers (SIC 371) with each of its manufacturing supplier industries grouped by the three supplier categories. The figure also includes the covariance volatility ratio for auto wholesale (SIC 501) and retail (SIC551) distributors, as well as other non-auto wholesalers and retailers. The left most bar gives the auto manufacturing variance volatility ratio as a basis for comparing the covariance ratios.

Figure reveals two important facts. First, it is immediately clear that auto manufacturers' sales covariance declined significantly and essentially across the board, except for a couple of unrelated industries (food and tobacco). Most covariances fell by more than half, especially those with suppliers and distributors, which often fell by 70 percent or more. The strong, positive covariance (and correlation) among the industries comprising the auto industry, broadly defined, that existed prior to 1984 once elicited the slogan, "What's good for GM is good for America." Since 1984, however, that covariance has diminished tremendously. Perhaps most surprisingly, auto manufacturers sales covariance with non-auto wholesale and retail trade industries declined almost as much the variance of auto manufacturers' sales. This result suggests that the covariance decline phenomenon is broader than simply an auto industry story.

Although reductions in covariance with the auto industry sales were widespread across industries, the cross sectional pattern of reductions clearly is correlated with auto manufacturers' supply and distribution chains. Consider first the covariance with auto distributors (wholesale and retail) – these covariances fell the most by far, so much that sales by auto manufacturers essentially have become completely uncoupled from their distributors' sales. On the supply chain side, sales covariance with auto manufacturers' major input suppliers declined the most – 70 percent or more in each case, about the same as the auto manufacturers' decline in variance.

Sales covariance with auto manufacturers' minor suppliers declined the next most, not far behind the decline with major suppliers. Overall, the covariance with sales of non-supplier manufacturers fell much less, although a few industries in this group experienced relatively large declines as well.

Most interesting in the non-supplier group is industry 37X, which represents the non-auto portion of the transportation industry. Its covariance with auto manufacturers only declined by about 20 percent. This industry grouping does contain some unusual industries, such as military vehicles, which may have been influenced greatly by idiosyncratic factors. Nevertheless, the striking difference between the 37X ratio and other ratios connected to auto manufacturers suggests that the covariance reductions probably resulted from developments specific to the auto industry and not from an aggregate factor that could explain reductions in transportation covariance more generally.

The variance of auto industry sales declined, as did the covariance of its sales with the sales of suppliers and distributors. Which reduction came first – the variance or covariance – we cannot say. The precise mechanisms by which changes in supply chains reduced the covariances between an industry and its suppliers needs to be modeled further. Among other things, we suspect that it has to do with changes in inventory and production management systems.

5 Industry Changes in Inventory Management and Output Volatility

To fully understand the role of supply and distribution chains in inventory management and production techniques, it is necessary to examine the behavior of sales and inventory investment at the detailed industry level. In this section, we look briefly at the connection between output volatility and inventory management at the industry level. Following Kahn, McConnell, and Perez-Quiros (2002), we interpret reductions in I/S ratios as evidence of improved inventory management. To quantify the magnitude of inventory management changes, we calculate the average I/S ratio of each industry in the early and late periods and take their ratio (late average I/S to early average I/S). Thus, a reduction in the average I/S ratio (ratio less than 1) is assumed to indicate improved inventory management. To better isolate the impact of inventory management change, we disaggregate inventories into their three stages of fabrication: raw materials and supplies, work-in-process, and finished goods.

The cross-section data provide evidence of a significant positive relationship between improved inventory management and the volatility of output and inventory investment, as shown in Figures 11 through 13. The literature argues that firms implementing inventory control techniques should experience reduced variance of output and inventory investment. If the I/S ratio change measure is an accurate proxy for the degree to which inventory control techniques or supply chain changes have reduced an industry's stocks, then the figures support this hypothesis. The regression lines indicate that volatility of output and inventory investment (both the growth rate and scaled absolute investment) tends to decline as the average I/S ratio declines. In other words, industries that improved their inventory management techniques more (i.e., reduced their I/S ratios more) experienced greater reductions in volatility.

An important feature of the result shown in Figure 11 is that the relationship between inventory management and output volatility is by far the strongest for raw materials inventories and weakest for finished goods inventories. This result suggests that theories purporting to explain the role of inventory management in output volatility should emphasize input inventories – raw materials and work-in-process stocks – and their effects on production behavior. Because only the usage of input inventories factors directly into production, the impact of improved management of input inventories on production volatility may be more complex. Attention to supply chains via stage-of-fabrication linkages between firms and industries engaged in input-output relationships may be warranted as well.

The evidence from these simple cross-section regressions is suggestive but incomplete. Much more analysis along these lines is required to provide more convincing and complete evidence. We plan to extend this approach in future research.

6 Output Volatility and Monetary Policy

To investigate the relationship between output volatility and monetary policy, we estimate the correlation across industries between changes in volatility and the sensitivity to monetary policy (i.e., interest sensitivity). For each industry, we calculate interest sensitivity using relatively simple versions of standard VAR models as described in Christiano, Eichenbaum, and Evans (1999). Our cross-sectional hypothesis is that improvements in monetary policy should produce a disproportionately greater reduction in volatility in industries that are relatively more interest sensitive.

Two caveats are immediately obvious. First, it is challenging to identify an industry's interest sensitivity separately from its sensitivity to aggregate activity. Although some of the VAR models attempt to do so, the interest sensitivity measures may reflect sensitivity to aggregate activity to some extent. Second, the reduction in output variance is endogenous and the direction of causation may run from volatility to interest sensitivity rather than vice versa. Highly interest sensitive sectors may have greater profit incentive to insulate themselves from fluctuations caused by monetary policy actions. If so, those industries may respond to poor monetary policy by investing in improved inventory and production techniques, for example.[20]

To generate robust results for this exercise, we use a variety of VAR models to measure sensitivity to monetary policy. One reason VAR models have been widely criticized is that their dynamic characteristics can be quite dependent on model specification and identification. Consequently, we consider variation in model specification along three dimensions: 1) model size, measured by number of variables; 2) identification, by alternative ordering of monetary policy; and 3) nonstationarity and data transformation.

The VAR models are two sizes, small and large. The small VAR is a trivariate model of industry sales and inventories, plus the federal funds rate: $\left[S_i, I_i, r^f\right]$.[21] The large VAR includes the small industry VAR and adds measures of aggregate activity in the form of consumer prices, real GDP, commodity prices, and asset (stock) prices: $\left[P, Y, S_i, I_i, r^f, P^c, A\right]$. The small VAR avoids misspecification problems that may arise from simple identification schemes in the large VAR, but at the cost of omitting potentially important variables, especially aggregate activity. The baseline identification scheme is the ordering shown in the preceding vectors (funds rate last in the small VAR, fifth in the large VAR). An alternative identification ordering puts the funds rate first. These two alternatives probably are sufficient because the response of sales or output to a federal funds rate shock is relatively insensitive to ordering in these types of VAR models. All data are in logs, except the funds rate. The two data specifications are levels and differences (i.e., growth rates).

[20] Both caveats indicate the need for a fully specified structural model with disaggregated industries to provide conclusive hypothesis tests, a task we leave for future research

[21] This model is similar to the those used by Gertler and Gilchrist (199x) to study the differential impact of financial market conditions on small and large firms.

Using these VAR models, we obtain estimates of industry sensitivity using two measures. First is the standard deviation of the impulse response function (IRF) of sales, which depends on identification.[22] The focus is on sales, rather than production, to capture the interest sensitivity of demand. The second measure is the sum of lagged coefficients (Coeffs) on the federal funds rate in the sales equation, which does not depend on identification. Not surprisingly for VAR models, the sensitivity measures vary widely across model specification. The cross-sectional rank correlation of industry sensitivity is more consistent, but there is still significant variation in rank as well. Nevertheless, on average, the VAR models tend to identify the same groups of industries as highly interest sensitive and relatively interest insensitive.[23]

To quantify the link between volatility change and monetary policy sensitivity, we run regressions of the volatility ratio on the measure of monetary policy sensitivity. The volatility ratios are $\left[\mathrm{Var}(y^L)/\mathrm{Var}(y^E)\right]$ and $\left[\Delta\mathrm{Cov}(y_i, y_j)/\mathrm{Var}(y_i^E)\right]$, where L denotes late period, E denote early period, and Δ denotes the change from early to late. The interest sensitivity measure pertains to the early period to minimize potential problems associated with endogeneity. [24] If the reductions in volatility (variance or covariance) occurred disproportionately in industries with relatively high interest sensitivity, the coefficients should be significantly negative for the IRF (larger standard deviations with lower volatility ratios) and significantly positive for the Coeffs (smaller, or more negative, coefficient sums with lower volatility ratios).

Table 4 reports the results. First, and most importantly, changes in output volatility are not correlated with interest sensitivity across industries at all. No sensitivity measure from any

[22] We scale each industry's sales IRF standard deviation by the average sales standard deviation across industries to guard against excessively volatile IRFs due to model misspecification, and to provide better interpretability.

[23] The highly sensitive industries are: Autos (manufacturing and retail), steel, electrical machinery, stone-clay-glass, rubber, and lumber. The relatively insensitive industries are: food (manufacturing and retail), paper, printing and publishing, nondurable goods wholesalers, plus apparel and other miscellaneous retail stores.

model exhibits a conclusive correlation with reductions in volatility measured by either variance or covariance – the highest t-statistic is 1.70, and most are well below the 10 percent level of significance. The point estimates from the variance regressions are all of the correct sign and the small VAR models' IRF standard deviations come closest to providing evidence of more volatility decline in interest sensitive industries. However, once aggregate activity is included in the large VAR there is no doubt about the absence of significant correlation. The covariance regressions are even less significant and the coefficients are often signed incorrectly.[25]

Apparently, changes in industry volatility occurred without any connection to industries' sensitivity to monetary policy. Although this result does not rule out conclusively the better monetary policy hypothesis, it poses challenges in addition to the covariance results in the preceding section. In particular, monetary policy must have improved in such a way as to reduce the variances of all industries proportionately without influencing interest-sensitive sectors relatively more.

7 Conclusions

Developments in the inventory-holding goods sector of the economy probably help explain a significant portion of the reduction in GDP volatility after 1984. This explanation, however, must be broader than simply the implementation of inventory management techniques to account for all of the change in GDP volatility. The variance of sales in the goods sector, the

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[24] We also ran regressions on the sensitivity rank, rather than the sensitivity measure itself, and the results are qualitatively similar.

[25] The regression results are robust to using sensitivity measured over the full sample. We also regressed the volatility ratios on sensitivity ratios (late-period sensitivity relative to early period) to ascertain whether the reductions in volatility are related to changes in interest sensitivity. These regressions, which may be subject to endogeneity problems, did not reveal much significant correlation either.

covariance between sales and inventory investment, and the covariance structure among industries' output and sales also have changed significantly and reduced GDP volatility.

Factors unrelated to inventory behavior might be able to explain some of these other developments, but the altered covariance structure seems particularly challenging for the kinds of theories put forward thus far. For example, it is unclear how improved monetary policy would have reduced the co-movement among industries' sales and increased the co-movement among industries' inventory investment. Looking at changes in the supply chain structure of the goods sector seems a more promising avenue of exploration.

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Table 1
Decomposition of Volatility Change in Aggregate Output Growth

	Volatility		Volatility Ratio (Late/ Early)	Share of GDP Volatility Change (percent)	
	Early (1959-83)	Late (1984-2002)		Total	Sector
Real GDP	20.0	5.17	.26	100.2	
Variance Terms				73.3	
Goods	12.70	3.25	.26	63.8	100
Final Sales	5.48	2.58	.47	19.6	30.7
Inventory Investment	7.65	3.03	.40	31.2	48.9
Covariance (S,ΔI)	-.22	-1.18		13.0	20.4
Services	.52	.50	.97	0.1	
Structures	1.79	.40	.22	9.4	
Covariance Terms				26.9	
Goods, Services	.43	-.04		6.4	
Goods, Structures	1.89	.51	.27	18.7	
Services, Structures	.18	.05	.25	1.8	

Note: Shares of growth contributions do not add to 100 because of rounding.

Source: Haver Analytics, Inc., NIPA data.

Table 2
Cross-Section Decomposition of Volatility Change in Output Growth of the Manufacturing and Trade Sector

	Volatility		Volatility Ratio (Late/ Early)	Share of Aggregate Volatility Change (percent)	
	Early (67-83)	Late (84-02)		Total Output	s or Δi
$\Delta\text{Var}(y)$	5.64	1.35	.24	100.0	
$\sum_j \Delta\text{Var}(y_j)$				69.8	
$2\sum_{j\neq k} \Delta\text{Cov}(y_j, y_k)$				28.1	
$\Delta\text{Var}(s)$	3.78	.72	.19	42.0	
$\sum_j \Delta\text{Var}(s_j)$				5.9	14.0
$2\sum_{j\neq k} \Delta\text{Cov}(s_j, s_k)$				36.8	87.6
$\Delta\text{Var}(\Delta i)$	2.08	.46	.22	51.2	
$\sum_j \Delta\text{Var}(\Delta i_j)$				64.4	125.8
$2\sum_{j\neq k} \Delta\text{Cov}(\Delta i_j, \Delta i_k)$				-11.7	-22.9
$2\Delta\text{Cov}(s, \Delta i)$	.15	-.10		6.9	

Note: y, s, and Δi are growth rates of output, sales, and inventory investment, respectively, and subscripts *j* and *k* denote industries. Shares do not add to 100 because of errors in the chain weight approximation.

Source: Haver Analytics Inc., BEA NIPA data.

Table 3
Manufacturers and their Distributors

Industry Name	SIC Codes	
	Manufacturer, Wholesaler	Manufacturer, Retailer
Automobile	371, 501	371, 551
Lumber	24, 503	24, 521
Furniture	25, 502	25, 571
Food	20, 514	20, 54
Apparel	23, 513	23, 56
Paper & Allied Prod.	26, 511	
Chemical & Allied	28, 516	
Petroleum	29, 517	
Metal	33, 505	
Fabricated Metal	34, 505	
Machinery	35, 508	

NOTE: See Appendix Table A1 for detailed descriptions.

Table 4
Monetary Policy Sensitivity Regressions

VAR Model Specification				Volatility Ratio Regressions			
				Variance		Covariance	
Size	**Data**	**Order**	**Sensitivity**	**Estimate**	**T-stat**	**Estimate**	**T-stat**
Small	Levels	1st	IRF	-.08	-1.84	-.75	-.69
Small	Levels	Last	IRF	-.03	-1.12	.49	.63
Small	Diffs	1st	IRF	-.09	-2.34	.64	.53
Small	Diffs	Last	IRF	-.06	-1.76	.46	.44
Large	Levels	1st	IRF	-.08	-1.41	-1.69	-1.00
Large	Levels	5th	IRF	-.09	-1.38	-1.60	-.92
Large	Diffs	1st	IRF	-.07	-1.27	-.54	-.35
Large	Diffs	5th	IRF	-.06	-1.32	-.21	-.15
Small	Levels	1st	Coeff. sum	.01	.15	-.65	-.57
Small	Diffs	1st	Coeff. sum	.05	1.15	-.31	-.20
Large	Levels	1st	Coeff. sum	.06	1.28	-1.55	-.91
Large	Diffs	1st	Coeff. sum	.26	1.20	-1.64	-.30

NOTE: See text for details of model specifications.

Appendix Table A1
SIC Codes and Industry Descriptions

Sector	SIC	Industry Description
Manufacturing	20	Food & Kindred Products
	21	Tobacco Products
	22	Textile Mills Products
	23	Apparel & Related Products
	24	Lumber & Wood Products
	25	Furniture & Fixtures
	26	Paper & Allied Products
	27	Printing & Publishing
	28	Chemicals & Allied Products
	29	Petroleum Refining
	30	Rubber & Plastic Products
	31	Leather & Leather Products
	32	Stone, Clay & Glass Products
	33	Primary Metal Products
	34	Fabricated Metal Products
	35	Industrial Machinery, Computer Equipment
	36	Electric & Electronic Machinery
	37	Transportation Equipment
	38	Instruments
	39	Miscellaneous Manufacturing Products
Wholesale	50	Wholesale Durable Goods
	501	Motor Vehicles
	502	Furniture/Home-furnishings
	503	Lumber/Construction Materials
	504	Professional/Commercial Equipment
	505	Metals & Minerals excluding Petroleum
	506	Electrical Goods
	507	Hardware and Plumbing
	508	Machinery/Equipment/Supplies
	509	Other Durable Goods
	51	Wholesale Non-durable Goods
	511	Paper Products
	512	Drugs and Sundries
	513	Apparel and Piece Goods
	514	Groceries
	515	Farm Products
	516	Chemicals and Allied Products
	517	Petroleum Products
	518	Alcoholic Beverages
	519	Other Non-durable Goods

Continued next page

Appendix Table A1 (continued)

Retail	521	Lumber & Building Materials
	531	Department Stores
	539	Other General Merchandise Stores
	54	Food Stores
	55	Automotives
	551	Motor Vehicle Dealers
	553	Auto & Home Supply Stores
	56	Apparel Stores
	571	Furniture/Home-furnishings
	579	Other Durable Goods
	59	Miscellaneous Retail Establishments

Figure 1
Real U.S. GDP Growth

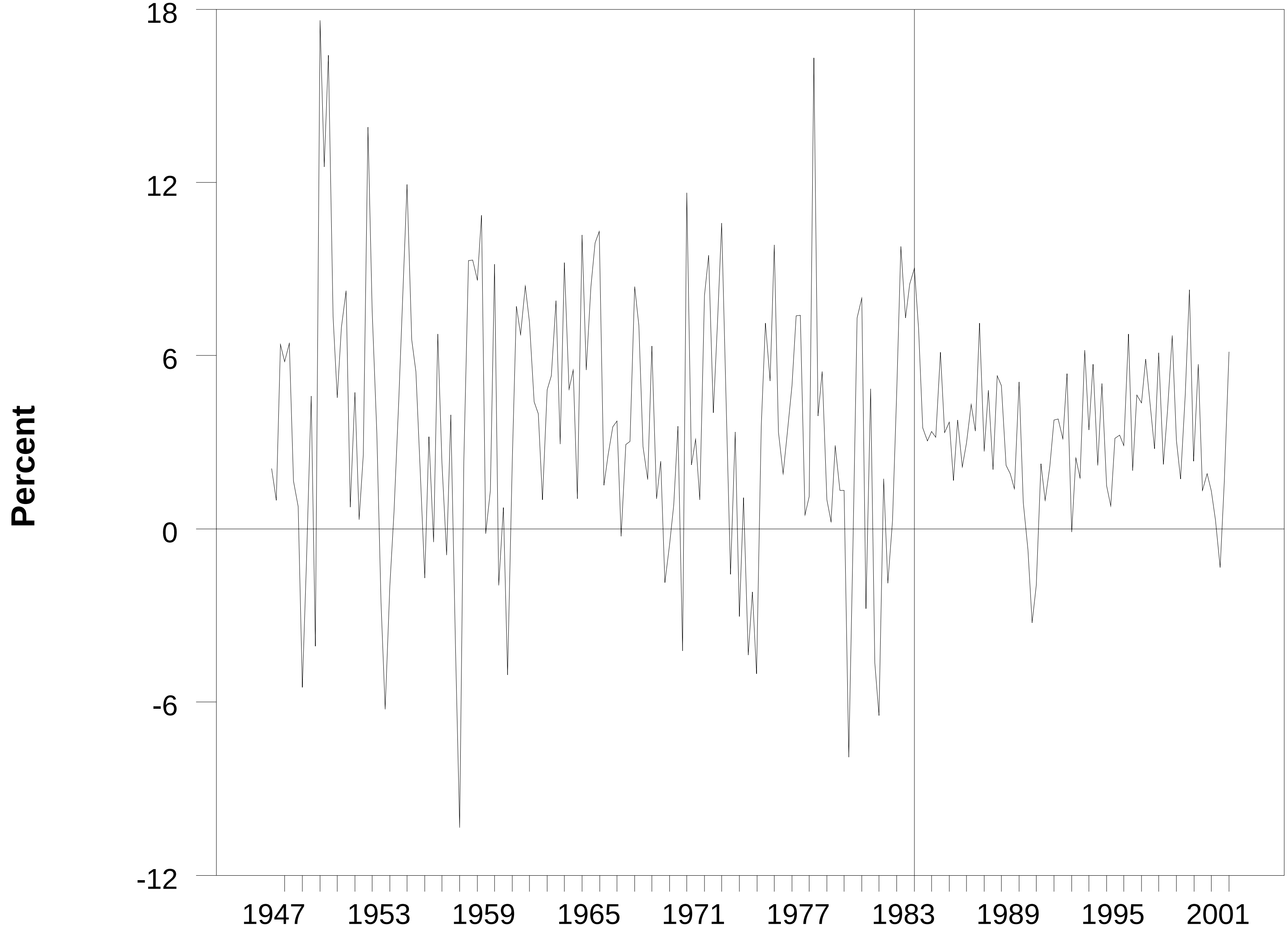


Figure 2
Contributions to Real GDP Growth

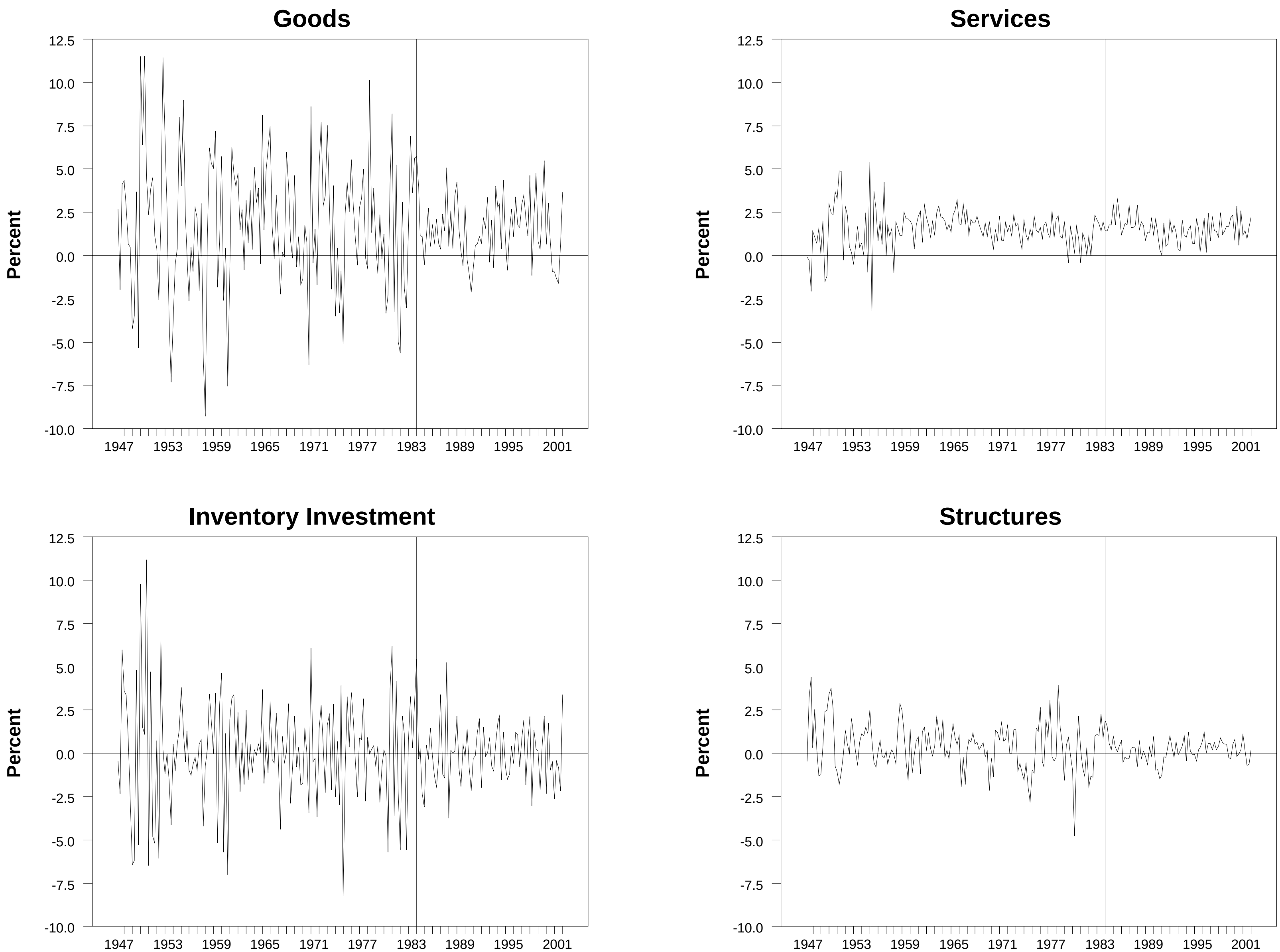


Figure 3
M&T Growth Rates in Gross Production and in NIPA Goods Value Added

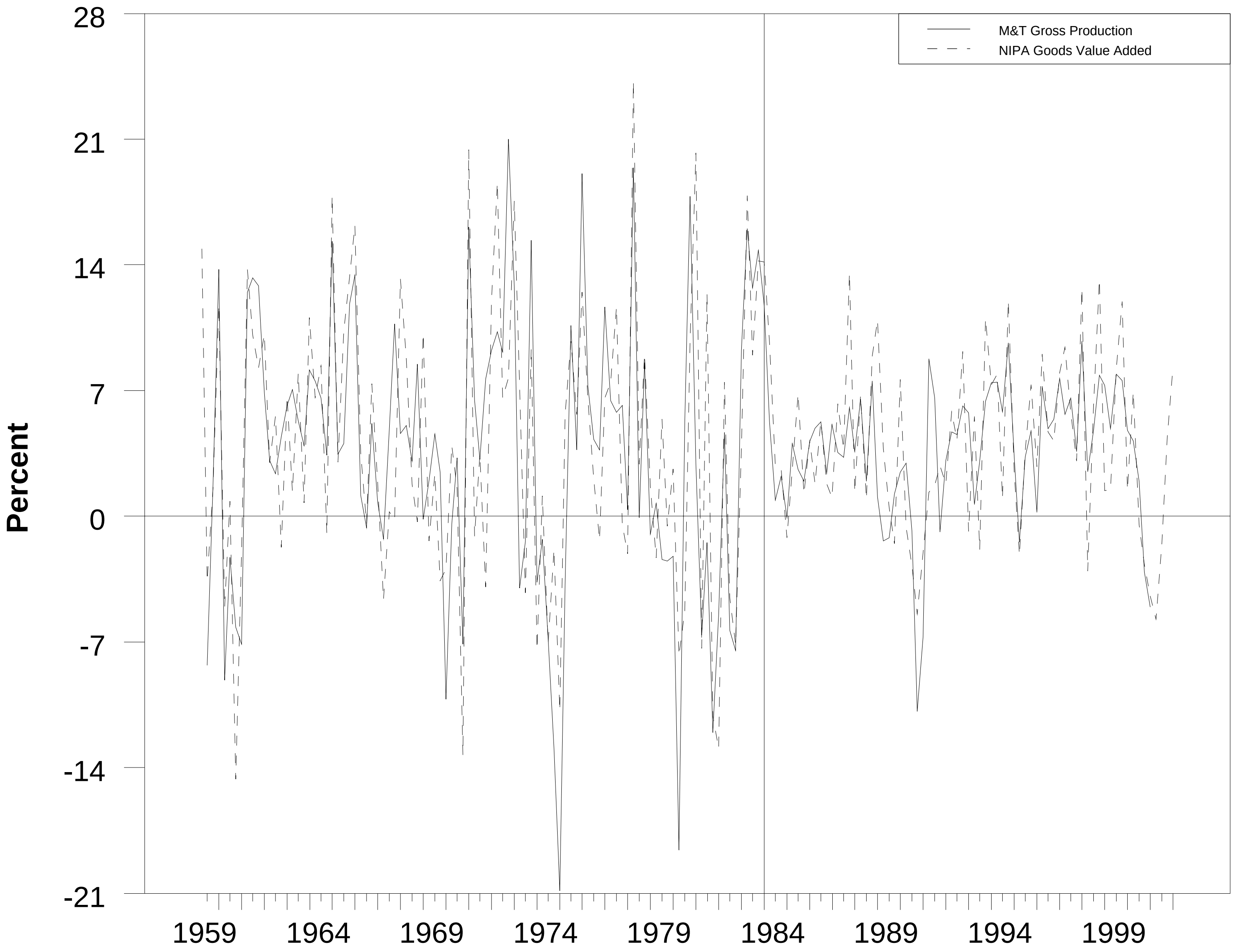


Figure 4: Frequency Distributions of Volatility Ratios

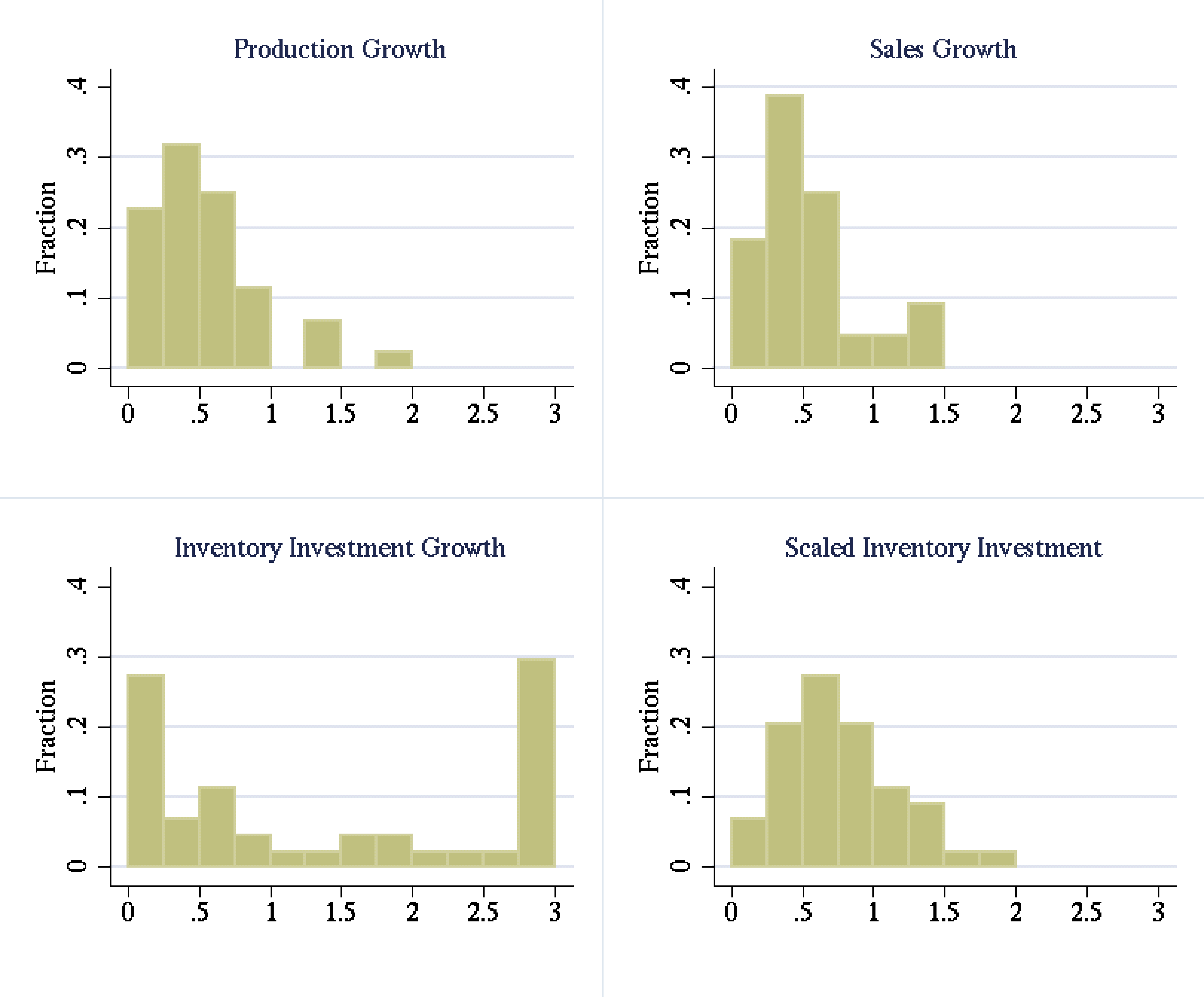


Figure 5
Industry Size and Change in Volatility of Production
Excluding SIC 504 & 509

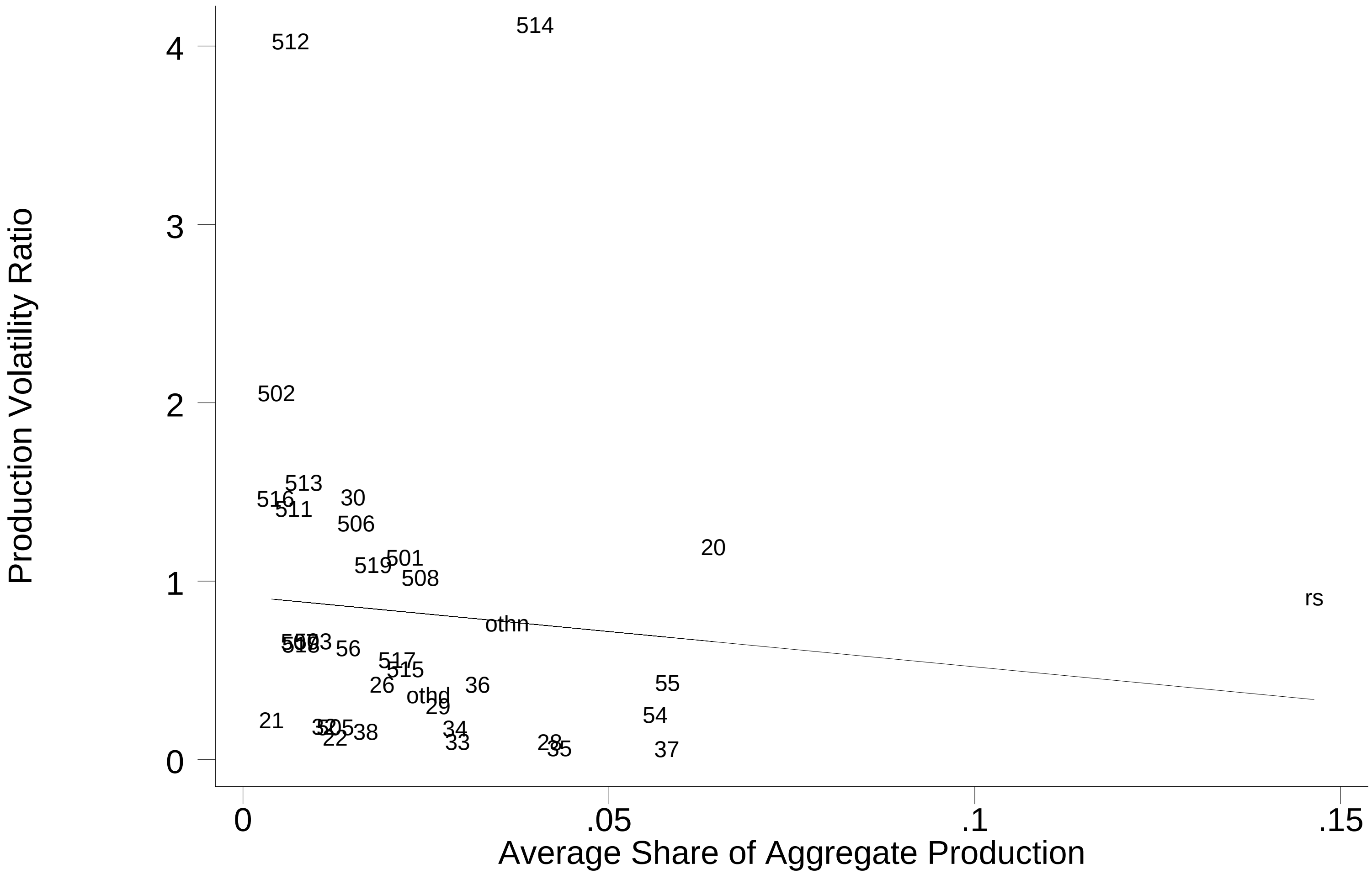
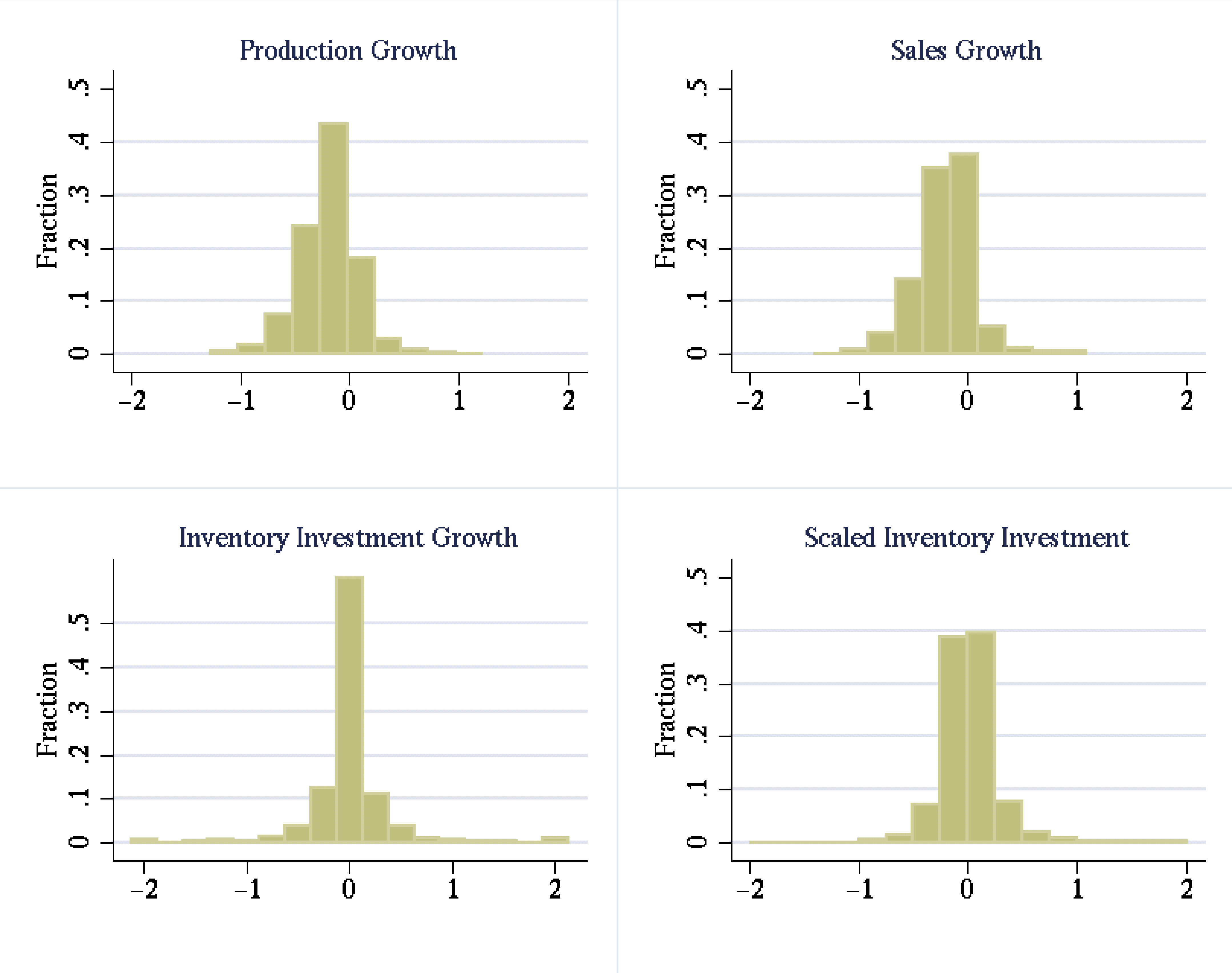
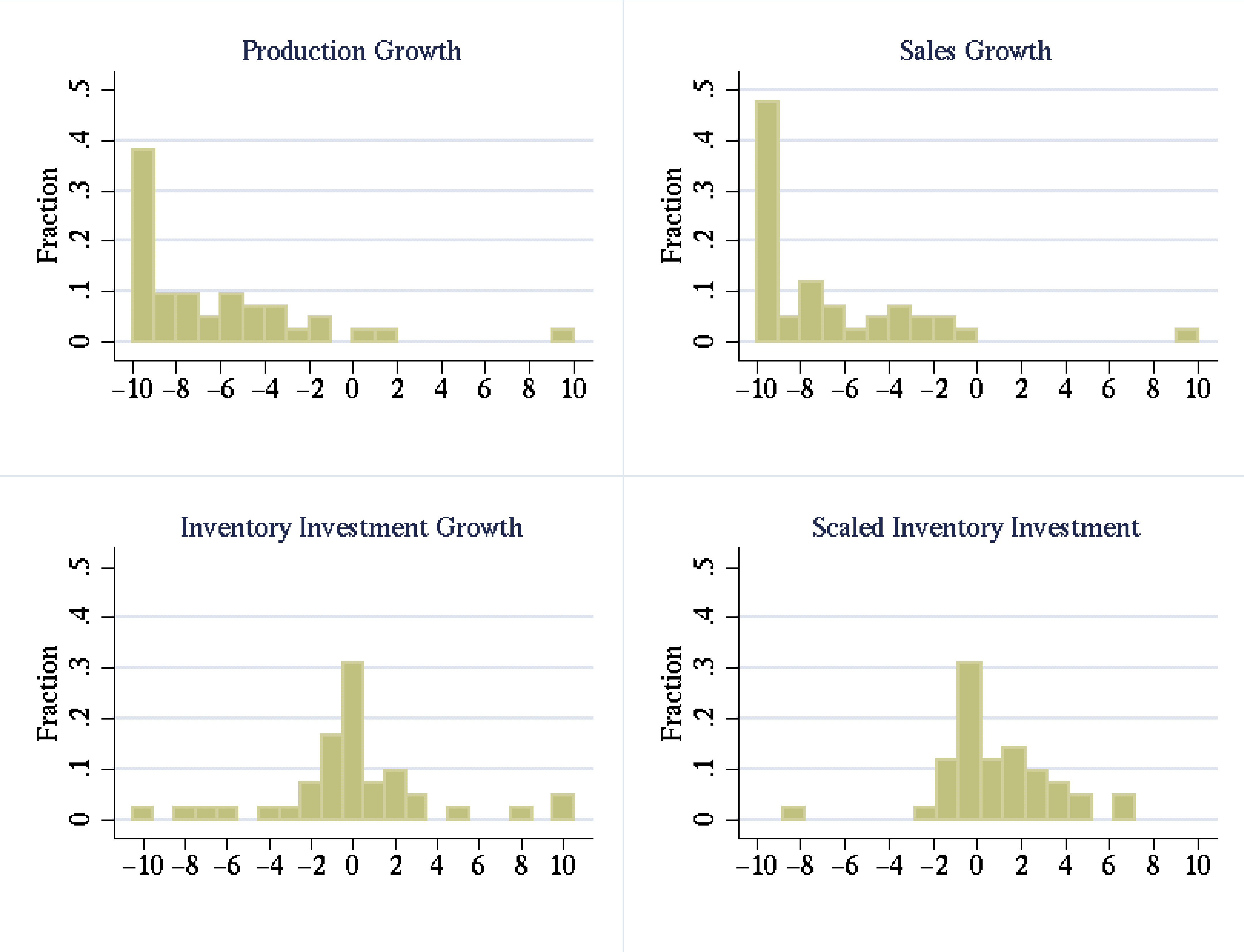


Figure 6a: Frequency Distributions of Covariance Changes



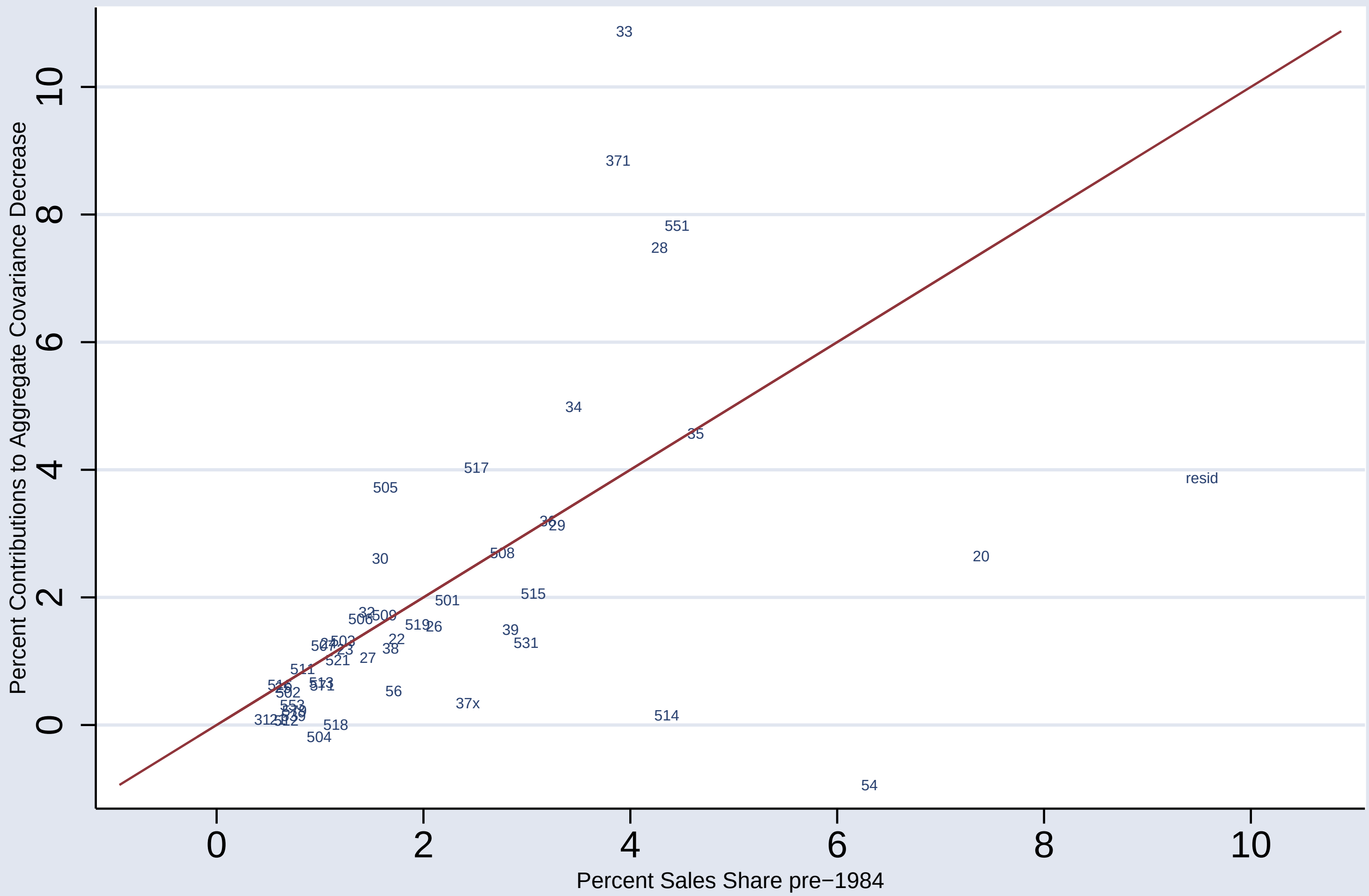
Note: Figure displays the change in pairwise covariances of industry−level series, scaled by the variance.

Figure 6b: Frequency Distributions of Covariance Changes by Industry



Note: Figure displays the change in pairwise covariances of industry–level series, scaled by the variance and summed by industry.

Figure 7 Aggregate Covariance Decrease vs.
Early Period Sales Share



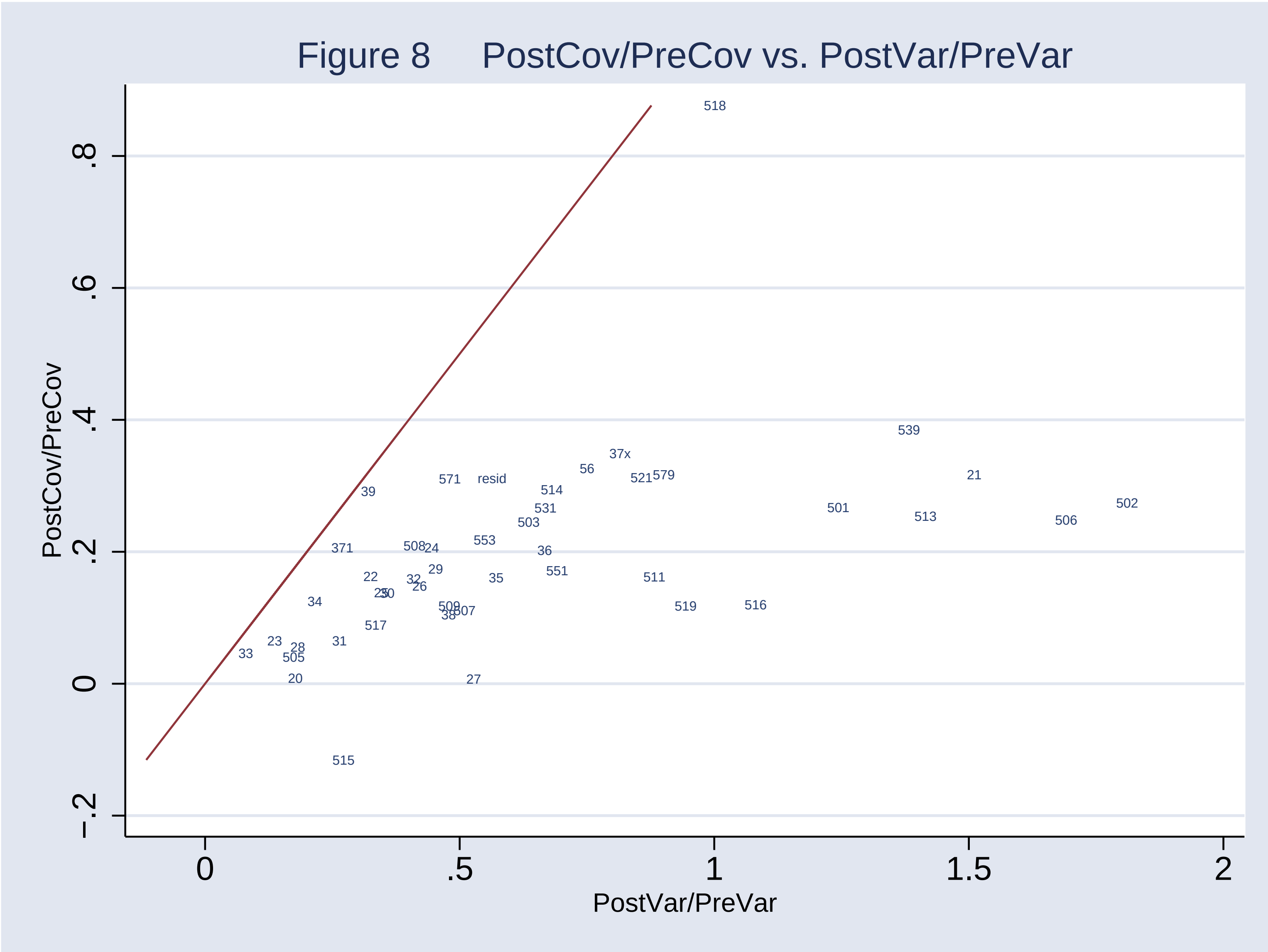


Figure 8   PostCov/PreCov vs. PostVar/PreVar
PostCov/PreCov
PostVar/PreVar
-.2
0
.2
.4
.6
.8
0
.5
1
1.5
2
518
539
21
502
506
513
501
37x
56
521579
571
resid
514
531
503
39
371
508
24
553
36
29
22
32
26
35
551
511
23
30
34
509
38
507
519
516
517
23
28
31
33
505
20
27
515

Figure 9 Sales Volatility Ratios versus
Relative Covariance Reduction with Distributors

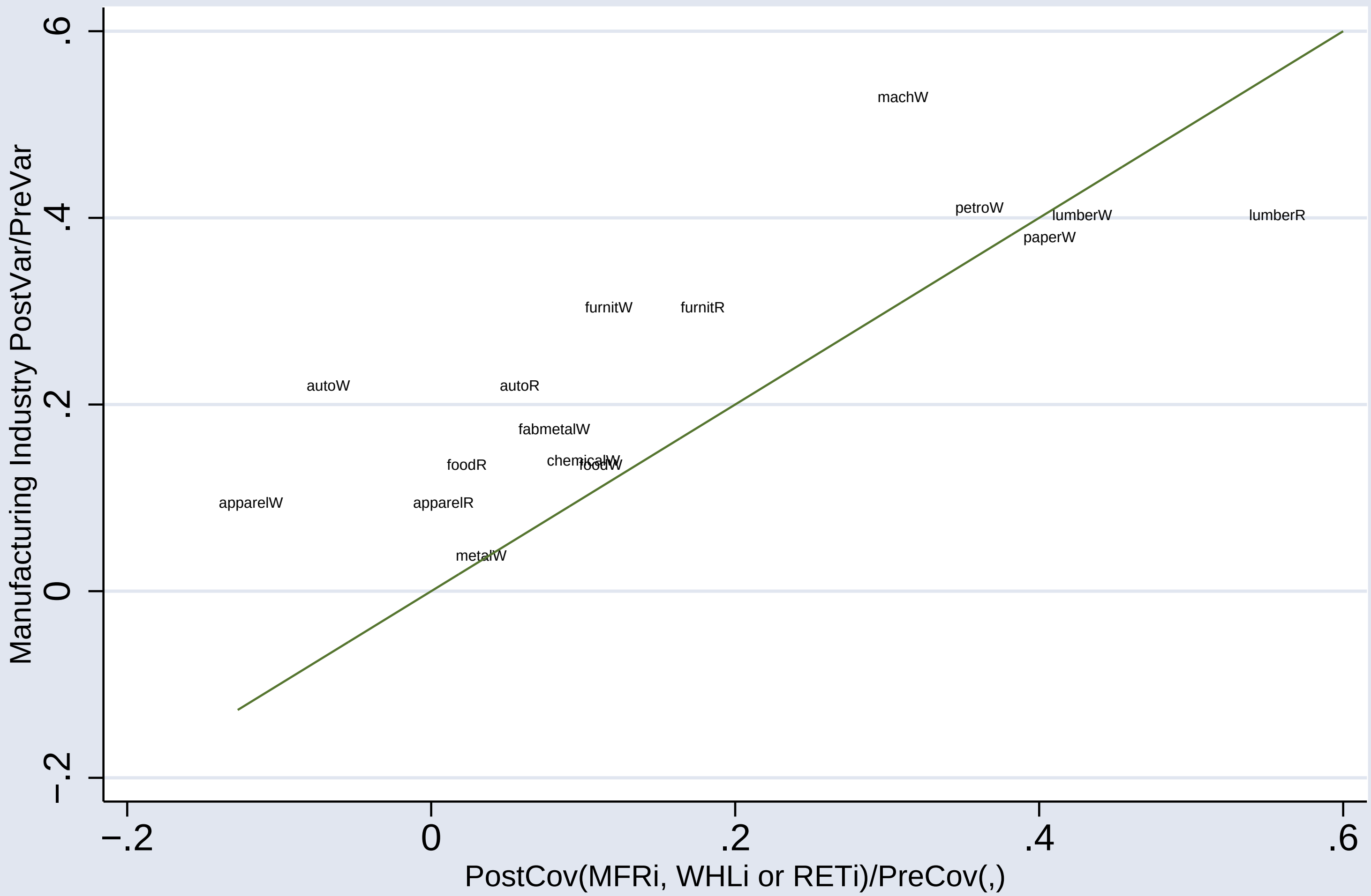


Figure 10 **Automobile Manufacturing PostCov(371,i)/PreCov(371,i)**

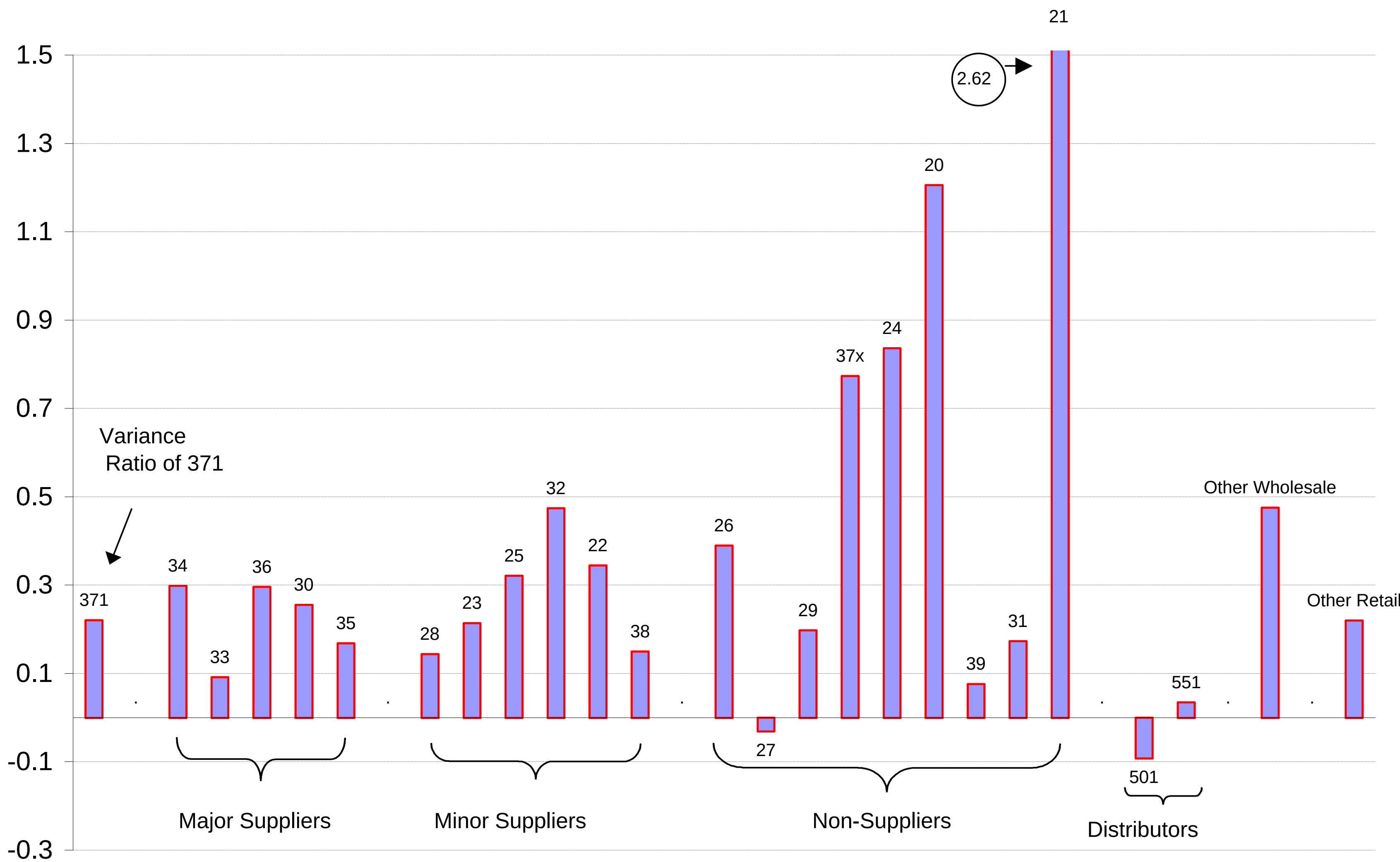


Figure 11: Change in Production Volatility vs. Change in Average I/S

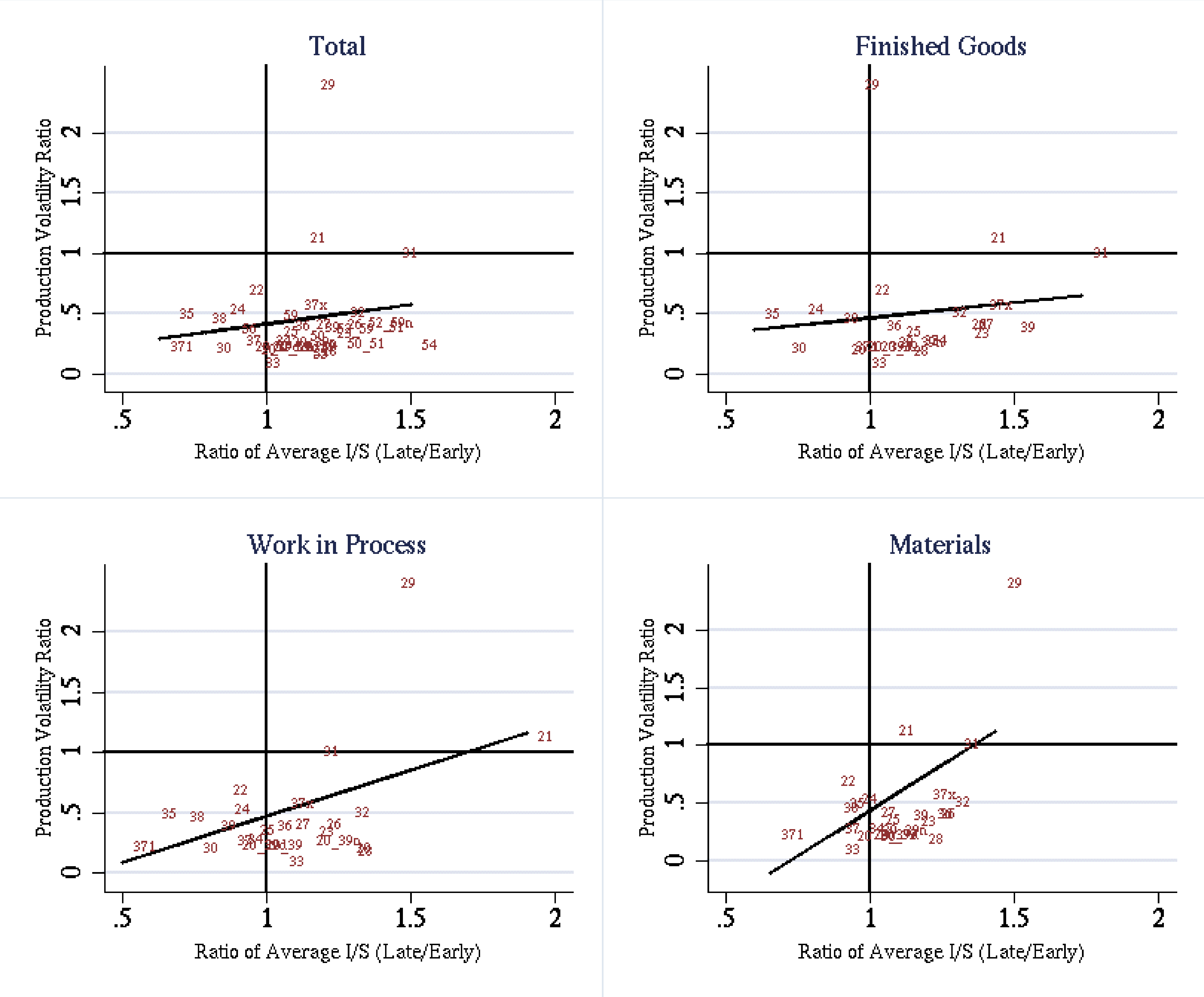


Figure 12: Change in Inventory Investment Growth Volatility vs. Change in Average I/S

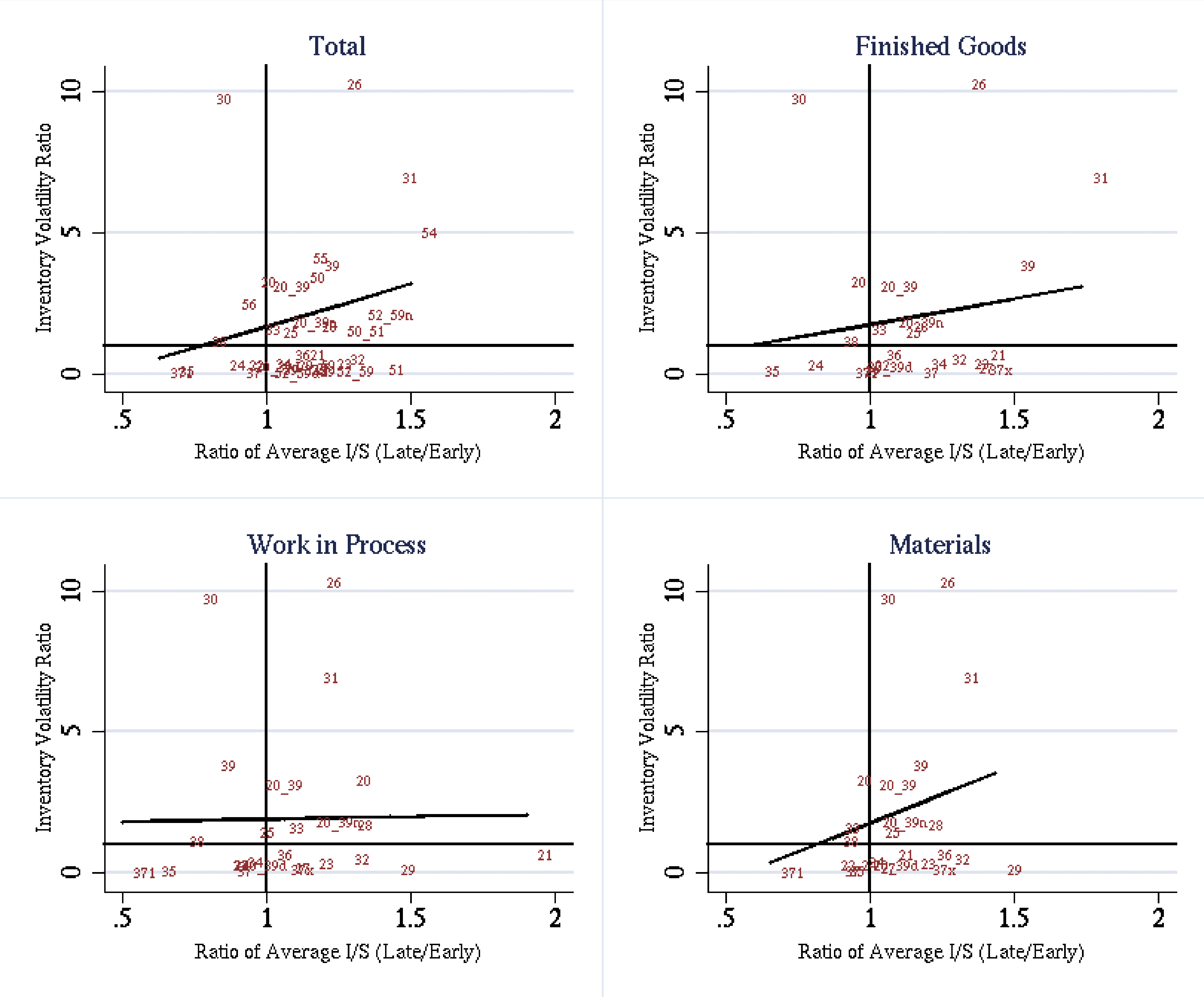


Figure 13: Change in Scaled Inventory Investment Volatility vs. Change in Average I/S