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The Roles of Comovement and Inventory Investment in the Reduction of Output Volatility

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Abstract:
Most of the reduction in GDP volatility since the 1983 is accounted for by a decline in comovement of output among industries that hold inventories. This decline is not simply a passive byproduct of reduced volatility in common factors or shocks. Instead, structural changes occurred in the long-run and dynamic relationships among industries' sales and inventory investment behavior—especially in the automobile and related industries, which are linked by supply and distribution chains featuring new production and inventory management techniques. Using a HAVAR model (Fratantoni and Schuh 2003) with only two sectors, manufacturing and trade, we discover structural changes that reduced comovement of sales and inventory investment both within and between industries. As a result, the response of aggregate output to all types of shocks is dampened. Structural changes accounted for more than 80 percent of the reduction in output volatility, thus weakening the case for "good luck," and altered industries' responses to federal funds rate shocks, thus suggesting the case for "better monetary policy" is complicated by changes in the real side of the economy.

JEL Classifications: E22, E32, E52, L16
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"*Everyone is so conscious of the business cycle because most sectors of the economy move up and down together. This phenomenon, referred to as comovement, is a central part of the official definition of the business cycle.*" Christiano and Fitzgerald (1998, p. 56)

1. Introduction

A substantial decline in the volatility of U.S. real GDP growth since the early 1980s, first observed by Kim and Nelson (1999) and McConnell and Perez-Quiros (2000), spawned a growing literature filled with attempts to explain the decline.[1] The primary explanations for more moderate business cycles are: 1) improved monetary policy; 2) "good luck" in the form of less variable shocks; 3) structural changes in the sales (demand) process; and 4) improved production and inventory management techniques. The inventory story has received only limited support, but no consensus has emerged yet on any of these explanations.[2]

A common feature of most prior studies is the use of aggregate models and data. Each of the leading explanations tends to abstract from heterogeneity among agents, and to view aggregate fluctuations as emanating from a single aggregate source, such as a monetary policy instrument or some kind of an aggregate shock. Even inventory-based explanations seem to implicitly presume there was a change in a general purpose technology or business practice that is common to all firms. In a single-sector aggregate model, fluctuations in an aggregate source produce comovement among variables, as explained by Christiano and Fitzgerald (1998).

While recognizing a potentially important role for changes in aggregate factors, we investigate the role of a different type of comovement – the synchronized actions of heterogeneous agents – in explaining the reduction in GDP volatility. This investigation is motivated by more recent studies that have turned to disaggregated data because they offer opportunities to exploit cross-section variation for better identification of the hypothesized explanations.[3] In particular, Irvine and Schuh (2005) observe that reductions in comovement among industries may have played a role in reducing aggregate volatility.

[1] The literature covering the most recent decline in volatility also includes Ahmed, Levin, and Wilson (2004); Blanchard and Simon (2001); Kahn, McConnell, and Perez-Quiros (2002); Kim, Nelson, and Piger (2001); Ramey and Vine (2004); Stiroh (2005); Stock and Watson (2002, 2003); and Warnock and Warnock (2000).
[2] McConnell and Perez-Quiros (2000) conclude, "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 speculate that reductions in the ratio of inventories to sales, which coincide with reductions in output volatility, reflect improved inventory management techniques resulting from information technology. Blanchard and Simon (2001) note that the correlation of inventory investment with sales growth declined (from positive to negative) and conclude, "This fact…. must have come from a change in the inventory management of firms."
[3] See Bivin (2003), Herrera and Pesavento (2003), Irvine and Schuh (2005), and McCarthy and Zakrajsek (2003).

In this paper, we provide evidence on the magnitude and nature of the reduction in comovement among industries, and offer an explanation based on structural changes in the production and inventory behavior within and between industries. Reductions in comovement were widespread but especially important among certain industries that are centered on motor vehicle production, closely connected by input-output linkages (supply and distribution chains), and widely noted for adoption of new inventory and production management techniques such as just-in-time production. These new techniques appear to manifest themselves as structural changes that have altered industries' long-run and dynamic behavior, reducing comovement between industries and thus dampening the response of aggregate output to all kinds of shocks.

Comovement among aggregate variables is well established, but comovement among industries (or sectors) has received less attention.[4] Most theories of sectoral comovement depend on input-output linkages, through which innovations in production and inventory management techniques would operate, but spillovers (Shea 2002), information externalities (Banerjee 1992), and complementarities (Cooper and Haltiwanger 1990, 1996) may be at work as well.[5] Regardless of the specific mechanism driving sectoral comovement, the main theoretical implication is that sectoral disturbances can induce aggregate fluctuations large enough to produce business cycles[6]. Long and Plosser (1983) showed that disturbances to individual industries, even if uncorrelated across industries, theoretically could cause both comovement among industries and aggregate fluctuations. Extending this work, Horvath (1998, p. 801) found that "the model suggests that two-digit SIC sectoral shocks alone can account for as much as 80 percent of the volatility in aggregate output growth rates" when input-output matrices are sparse (that is, a small number of relatively independent supply and distribution chains) like those in the United States. Other empirical evidence also corroborates the importance of sectoral comovement.[7]

Our findings relate closely to the comovement literature because the greatest reduction in comovement occurred among industries that are linked by supply and distribution chains. These

[4] Christiano and Fitzgerald (1998) describe two types of comovement within the context of standard RBC models: 1) comovement of aggregate variables in representative agent models with aggregate shocks only; and 2) comovement among sectors in multi-sector models with aggregate and sectoral shocks. Most theories of comovement focus on the former type, but we focus on the latter type.

[5] For more details on input-output linkages, see Long and Plosser (1983), Hornstein and Praschnik (1997), Horvath (1998, 2000), Huang and Liu (2001), Shea (2002), and Conley and Dupor (2003).

[6] Firm-level (idiosyncratic) disturbances may also generate large aggregate fluctuations provided the size distribution of firms is "fat-tailed", as argued by Gabaix(2005). However, in this case, some mechanism such as demand linkages among firms is needed to generate comovement.

linkages represent the channels of the sparse input-output structure along which both sector-specific and aggregate shocks ripple through the economy. However, we do not find much empirical evidence that either the volume of input-output activity in these chains, or the sparseness of the economy, has declined much. Instead, the sales and inventory behavior among industries along these chains apparently changed and led to a reduction in aggregate output volatility.

A link between reduced aggregate volatility and structural changes in comovement among industries has not been shown until recently. Table 1 summarizes the contributions to the reduction in variance of GDP growth between the two periods identified by McConnell and Perez-Quiros (with a break in 1984). Covariance terms at this level of aggregation account for 40 percent of the total reduction in the variance of real GDP growth: 27 percent come from reductions in covariance among three broad sectors, and 13 percent from covariance between sales and inventory investment (see Irvine and Schuh 2005). In this paper, we extend this analysis by decomposing the variance of the main inventory-holding sector (goods) and find that more than 80 percent of the reduction in variance of goods output growth is attributable to reductions in covariance among 2-digit and 3-digit SIC industries. Thus, the reduction in GDP volatility appears to be connected to an uncoupling of industries that once moved together closely.[8] A central question is: How are the reductions in sectoral comovement and aggregate volatility related?

Comovement could have declined for many reasons: because of changes in a common (aggregate) factor, such as a monetary policy instrument; because of changes in idiosyncratic factors, such as sector-specific shocks; or because of changes in behavioral relationships in the economy, such as the input-output structure among firms and industries along supply and distribution chains via inventory behavior (as in Cooper and Haltiwanger 1990). Testing these competing hypotheses about the source(s) of decline in comovement and aggregate volatility requires a macroeconometric framework with heterogeneous agents and complete aggregation conditions that can encompass all of

[7] For example, Shea (2002, p. 413) reports that comovement among 3-digit SIC industries accounts for almost 95 percent of the level of aggregate manufacturing employment volatility. Conley and Dupor (2003, p. 337) attribute 50 to 60 percent of aggregate variance to the "off-diagonal" elements of the covariance matrix.

[8] The connection between reduced output volatility and reduced comovement among industries is not universal, however. Output volatility declined at all levels of industrial aggregation, but changes in comovement are weaker at higher levels of aggregation. Conversely, the volatility of sales at individual firms actually *increased* (Comin and Mulani 2004a), even though comovement among firms *decreased* (Chun, Kim, Lee, and Morck 2004). Thus, changes in volatility and changes in comovement are inversely correlated across levels of aggregation. Francois and Lloyd-Ellis (2003) and Comin and Mulani (2004b) argue that macroeconomic volatility declined because of improvements in microeconomic innovation and creative destruction. According to Gabaix's(2005) analysis, changes in the size distribution of firms is also a potentially important determinant of the change in aggregate volatility. Rather than trying to offer a grand explanation for all the facts, we try to explain the data at intermediate levels of aggregation where volatility and comovement both declined.

the hypotheses. We use two frameworks – one with, and one without, explicit structural relationships among industries – to evaluate and interpret the data.

One framework is a standard factor model, which does not include an explicit role for structural relationships among industries. The factor model implies that less comovement among industries is simply an indirect consequence of a reduction in the variance of common factors. Our estimates indicate that, on average, the actual change in correlation among industries after 1983 is roughly consistent with the prediction of the factor model – but only if the model is given perfect foresight of the decline in variance of the common factors. However, even with this perfect foresight, the factor model does not predict well the observed cross-section pattern of correlation between pairs of industries since 1983 (R^2 of .11). Thus, the factor model cannot provide reliable interpretations of the role of structural changes in relationships among industries. We conclude that the decline in aggregate output volatility was not due *primarily* to lower volatility of an aggregate factor, although less variable aggregate factors may have contributed to the reduction as well.[9]

A second framework is the heterogeneous-agent VAR (or HAVAR) macroeconometric model of Fratantoni and Schuh (2003). The HAVAR model is well suited to evaluate the effects of structural changes on comovement because it permits disaggregation of industries within an otherwise standard macroeconomic VAR while maintaining all necessary aggregation conditions. Unlike the factor model, the HAVAR model explicitly parameterizes the dynamic structural relationships among industries as well as the structural relationships among aggregate variables and relationships between industry and aggregate variables. Furthermore, the HAVAR model separately identifies roles for economically well-defined aggregate and sector-specific shocks. Because it is a complete macroeconomic framework, the HAVAR model can quantify the effects of changes in the relationships among industries on aggregate volatility.

The HAVAR model estimates reveal changes in structural relationships among industries' sales and inventory investment that are essential to understanding the decline in both comovement and aggregate volatility. An identified HAVAR model with minimal disaggregation – only two sectors, manufacturing and trade – attributes more than 80 percent of the decline in aggregate output volatility to changes in model structure and less than 20 percent to shocks. In contrast, standard macroeconomic VARs without between-industry relationships attribute more than 60 percent of the change in aggregate volatility to shocks. These results weaken the case for the "good luck" hypothesis and demonstrate the importance of heterogeneity in macroeconomic analysis.

The HAVAR model also provides evidence that the structural changes were associated with the adoption of new inventory and production management techniques. Input-output data for key aggregate industrial sectors do not show evidence of much change in the input-output structure *per se*. However, parameter estimates from the HAVAR model reveal significant changes in the long-run and dynamic interactions between sales and inventory investment among the manufacturing and trade sectors, even after conditioning on other macroeconomic variables. In general, structural changes in the relationships between industries dramatically reduced the correlation between sales and inventory investment, both within and between industries, which generally led to more production smoothing by industries and less comovement of output among industries. These changes also help explain the reduced persistence of sales noted by Ramey and Vine (2004).

Previous studies, which generally relied on aggregate data, appear to have mistakenly attributed the reduction in output volatility primarily to "good luck" or monetary policy alone by ignoring relationships between industries. Indeed, the impulse responses of industry output to a federal funds rate shock in the HAVAR model reveal significant and heterogeneous changes in the structure of the real economy, especially the trade sector. Firms in the interest-sensitive goods sector may have implemented these changes to in part to insulate themselves from monetary policy fluctuations. In contrast, the HAVAR model reveals little evidence of structural change in the parameters associated with the purely macroeconomic variables. The only exception is a large and significant increase in the impact of inventory investment on the federal funds rate since 1983.

2. Context and Motivation from the Automobile Industry

To preview our ideas and results, consider the U.S. automobile industry, which plays a disproportionately important role.[10] Figure 1 plots quarterly real sales growth for auto manufacturers (SIC 371) and auto retailers (SIC 551). One can see a large reduction in the variance of sales in both segments: between the periods demarcated by 1984, the variance declined 80 percent for manufacturers and 60 percent for retailers. Upon closer inspection, one can also see that comovement between them dropped just as precipitously. Whereas sales of auto manufacturers and auto retailers moved together before 1984, sales have become almost completely uncorrelated since.

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[9] Conley and Dupor (2003) also conclude that a common factor is not the primary cause of comovement, but they do not examine the question of a decline in aggregate volatility.

[10] Our finding of an important role for the automobile industry is complementary to Ramey and Vine (2004), who focus exclusively on the auto industry. We examine the macroeconomic implications of supply and distribution chains more generally, but the auto sector behavior is important enough to influence aggregate behavior.

Table 2 reports the complete set of correlations for sales and inventory investment during the two periods plus the changes in correlation. The correlation *between* manufacturing and retail sales, illustrated in Figure 1, dropped from .63 to .08. Another large decline occurred *within* the retail industry: the correlation between sales and inventories fell from .15 to -.44. A natural question is: are these two correlation changes related and, if so, what role did production and inventory management techniques in each sector play? After all, the U.S. auto industry is recognized widely as having undergone extensive changes in these techniques around the time when volatility declined. The nontrivial changes in the correlation of retailers' inventories with manufacturing sales ($-.16$) and with manufacturing inventories (.23) shown in Table 2 suggest that this question is right on track.

One potential explanation for these changes in correlation among industries in the auto sector is a change in the input-output structure. Table 3 reports the input structure for motor vehicle manufacturers and for retail trade during the 1977-82 and 1987-92 periods.[11] For each industry, the columns contain percentages of total intermediate inputs into that industry. The inputs with the six largest shares in each period are included. Judging from the change in shares between periods (last column), there is little evidence of major quantitative changes in the input-output structure, especially among the largest inputs. Moreover, the sales data described in Figure 1 predominantly represent the gross sales value of finished automobiles being passed along the distribution chain. The Commerce Department treats these gross sales as intermediate goods and excludes them from input-output tables altogether; they only appear in final sales (consumption and investment). Thus, not only did the input-output structure remain relatively stable, but input-output data do not even identify or reflect potential changes in the structure of goods being passed along supply and distribution chains.

The changing correlation structure in the auto industry is a representative and notable illustration of the broader results of this paper. Because of the size and importance of the auto industry, these changes may be responsible for much of the results noted in the literature and this paper.[12] In fact, the identified HAVAR model of the main inventory-holding sectors (manufacturing and trade) yields econometric evidence that the most important structural changes occurred precisely in the model's structural parameters that govern these correlations. Apparently, structural change in

[11] Unfortunately, separate data for retail automobile dealers were unavailable.
[12] For example, the sizable reduction in correlation between sales and inventory investment for auto retailers possibly underlies the similar, but smaller, finding by Blanchard and Simon (2001) in the aggregate data. And McConnell, Kahn, and Perez-Quiros (2002) emphasize the importance of durable goods industries, of which the auto industry is a major part.

the auto industry is large enough to have affected the aggregate economy.[13]

3. Goods Sector Variance Decomposition

Irvine and Schuh (2005) reported that a reduction in the volatility of goods-sector output accounts for nearly two-thirds of the reduction in GDP volatility. Here, we report the results of an analogous variance decomposition of the goods sector using data for manufacturing and trade (M&T), which represent the bulk of the goods sector in the National Income and Product Accounts (NIPA). We provide a complete accounting of the change in the variance of aggregate production growth, y_t, in terms of changes in the variance-covariance structure of the growth contributions (denoted by tilde) of industry-level sales, $\tilde{s}_t$, and inventory investment, $\Delta\tilde{i}_t$.

3.1. Measurement of Output Growth

In the NIPA, output (real GDP) of the goods sector is the sum of the levels of real 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 stocks: finished goods, work-in-process, and materials and supplies. We use quarterly data from the Bureau of Economic Analysis (BEA) for the manufacturing and trade (M&T) sector divided into 2-digit and 3-digit SIC industries during the period 1967:Q1 through 2001:Q1.[14] NIPA value-added data are not available at this frequency and level of industry detail.

Three important differences arise between the NIPA and the M&T output data. First, the M&T sector represents only a subset of the NIPA goods sector, which also includes mining, agriculture, utilities, and construction. Second, the M&T sales data include input costs; thus M&T output is gross production rather than value added.[15] Third, M&T real chain-weighted output data and growth contributions are not published but must be constructed from the sales and inventory investment data.

[13] Other industries also adopted similar production and inventory control systems. Of course, a complete understanding of the economic behavior underlying this change in comovement requires a structural model of production and inventory investment that incorporates the general equilibrium interactions between industries (or firms) characterized in this paper. Blanchard's (1983) study of the automobile industry, Cooper and Haltiwanger's (1990) model in which inventories transmit sectoral shocks, and Humphreys, Maccini, and Schuh's (2001) model of input and output inventories are ideal starting places. Changes in markups, as described in Bils and Kahn (2000) and Burstein, Eichenbaum, and Rebelo (2004), may also be important, especially for prices charged along supply chains and distribution chains.

[14] The SIC-based data have been discontinued and thus are not up to date. Data based on the new NAICS industry classification system are not available far enough back in time to conduct this study. See Appendix Table 1 for a complete list of the SIC industries.

[15] See the discussion in Irvine and Schuh (2005). The variance properties of M&T gross production are very similar to those of NIPA goods value added, and the correlation between the two aggregate growth rate measures is .7.

Constructing real output growth and growth contributions with industry sales and inventory data is challenging with chain-weighted data (see the Data Appendix for details). Our preferred method is a three-variable Tornqvist approximation, $\tilde{y}_t = \tilde{s}_t + \tilde{i}_t - \tilde{i}_{t-1}$ where the growth contributions are growth rates of real chain-weighted levels weighted by the shares of the nominal data. Because of the difficulties with constructing M&T real output data and contributions, we also tested our results with other data measures of output. None of our main findings in this section is sensitive to data measurement, so we use only our preferred method for the remainder of the paper.

3.2. Variance Decomposition of Output Growth

Table 4 reports the variance decomposition of M&T output growth in the early (1967-1983) and late (1984-2001) periods plus the change between periods. The rows of the first panel pertain to the cross-section decomposition:

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

The rows of the remaining panels pertain to the cross-section decomposition:

$$\begin{aligned} \mathrm{Var}(\tilde{y}) &= \sum_{j=1}^{J} \left[\mathrm{Var}(\tilde{s}_j) + \mathrm{Var}(\Delta\tilde{i}_j) + 2\mathrm{Cov}(\tilde{s}_j, \Delta\tilde{i}_j) \right] \\ &+ 2\sum_{j>k} \left[\mathrm{Cov}(\tilde{s}_j, \tilde{s}_k) + \mathrm{Cov}(\Delta\tilde{i}_j, \Delta\tilde{i}_k) \right] + 2\sum_{j \neq k} \mathrm{Cov}(\tilde{s}_j, \Delta\tilde{i}_k) \;, \end{aligned} \tag{2}$$

which isolates the within-industry component (first term, right-hand side) and between-industry component (second and third terms). The second and third columns report the variances in each period, and the fourth column reports their ratio (late/early), which we call the variance volatility ratio. The fifth column reports the shares of each variance component in the total change in aggregate M&T output variance, and the final column reports the shares for the subcategory, where relevant.

The variance of M&T output declined by 82 percent, as indicated by the volatility ratio in Table 4, compared with a 74 percent reduction in the NIPA goods sector reported in Irvine and Schuh (2005). The reduction was smaller for the industry variances (73 percent) and higher for covariance among industries (84 percent). Because covariance accounted for a large majority of the total M&T variance in the early period, the covariance reduction arithmetically accounts for most of the decline in M&T variance (82.2 percent). For comparison and perspective, we also report the mean correlation between industries, which dropped by about half (47 percent) in the late period. Thus, our first important result is that the reduction in aggregate output volatility occurred primarily through a reduction in covariance (and correlation) among industries.[16]

The implications of Table 4 are significant for understanding the reduction in volatility of GDP. Irvine and Schuh (2005) report that the reduction in NIPA goods sector output volatility accounts for 64 percent of the decline in GDP volatility, whereas here the reduction in covariance among M&T industries accounted for 82 percent of the decline in M&T output volatility. Therefore, if M&T is representative of the NIPA goods sector, then the reduction in covariance among industries in the goods sector would account for 52 percent ($.64 \times .82$) of the decline in GDP volatility. Adding the decline in covariance among the last three sectors from Table 1, lower covariance accounts for at least 79 percent of the total decline in GDP volatility. The contribution of covariance probably would be even larger if the structures and services sectors were disaggregated into detailed industries.

Sales covariance and the covariance between sales and inventory investment also declined, but covariance reduction is notably less important for inventory investment itself. The second panel of Table 4 shows that sales variance declined 81 percent and changes in covariance among industries accounted for 86.1 percent of that decline. Likewise, the last panel shows that covariance between sales and inventory investment declined by 77 percent, and covariance among industries accounted for 88.9 percent of that decline.[17] The third panel shows that M&T inventory investment variance declined by 82 percent, very similar to the decline in sales variance. However, reductions in covariance among industries' inventory investment accounts for only slightly more than half (52.6 percent) of the reduction of inventory investment volatility.

The results in Table 4 suggest a role for improved inventory management in reducing variance by operating through lower covariance. The direct contribution of inventories to the reduction in aggregate output volatility is 27.1 percent (13.0 percent for inventory investment and 14.1 percent for its covariance with sales). Most of that contribution occurred through covariance among industries, as industries' inventory investment and sales essentially became uncoupled from those of other industries. Covariance between sales and inventory investment did decline, as Blanchard and Simon (2001) noted; however, the decline in this covariance within industries only accounts for 11.1 percent of the decline in covariance between sales and inventory investment, or less than 2 percent of the total decline in aggregate output volatility. This central role for reduced

[16] We performed analogous decompositions of M&T output growth with three alternative output measures: 1) BEA data using the residual method (see the Data Appendix); 2) industrial production data from the Federal Reserve; and 3) labor hours data from the Bureau of Labor Statistics. Each method yields virtually identical results to those in Table 4. Aggregate M&T output variance declined by 81 to 85 percent, and industry output covariance accounted for 81 to 87 percent of this decline in aggregate variance.

[17] In contrast, the variance of NIPA Goods Sector sales declined by 53 percent, and the variance of inventory investment declined by 60 percent (see Irvine and Schuh 2005).

covariance suggests that sales shocks and excess inventory buildups in one firm or industry were much less likely to spill over to other firms and industries during the later sample period.

Less spillover among firms and industries might arise in at least two ways. First, the adoption of better inventory management techniques *within* an industry might be expected to reduce the volatility of output and reduce the covariance between sales and inventory investment (making it more negative). Perhaps these changes occurred through improvements in sales forecasting and production flexibility made possible by information technology or other high-tech innovations, as suggested by Kahn, McConnell, and Perez-Quiros (2002). Second, the adoption of better inventory management techniques *between* industries might be expected to reduce comovement of one industry's inventory investment with another industry's sales and inventory investment, as with auto manufacturers and retailers. Perhaps these changes occurred through improvements in supply and distribution chains also made possible by information technology and other high-tech innovations, such as just-in-time production, flexible manufacturing, outsourcing, information sharing, and changes in transportation and production relocation decisions.

However, most of the reduction in output volatility occurred through a decline in sales variance (73.0 percent), and most of that decline occurred through lower covariance among industries' sales (86.1 percent). Thus, although changes in inventory behavior contributed directly to the reduction in output volatility, inventory behavior alone does not appear to be able to explain most of the volatility reduction unless the changes contributed indirectly to the reduction in covariance among industries' sales as well. Changes in production and inventory management techniques that govern the relationships between firms and industries are a good candidate for explaining the change in sales covariance.

3.3 Industry-Level Changes in Covariance

Before proceeding to formal models, it is important to know whether the covariance changes were spread evenly among industries, or whether certain large and cyclical industries dominated the reduction in covariance. We find that covariance reductions were widespread but that the automobile and related industries contributed disproportionately, suggesting that the covariance reductions may be linked to supply and distribution chains among these industries.

Most industries experienced very large reductions in their covariance with other industries.[18] Figures 2 and 3 depict these reductions by plotting distributions of volatility ratios for covariance

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

among industries' output, sales, and inventory investment growth.[19] Covariance volatility ratios are analogous to the variance volatility ratios in the previous section and are defined as

$$\left[\Delta \mathrm{Cov}(\tilde{x}_j, x_k) / \mathrm{Var}(x_j^E)\right] \qquad \left[\sum_{j \neq k} \Delta \mathrm{Cov}(\tilde{x}_j, x_k) / \mathrm{Var}(x_j^E)\right].$$

The ratios plotted in Figure 2 are changes in each individual pair-wise covariance scaled by industry variance in the early period, where $\tilde{x}$ denotes growth contributions of production, sales, or inventory investment; E denotes the early period; and Δ indicates the change from early to late period.[20] The ratios in Figure 3 are changes in total industry covariance with all other industries, also scaled by industry variance in the early period. Scaling total industry covariance in this manner typically yields ratios much larger than one, indicating that the covariance reduction is even larger than total industry variance.[21]

For most industries, the covariance of their output and sales with those of other industries declined significantly after 1983. Figure 2 shows that nearly eight in ten output covariance pairs declined. The median and mean reductions in covariance between industries' output growth were 11 and 29 percent, respectively, of an industry's early-period output variance. Figure 3 reveals that virtually every industry experienced a decline in the total output covariance with all other industries. The median decline in total-industry output covariance was about 7.4 times an industry's early-period variance; nearly all declined by more than double the industry's early-period variance. These results portray a broad-based uncoupling of industries' output and sales rather than uncoupling in only a small group of industries.

In contrast with output and sales, changes in the covariance structure of inventory investment were smaller and more heterogeneous. Figure 2 shows that changes in individual pair-wise covariances among industry inventory investment were much smaller and more evenly distributed around zero. Figure 3 shows that only about two-thirds of the aggregate industry inventory investment covariances decreased.

Although virtually all covariances declined, certain very large or highly volatile industries may have accounted for much of the decline in aggregate covariance. Figure 4 provides evidence on the importance of industry size by plotting their shares of M&T nominal sales in the early period against their contributions to the decline in aggregate sales covariance. Most industries tend to lie

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[19] The lower-right-hand box in each figure is a plot of the absolute value of inventory investment divided by the previous quarter's sales level.
[20] Scaling by industry variance, rather than covariance, avoids confusion arising from sign changes in the numerator versus denominator; if the ratio is negative, it indicates unambiguously that covariance between industries declined.
[21] Virtually all covariance among industries was positive in the early period and it was lower in the late period.

along the solid 45-degree line, indicating that they contributed to the decline in aggregate sales covariance roughly in proportion to their size. However, two groups of relatively large industries (3 percent or greater sales share) stand out as notable exceptions in Figure 4. Two groups – the auto industry (SIC industries 371, 551) and some of its main suppliers, the primary and fabricated metals (SIC 33 and 34), rubber (SIC 30), and chemical (SIC 28) industries – accounted for disproportionately *large* shares of the decline in aggregate sales covariance. Other groups – the food industry (SIC 20, 514, and 54) and a residual of retail industries – accounted for disproportionately *small* shares of the decline in aggregate sales covariance.

4. Factor Model Analysis of Covariance

The results so far suggest that a reduction in covariance played an important role in the reduction of output volatility. To draw conclusions about an independent or causal role for covariance in the reduction in output variance, one must formally model the relationship between variance and covariance. This section uses a standard factor model for that purpose.[22] Factor models are commonly used for describing the macroeconomic implications of microeconomic behavior. Although they abstract from explicit behavioral interactions among microeconomic agents, they can quantify the extent to which common factors explain the empirical relationship between variance and covariance.

4.1 Benchmark Factor Model

A benchmark factor model with an aggregate and an idiosyncratic (industry) shock predicts a direct and constant link between reductions in the variance of common factors and reductions in covariances among industries. Principal component analysis offers a statistical way to identify common factors. Hence, a factor model can be used to quantify the extent to which these common factors explain the observed covariance structure of the data.

The basic factor model of growth for an industry variable, $x_{jt} = \left\{ \tilde{y}_{jt}, s_{jt}, \Delta\tilde{i}_{jt} \right\}$, is

$$x_{jt} = f_j C_t + \eta_{jt} \ , \qquad (3)$$

where C_t is a factor common to all industries (denoted by subscript j) with variance σ_C^2, f_j is a fixed parameter, and η_{jt} is an i.i.d. shock that is idiosyncratic to industry j with variance σ_η^2. The model may contain more than one common factor.

[22] We thank Todd Clark and Andrew Levin for independently suggesting this idea. See also Stock and Watson (2002).

Two basic assumptions of this factor model are 1) the idiosyncratic factors are orthogonal to the common factor(s) and to each other, $\text{Cov}\left(C_t, \eta_{jt}\right) = 0 \ \forall j$ and $\text{Cov}\left(\eta_{jt}, \eta_{kt}\right) = 0 \ \forall j \neq k$; and 2) the second moments are:

$$\text{Var}\left(x_{jt}\right) = f_j^2 \sigma_C^2 + \sigma_\eta^2 \tag{4}$$

and

$$\text{Cov}\left(x_{jt}, x_{kt}\right) = f_j f_k \sigma_C^2 \ \forall j \neq k \ . \tag{5}$$

Note that covariance does not depend on the idiosyncratic industry shocks. Therefore, because the industry shocks are orthogonal and because the model abstracts from direct structural (behavioral) economic relationships among industries, industries are related only indirectly through their relationships with the common factor. There is no independent role for supply or distribution chains, or other explicit behavioral relationships among groups of industries.

With regard to our empirical observations, the primary implication of the factor model is that changes in covariance between industries are a function solely of the change in the variance of the common factor ($\Delta\sigma_C^2$). For any pair of industries, the factor model predicts that covariance between them changes by the same proportion as the change in the common factor variance, scaled by the constant proportion $f_j f_k$.

The change in microeconomic covariance implied by the factor model can be tested with the data. If the change in the covariance can be explained well by the change in common factor variance, then our empirical observations about the role of covariance could be viewed as simple byproducts of the changes in variances of aggregate common factors. If not, then specific behavioral relationships among industries, such as supply or distribution chains, may have played an important independent role in the change in covariance, and therefore in the change in aggregate variance.

Principal component analysis identifies common factors. Each common factor (denoted by subscript p) is obtained by maximizing the variance of a linear combination of industry growth rates, $C_{pt} = \sum_j A_{jp} x_{jt}$, subject to the constraints that $\sum_j A_{jp}^2 = 1$ and $\text{Cov}\left(C_p, C_q\right) = 0 \ \forall p \neq q$. Factors are identified sequentially so each factor is orthogonal to the rest. The first identified factor has the largest variance, the second has the next largest, and so on.

4.2 Changes in Covariance and Correlation among Industries

Using the M&T industry-level data, we obtained estimates (denoted by ^) of the parameters $\hat{f}_j$; the principal components (common factors) $\hat{C}_{pt}$; and the common factor variances[23]

$$\left(\hat{\sigma}_p^2\right)^E = Var\left(\sum_{j=1}^{J} \hat{A}_{jp} x_{jt}^E\right) \qquad \left(\hat{\sigma}_p^2\right)^L = Var\left(\sum_{j=1}^{J} \hat{A}_{jp} x_{jt}^L\right) \quad .$$

With these estimates, the model can generate in-sample, or fitted, estimates of covariance for each industry pair:

$$\hat{\sigma}_{jk}^E = \sum_{p=1}^{P} \hat{f}_{jp}^E \hat{f}_{kp}^E \left(\hat{\sigma}_p^2\right)^E \qquad \text{and} \qquad \hat{\sigma}_{jk}^L = \sum_{p=1}^{P} \hat{f}_{jp}^L \hat{f}_{kp}^L \left(\hat{\sigma}_p^2\right)^L \quad .$$

The model also can generate out-of-sample predictions (denoted by $\hat{\wedge}$):

$$\hat{\hat{\sigma}}_{jk}^L = \sum_{p=1}^{P} \hat{f}_{jp}^E \hat{f}_{kp}^E \left(\hat{\sigma}_p^2\right)^L \quad .$$

In making this out-of-sample prediction, we are allowing the common factor variances to change but not the factor model parameters. Thus, the estimated late-period covariance is what the factor model would have predicted in 1983 if it had been told that the *actual* common factor variances after 1983 were going to decline by exactly the amount they declined. In other words, this prediction is like a perfect foresight forecast. Although unrealistic (no one predicted the post-1983 decline in GDP volatility, much less the actual magnitude of decline), this prediction is a generous way to give the factor model every chance to predict the actual change in covariance.

Figure 5 shows how well the factor model would have predicted the post-1983 decline in covariance. It depicts the relationship between industry variance and total industry covariance (sum over all industries) volatility ratios (it is infeasible to plot and label all the industry-level pair-wise covariance ratios). For each industry, the figure includes the actual data (SIC numbers) and the covariance ratios predicted (out-of-sample) by two versions of the factor model: a one-factor model (the dashed, horizontal line) and a five-factor model (dots) that account for about four-fifths of industry output variance. One can compare actual and predicted observations by scanning vertically for any variance ratio.

The one-factor model clearly does not predict well the reduction in aggregate industry covariance. Although the one-factor model's prediction of a 79 percent decline in output covariance

[23] We estimate principal component factor loadings ($\hat{A}_p$) over the full sample to prevent their nature from changing between periods, but none of the results is sensitive to the use of split-sample estimates.

is relatively close to the data *on average*, it misses badly many of the industry covariance ratios – particularly those for industries with very small variance ratios. The overall poor performance of the one-factor model is evidence against the hypothesis that the reduction in output volatility can be attributed primarily to one source, such as monetary policy.

However, the five-factor model's predictions are better, aside from a few outliers (for example, SIC 54 and 37X). In most cases, the extra factors move the predicted covariance volatility ratio in the direction of the data relative to the one-factor model, but room for improvement remains. The relatively good performance of the five-factor model is evidence that it can explain some of the cross-section variation in the decline of covariance, at least for total industry covariance.

Nevertheless, Figure 5 obscures the critical fact that even the five-factor model does a poor job of predicting changes in pair-wise industry-level covariance. To show this, we switch to correlation because covariance is influenced heavily by industry size. To quantify the model's prediction, we estimated cross-section regressions of industry-level correlation, $\rho_{jk} = \sigma_{jk} / \left(\sigma_j \sigma_k\right)$, for all $j > k$ on the predicted correlation from the factor models. The early period regression is

$$\rho_{jk}^{E} = \alpha^{E} + \beta^{E} \hat{\rho}_{jk}^{E} + \varepsilon_{jk}^{E} \quad \forall j > k, \tag{6}$$

where $\hat{\rho}_{jk}^{E} = \hat{\sigma}_{jk}^{E} / \left(\sigma_j^{E} \sigma_k^{E}\right)$ is the in-sample fitted value of correlation from the factor model estimated over the early period. Note, however, that the standard deviations are calculated from the actual data. The late period regression is

$$\rho_{jk}^{L} = \alpha^{L} + \beta^{L} \hat{\hat{\rho}}_{jk}^{L} + \varepsilon_{jk}^{L} \quad \forall j > k, \tag{7}$$

where $\hat{\hat{\rho}}_{jk}^{L} = \hat{\hat{\sigma}}_{jk}^{L} / \left(\hat{\hat{\sigma}}_j^{L} \hat{\hat{\sigma}}_k^{L}\right)$ is the out-of-sample predicted value from the factor model in the late period.[24] In calculating this correlation prediction, it is necessary to predict the variance of output growth for each industry. To do so requires forecasts of the factor loadings and idiosyncratic variances, both of which are difficult to predict. We assume that they remain the same as in the earlier period so that

$$\left(\hat{\hat{\sigma}}_j^{2}\right)^{L} = \sum_{p=1}^{P} \left(f_j^{2}\right)^{E} \left(\sigma_{F_p}^{2}\right)^{L} + \left(\sigma_{\eta_j}^{2}\right)^{E}, \tag{8}$$

[24] Note that the predicted change in correlation is implied by the two correlation regressions.

and thus the predicted variance of industry output depends only on the actual variance of the common factor(s) in the late period. To measure the ability of the factor model to explain cross-section correlation across all industry pairs, we rely on the regression R^2.[25]

Table 5 reveals that the factor model does a poor job of explaining the changes in cross-section correlation. The table reports statistics for the cross-section correlation regressions for each of the first five factors individually, and for groups of factors. The five-factor model fits the cross-section correlation structure in the early period well, with $R^2 = .78$. Factors 1 and 3 also do fairly well individually, and collectively they explain two-thirds of the cross-section correlation structure. However, even the five-factor model's out-of-sample prediction is very poor, with $R^2 = .11$, about the same as that of the model with Factor 1 alone. In other words, the factor model does not accurately explain the change in correlation for individual pairs of industries.

We conclude from these results that the factor model would not have been a good framework in 1983 for understanding the nature of the coming reduction in aggregate output volatility – even if one had known in 1983 exactly how much the common factor variances would decline (which no one did). Although the factor model would have predicted fairly well the changes in total industry covariance (Figure 5), it would not have been able to identify the correct pattern of correlation change among industry pairs. Hence, the decline in covariance between pairs of industries cannot be explained by the decline in the variance of common factors.

Overall, the results suggest that it is necessary to allow for structural change in the relationships among industries to fit the data. Because the factor model does not take into account relationships among industries, it is not well suited to evaluate the hypothesis that aggregate volatility declined because of structural changes in the covariance and correlation among industries.

4.3 Characteristics of Common Factors

Appendix B examines the characteristics of the estimated common factors in more detail. Although factor analysis does not identify structural economic behavior, it is a useful exploratory tool for identifying significant sources of independent variation in the data that may have sensible economic interpretations (Maddala 1988, pp. 237-243). Stock and Watson (2002) find that factors in a dynamic model are useful for macroeconomic forecasting, which "suggests briefly characterizing the first few factors" (p. 153). They do so by quantifying factors' correlation with the data, which reveals the industries most heavily "loaded" in the factor as well as the industries most heavily

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[25] Unreported tests of the null hypothesis $H_0: \alpha = 0,\ \beta = 1$, a procedure common in the literature on testing rationality of forecasts, produce even stronger results against the factor model.

influenced by the factor. The industry configurations shown in the appendix provide some basis for economic interpretation.

We find that the common factors reflect the disproportionate influence of a relatively small number of specific industries – especially autos, but also oil, capital goods, and food – in determining the variance of output. If structural changes occurred in the nature of supply and distribution chains, and these changes influenced aggregate output volatility, these industries would be the most likely to have exhibited those structural changes. Also notable is the omission from the top five factors of one dominant factor with a broad-based impact on industry output growth that could be interpreted as emanating from a single economic source.

Overall, the factor analysis has several limitations. One is that it is based on unconditional variances, whereas some studies find evidence of change in the autoregressive structure of sales and inventory investment. Ramey and Vine (2004) highlight a change in the sales process for the auto industry, while Kahn, McConnell, and Perez-Quiros (2002) highlight an increase in the importance of lagged inventory investment in a VAR with sales for the durable goods sector. However, the factor analysis cannot identify such changes. Another limitation is that the analysis does not identify economic behavior through structural (behavioral) restrictions. Variation in aggregate output volatility can only be understood fully with a model that accounts for the structural relationships between industries, to which we turn next.

5. HAVAR Model

To quantify the effects of changes in structural relationships among industries on aggregate output growth since 1983, we apply the HAVAR framework of Fratantoni and Schuh (2003) with output split into sales and inventory investment in a small, modestly identified macro model. Although the HAVAR model is not tied explicitly to basic preference and technology parameters, it is consistent with the reduced-form of a multi-sector dynamic optimizing model.[26] However, such models quickly become intractable for large numbers of agents (industries), and there are "conceptual difficulties inherent in thinking about an economy with many sectors" (Christiano and Fitzgerald 1998, p. 56). At the cost of some structural identification, the HAVAR framework offers a tractable avenue toward quantifying the potential impact of changing structural relationships between industries on the volatility of aggregate output.

[26] See Abadir and Talmain (2002) for an example of this approach.

Using a modestly identified two-sector HAVAR model of manufacturing and trade (M&T), we conduct four exercises. First, we examine the HAVAR model's ability to explain the role of structural changes in comovement among industries in the reduction in aggregate output volatility by decomposing the change in aggregate output variance into changes in model structure versus changes in shocks. Second, we conduct counterfactual simulations to identify the roles of changes in economic structure versus shocks. Third, we analyze the parameter estimates of the HAVAR model to gain an economic interpretation of the structural changes in the model. And fourth, we examine the impulse response functions of the model. A final subsection provides an economic interpretation of the results.

5.1 Benchmark Macro VAR Model

To begin, consider a simple benchmark macro VAR model of inflation, π_t; the nominal interest rate (federal funds), f_t; and real M&T output growth, $\tilde{y}_t$, which can be decomposed into sales and inventory contributions, $\tilde{s}_t$ and $\Delta\tilde{i}_t$.[27] The four-variable version of the model has vectors $Z_t = \left[\pi_t \; f_t \; \tilde{s}_t \; \Delta\tilde{i}_t\right]'$ and $\varepsilon_t = \left[\varepsilon_{\pi t} \; \varepsilon_{ft} \; \varepsilon_{st} \; \varepsilon_{\Delta it}\right]'$, and the structural model is

$$\Gamma_0 Z_t = \Gamma + \sum_{l=1}^{L} \Gamma_l Z_{t-l} + \varepsilon_t , \tag{9}$$

where Γ is a vector of constants. Following standard practice in the literature, we identify the structural parameters from OLS estimates of the reduced-form parameters of the unrestricted VAR,

$$Z_t = \Phi + \sum_{l=1}^{L} \Phi_l Z_{t-l} + u_t , \tag{10}$$

where $\Phi = \Gamma_0^{-1}\Gamma$, $\Phi_l = \Gamma_0^{-1}\Gamma_l$, and $u_t = \left[u_{\pi t} \; u_{ft} \; u_{st} \; u_{\Delta it}\right]'$, using OLS estimation. The structural parameters and innovations, Γ_0 and ε_t, can be identified by Cholesky decomposition (variable ordering) or by specifying structural relationships in Γ_0 and estimating the variance-covariance relationships implied by $u_t = \Gamma_0^{-1}\varepsilon_t$ using maximum likelihood.

[27] Inflation is measured with the CPI excluding food and energy. This VAR model is similar to that used by Ahmed, Levin, and Wilson (2004) and Stock and Watson (2002), among others. Three differences are: 1) it decomposes output into growth contributions that sum to output growth; 2) it excludes commodity prices, although our results are robust to their inclusion; and 3) it includes only M&T output growth. Although these two sectors account for a minority of total output in the economy, the goods sector overwhelmingly accounts for the bulk of the volatility of GDP growth (see Irvine and Schuh 2005 for details).

In the empirical work below, we compare three- and four-variable macro VARs (called Macro 3 and Macro 4) with the HAVAR model, which is a four-variable VAR with industries. The macro VARs are identified by Cholesky decomposition (ordered $[\pi_t \quad y_t \quad f_t]$ and $[\pi_t \quad s_t \quad \Delta i_t \quad f_t]$, respectively). We use maximum likelihood to estimate Γ_0 for the HAVAR identification scheme.

5.2 HAVAR Model

To investigate the relationships among industries, one must disaggregate the benchmark macro model by incorporating industry-level output growth – exactly the task that the HAVAR framework was designed to do. Define the HAVAR data and innovation vectors as

$z_t^* = [\pi_t \; f_t \mid \tilde{s}_{1t} \; \Delta\tilde{i}_{1t} \; \ldots \; \tilde{s}_{Jt} \; \Delta\tilde{i}_{Jt}]'$ and $\varepsilon_t^* = [\varepsilon_{\pi t} \; \varepsilon_{ft} \mid \varepsilon_{s1,t} \; \varepsilon_{\Delta i1,t} \; \cdots \; \varepsilon_{sJ,t} \; \varepsilon_{\Delta iJ,t}]'$,

where $j = \{1, 2, \ldots, J\}$ denotes industries, and the partition separates conceptually the macro variables (denoted by superscript m) from the aggregated variables (denoted by superscript a). Representative agents determine the macro variables in common macro markets. Individual agents determine the aggregated variables in micro markets, but the aggregated values of the micro variables have macroeconomic importance. The structural HAVAR model is

$$\Gamma_0^* z_t^* = \Gamma^* + \sum_{l=1}^{L} \Gamma_l^* z_{t-l}^* + \varepsilon_t^* , \tag{11}$$

and the reduced-form HAVAR model is

$$z_t^* = \phi^* + \sum_{l=1}^{L} \phi_l^* z_{t-l}^* + u_t^* . \tag{12}$$

Estimation and identification issues are analogous to those in the benchmark macro VAR model, but more challenging and addressed below in detail.

It is important to note that the *aggregate* HAVAR model, which is obtained by aggregating all output variables across industries, has two nonlinear properties.[28] Define the data vector as

$Z_t^* = [Z_t^m \mid Z_t^a]' = [\pi_t \; f_t \mid \tilde{s}_t^a \; \Delta\tilde{i}_t^a]'$, where superscript a denotes Tornqvist aggregation ($\tilde{x}_t^a = \sum_{j=1}^{J} \theta_{jt}^x x_{jt}$ for any growth contribution $\tilde{x}$). The residual vector is defined analogously. Then the reduced-form aggregate HAVAR model is

$$Z_t^* = \Phi_t^* + \sum_{l=1}^{L} \Phi_{t-l}^* Z_{t-l}^* + U_t^* . \tag{13}$$

[28] See Fratantoni and Schuh (2003) for more details.

This model exhibits nonlinearity through time-varying reduced-form parameters, due to aggregation, and through state-dependency on the initial output conditions of each industry, due to the presence of lagged industry-level innovations in the aggregate structural innovation. These nonlinear properties make HAVAR impulse responses time varying and state dependent, but we do not explore these features in this paper.

To simplify the notation for the purpose of addressing identification and estimation issues, we rewrite the contemporaneous portion of the HAVAR model as

$$\Gamma_0^* Z_t^* = \left[\begin{array}{c|c} \Gamma_0^{mm} & \Gamma_0^{ma} \\ \hline \Gamma_0^{am} & \gamma_0^{aa} \end{array}\right] \left[\begin{array}{c} Z_t^m \\ \hline \tilde{z}_t^a \end{array}\right] = \left[\begin{array}{c|cccc} \Gamma_0^{mm} & \Gamma_{0,1}^{ma} & \Gamma_{0,2}^{ma} & \cdots & \Gamma_{0,J}^{ma} \\ \hline \Gamma_{0,1}^{am} & \gamma_{0,11}^{aa} & \gamma_{0,12}^{aa} & \cdots & \gamma_{0,1J}^{aa} \\ \Gamma_{0,2}^{am} & \gamma_{0,21}^{aa} & \gamma_{0,22}^{aa} & & \vdots \\ \vdots & \vdots & & \ddots & \\ \Gamma_{0,J}^{am} & \gamma_{0,J1}^{aa} & \cdots & \cdots & \gamma_{0,JJ}^{aa} \end{array}\right] \left[\begin{array}{c} Z_t^m \\ \hline \tilde{z}_{1t}^a \\ \tilde{z}_{2t}^a \\ \vdots \\ \tilde{z}_{Jt}^a \end{array}\right], \tag{14}$$

where $Z_t^m = [\pi_t\ f_t]'$ contains the "macro" variables (superscript m) and $\tilde{z}_t^a = [\Delta\tilde{s}_{1t}\ \ \tilde{i}_{1t}\ \ldots\ s_{Jt}\ \ i_{Jt}]'$ contains the "aggregated" variables (superscript a). In this form, it is generally impossible to estimate for large J because the number of unrestricted parameters in γ_0^{aa} is large relative to the degrees of freedom in the available data. More identifying restrictions are needed to proceed.

5.3 Identification and Estimation

Identification issues differ for each quadrant of Γ_0, which contains $N^2 = (2J+2)^2$ potential parameters but only $N(N-1)/2$ unique parameters may be identified (see Christiano, Eichenbaum and Evans 1999). The simplest quadrant is Γ_0^{mm}, which contains only two off-diagonal parameters, but the other quadrants involve J industries and thus many more parameters. The two matrices governing interaction between the macro and aggregated variables, Γ_0^{ma} and Γ_0^{am}, each have $4J$ potentially different parameters. Following Fratantoni and Schuh (2003), we make a representative agent assumption for macro variables; hence $\Gamma_{0,j}^{ma} = \Gamma_0^{ma}\ \forall j$, so that only aggregate sales and aggregate inventory investment influence inflation and the federal funds rate. However, we do not make an analogous restriction on $\Gamma_{0,j}^{am}$, so macro variables have heterogeneous effects on industry output.[29]

[29] Heterogeneous responses of industry output to the fed funds rate and inflation (or the real rate) could arise for many reasons. Consumption of industries' final products, such as durable versus non-durable goods, may be interest sensitive in different ways. Firms within industries may experience different degrees of financial market imperfections, hence differential sensitivities to interest rates. These are two examples, but there may be others.

The most nettlesome identification issue pertains to γ_0^{aa}. This matrix contains by far the most potential parameters, with up to $4\left[J\times(J-1)\right]$, but it is precisely where the HAVAR model affords the opportunity to capture structural relationships among industries. We want to consider two characterizations of γ_0^{aa},

$$\gamma_{0,U}^{aa}=\begin{bmatrix}\gamma_{0,1}^{aa} & 0 & \cdots & 0\\ 0 & \gamma_{0,2}^{aa} & & \vdots\\ \vdots & & \ddots & 0\\ 0 & \cdots & 0 & \gamma_{0,J}^{aa}\end{bmatrix} \quad \text{and} \quad \gamma_{0,C}^{aa}=\begin{bmatrix}\gamma_{0,11}^{aa} & \gamma_{0,12}^{aa} & \cdots & \gamma_{0,1J}^{aa}\\ \gamma_{0,21}^{aa} & \gamma_{0,22}^{aa} & & \vdots\\ \vdots & & \ddots & \vdots\\ \gamma_{0,J1}^{aa} & \cdots & \cdots & \gamma_{0,JJ}^{aa}\end{bmatrix},$$

representing an uncoupled (U) and coupled (C) economy, respectively. Comparing changes in structural parameters and the variances of structural innovations in both economies helps to quantify the importance of changes in comovement in a way that a purely aggregate model cannot. The uncoupled economy contains a small, more feasible number of parameters to identify, but it forfeits the chance to characterize the importance of relationships between industries. On the other hand, as J increases, estimation of the coupled economy demands greater and greater identifying restrictions on the relationships between industries.

Faced with the cost-benefit tradeoff of disaggregation, we take a simple first step and construct a two-industry $(J=2)$ HAVAR model for manufacturing (M) and trade (T), the latter including wholesale and retail. Given the importance of the correlation changes in the auto industry between manufacturers and retailers highlighted in Section 2, and the disproportionate importance of the auto industry, this two-sector simplification likely captures the most important aspects of the aggregate implications of changes in relationships among industries.[30] Furthermore, to minimize the scope for spurious changes in coefficients caused by over-fitting, we demonstrate the importance of comovement in the most highly aggregative model before disaggregating more.

The most general version of the model's contemporaneous matrix is:

$$\Gamma_0^* Z_t^* = \left[\begin{array}{cc|cccc} 1 & \gamma_{\pi f} & \gamma_{\pi s}^{T} & \gamma_{\pi\Delta i}^{T} & \gamma_{\pi s}^{M} & \gamma_{\pi\Delta i}^{M}\\ \gamma_{f\pi} & 1 & \gamma_{fs}^{T} & \gamma_{f\Delta i}^{T} & \gamma_{fs}^{M} & \gamma_{f\Delta i}^{M}\\ \hline \gamma_{s\pi}^{T} & \gamma_{sf}^{T} & 1 & \gamma_{s\Delta i}^{TT} & \gamma_{ss}^{TM} & \gamma_{s\Delta i}^{TM}\\ \gamma_{\Delta i\pi}^{T} & \gamma_{\Delta if}^{T} & \gamma_{\Delta is}^{TT} & 1 & \gamma_{\Delta is}^{TM} & \gamma_{\Delta i\Delta i}^{TM}\\ \gamma_{s\pi}^{M} & \gamma_{sf}^{M} & \gamma_{ss}^{MT} & \gamma_{s\Delta i}^{MT} & 1 & \gamma_{s\Delta i}^{MM}\\ \gamma_{\Delta i\pi}^{M} & \gamma_{\Delta if}^{M} & \gamma_{\Delta is}^{MT} & \gamma_{\Delta i\Delta i}^{MT} & \gamma_{\Delta is}^{MM} & 1 \end{array}\right] \left[\begin{array}{c}\pi_t\\ f_t\\ \hline \tilde{s}_t^{T}\\ \Delta\tilde{i}_t^{T}\\ \tilde{s}_t^{M}\\ \Delta\tilde{i}_t^{M}\end{array}\right]. \tag{15}$$

[30] In future work we plan to explore larger industry HAVAR systems based on the principal component results earlier in the paper that highlight the importance of specific industries such as autos, oil, and food.

This specification contains 30 parameters but only 15 can be identified and estimated. Using the HAVAR approach, we impose the following restrictions:

- In Γ_0^{mm}, we impose an ordering of π and f, appealing to short-run price stickiness and inflation persistence ($\gamma_{\pi f} = 0$).
- In Γ_0^{ma}, we make a representative agent assumption such that only the aggregate values of the industry variables influence the macro variables ($\gamma_{\pi s}^{T} = \gamma_{\pi s}^{M}$ and likewise for the other parameters). We also impose an ordering of π and y, again appealing to short-run price stickiness and inflation persistence ($\gamma_{\pi y} = \gamma_{\pi \Delta i} = 0$).[31] Note that the federal funds rate equation is analogous to a Taylor-type monetary policy rule, except that output is expressed as a growth rate rather than a gap from potential output. Here the representative agent assumption is justified: the monetary authority only targets aggregate variables. However, it is interesting to test whether the federal funds rate responds similarly to sales and inventories ($\gamma_{fs} = \gamma_{f\Delta i} = \gamma_{fy}$), as is commonly assumed.
- In Γ_0^{am}, we restrict the parameters on π and f such that the *ex post* real rate influences the industry variables ($\gamma_{sf}^{T} = -\gamma_{s\pi}^{T}$, and likewise for the other parameters). However, we allow the effects to differ across industries and for sales versus inventories.
- In Γ_0^{aa}, the restrictions are not obvious and there is little empirical precedent, so the final decisions were made after iterating between theory and evidence. First, we impose an ordering of Δi and s *within* industries, so innovations to inventory investment do not affect sales contemporaneously ($\gamma_{s\Delta i}^{T} = \gamma_{s\Delta i}^{M} = 0$). Innovations to sales, on the other hand, do affect inventory investment ($\gamma_{\Delta is}^{T}, \gamma_{\Delta is}^{M} \neq 0$), and the effect differs across industries. These parameters will be negative (hence a positive correlation between inventory investment and sales) if expected sales dominate movements in total sales and vice versa if unexpected sales dominate. This ordering leaves the diagonal industry sub-matrices in Γ_0^{aa} as lower triangular.

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[31] This ordering restriction is supported by the data as well. Not only are these coefficients statistically insignificant, allowing them to be nonzero causes problems in the estimation of the other parameters.

- Finally, we address the off-diagonal, *between*-industry sub-matrices in Γ_0^{aa}. These parameters are important determinants of manufacturing and trade linkages through supply and distribution chains. One possibility is a strict ordering of industries (γ^{aa} lower triangular), most likely trade first then manufacturing. However, this strong assumption is sensible only if all manufactured goods are distributed to the trade sector before going to final customers, and the main driving force behind output fluctuations is changes in domestic final demand.[32] Instead, we argue for a small number of theoretically intuitive and empirically supported linkages. First, we link industries' sales ($\gamma_{ss}^{TM}, \gamma_{ss}^{MT} \neq 0$). Regardless of whether driving forces originate on the final demand side or the upstream supply side, sales shocks in one sector should influence sales contemporaneously in the other. Whether the linkage is the same in both directions is an empirical issue – because we cannot reject that hypothesis, we restrict the sales linkage parameter accordingly ($\gamma_{ss}^{TM} = \gamma_{ss}^{MT} = \gamma_{ss}$). Theoretical linkages between industries are much less clear for inventories. None of the remaining six parameters involving inventories offers a compelling reason for being *necessarily* nonzero, so we let the data decide which to include. Only one parameter ($\gamma_{s\Delta i}^{MT}$) showed any evidence of being statistically and economically significant, and it changed dramatically between periods. Apparently, shocks to trade inventory investment necessarily influence domestic manufacturing sales contemporaneously.[33] Rather than allowing for spurious linkages admitted through imprecise econometric estimates, we set the other five parameters to zero.

[32] This industry ordering could be violated for many reasons. Most obviously, upstream supply shocks could hit manufacturers first and then influence trade. Furthermore, manufacturers can do business directly with foreign firms and consumers (exports and imports), or they can bypass the domestic trade industry and sell directly to domestic customers. Also, trade includes wholesalers, some of whom supply intermediate goods to manufacturers. These are a few examples of how a strict ordering (distribution chain) may break down. In any case, industry ordering has little effect on the dynamic characteristics of aggregate variables in the identified M&T HAVAR model.

Together, these restrictions redefine the contemporaneous HAVAR relationships as follows:

$$\Gamma_0^* z_t^* = \left[\begin{array}{cc:cccc} 1 & 0 & 0 & 0 & 0 & 0 \\ -\gamma_{f\pi} & 1 & -\gamma_{fs} & -\gamma_{f\Delta i} & -\gamma_{fs} & -\gamma_{f\Delta i} \\ \hdashline -\gamma_{sr}^{T} & \gamma_{sr}^{T} & 1 & 0 & -\gamma_{ss} & 0 \\ -\gamma_{\Delta ir}^{T} & \gamma_{ir}^{T} & -\gamma_{is}^{TT} & 1 & 0 & 0 \\ -\gamma_{sr}^{M} & \gamma_{sr}^{M} & -\gamma_{ss} & -\gamma_{s\Delta i}^{MT} & 1 & 0 \\ -\gamma_{\Delta ir}^{M} & \gamma_{ir}^{M} & 0 & 0 & -\gamma_{is}^{MM} & 1 \end{array}\right] \left[\begin{array}{c} \pi_t \\ f_t \\ \hdashline \tilde{s}_t^T \\ \tilde{i}_t^T \\ \tilde{s}_t^M \\ \tilde{i}_t^M \end{array}\right]. \quad (16)$$

With only 11 parameters to estimate, this specification is over-identified.

We have explored many alternative identification schemes and found the qualitative dynamic properties of the model to be relatively robust. The standard ordering identification of inflation, output, and the interest rate $[\pi_t \quad s_t \quad \Delta i_t \quad f_t]$, which is relatively common in the literature, produces qualitatively similar impulse responses.[34] The only qualitative difference is that the HAVAR model allows a contemporaneous effect of real rates on output while the ordering identification does not. Alternative orderings and restrictions among the between-industry parameters on sales and inventory investment have very little effect on the dynamic properties of aggregate variables (although they do affect the dynamic properties of the industries, obviously).

5.4 HAVAR Model Variance Decompositions

Our first exercise decomposes the unconditional variances of model variables into structure versus model residuals, and calculates their implied contributions to change from the early period to the late period. Table 6 reports the decomposition for the reduced-form model (structure Φ and residuals u_t), and Table 7 reports the decomposition for the identified model (structure Γ and innovations ε_t). Both tables report results for a three-variable aggregate model (Macro 3) and a four-variable aggregate model (Macro 4), as well as the coupled HAVAR model.[35]

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[33] The reason probably is because the main way for domestic trade firms to build up trade inventories is to buy goods from domestic manufacturers. Trade firms could buy (import) or sell (export) goods from/to foreign producers too, but it seems unlikely that domestic trade firms could rely exclusively on foreign trade.

[34] To obtain results comparable to the literature, especially Ahmed, Levin, and Wilson (2004) and Stock and Watson (2003), we identified a HAVAR model using a variable ordering scheme that is close to the Cholesky decomposition. All of the results under this alternative identification are qualitatively similar and available from the authors upon request. However, identification by strict ordering of variables poses a potential problem for the HAVAR model because it imposes order among the microeconomic agents – in this case two large, interrelated industries – that may not be warranted. Another potential problem is that it is unlikely that any industry is unresponsive to shocks in another industry for an entire quarter (frequency of our data).

[35] The uncoupled HAVAR model results are not reported because they tend to be quite similar to the four-variable macro VAR, apparently because the most important structural changes occurred in the parameters governing the relationships between industries rather than between each industry and the aggregated and macro variables.

The structure of the reduced-form models account for less than half the change in output variance. Table 6 shows that the macro VAR models account for 39 to 44 percent of the change in output variance, and the reduced-form HAVAR model structure accounts for only 45 percent – a negligible improvement. The remainder is accounted for by the reduced-form residuals. Note that these reduced-form models account for much more of the change in volatility of inflation (64 percent) and the funds rate (87 percent). This finding is consistent with the literature.

However, these results mask the importance of contemporaneous correlation among the system variables. The analogous exercise for the identified HAVAR model (Table 7) shows a much more substantial increase in the importance of the estimated structure in explaining the change in output variance. For Macro 3, the estimated structure accounts for only 39 percent of the change in output volatility, the same as the reduced form. The decomposition of output into sales and inventory investment in Macro 4 raises the contribution of the structure to 54 percent. This nontrivial increase is important in its own right.[36]

The importance of structural change increases markedly more when output is disaggregated into two industries (bottom panel, Table 7). The estimated structure of the coupled HAVAR model accounts for 82 percent of the change in output volatility, while innovations (shocks) account for only 18 percent. Changes in the structure are more important for aggregate sales (82 percent) than for aggregate inventory investment (60 percent).

Because VAR models are well known to be sensitive to identifying restrictions, we explored the full range of potential alternative ordering schemes to ensure that our results on HAVAR decompositions are robust. For each ordering of the macroeconomic variables and each ordering among the sales and inventory investment variables, we recalculated the variance decompositions. The last two rows of Table 7 report the average decomposition ($\bar{y}$) and the standard deviation of the decompositions over the alternative orderings, (s.d.). The average contribution of the structure in the HAVAR model to the change in output variance is 88 percent – even higher than the benchmark identification given by equation (16) – and variation across orderings is modest, with contributions ranging from 80 to 96 percent for two standard deviations.

The results in Table 7 show that accounting for changes in structural relationships among industries weakens the case for "good luck" in explaining the reduction of output volatility. Instead, the HAVAR model reveals a much greater potential role for changes in inventory and production

[36] Ahmed, Levin, and Wilson (2004) also point out that decomposing output into sales and inventory investment components weakens their evidence for the good luck hypothesis, with the change in their model structure accounting for almost half of the change in variance. Our HAVAR results amplify and clarify this point.

management techniques – economic behavior revealed in the structure – in explaining the volatility reduction. Interestingly, the HAVAR structure does not alter by much the estimated contribution of the structure to changes in the volatility of the other two macroeconomic variables, π_t and f_t. Rather, the results underscore the critical importance of recognizing and estimating the change in the covariance structure among the aggregated (industry) variables in the economy instead of among the macroeconomic variables.

5.5 HAVAR Model Counterfactual Simulations

Our second exercise is a series of counterfactual simulations of the coupled HAVAR model, reported in Table 8. The table contains the unconditional variances of model variables from simulations that mix and match the estimated structure (Γ) in the early and late periods with the estimated innovations (ε_t) in the two periods.[37] The first panel reports simulations designed to match the data with structure and shocks from the same period. The first line shows that the early-period HAVAR structure produced a simulated unconditional variance of output growth of 5.01, quite close to the actual early-period variance of 5.15 in Table 4. Simulated output variance fell to 0.77 in the later period, a decline of 4.24. When the volatile early-period innovations are combined with the late-period HAVAR structure, the simulated unconditional variance of output growth falls to 3.36 (line 4). Thus, changes in the HAVAR structure alone account for a 39 percent decline in output volatility ($5.01 - 3.36 = 1.65$, as a percent of the 4.24 point decline). Thus, according to the HAVAR model, changes in the economic structure among industries likely had a significant damping effect on shocks to the system.

The estimated contribution of changes in structure to the reduction in output volatility is lower in the counterfactual simulations of Table 8 than in the complete decompositions of Table 7 (39 versus 82 percent). Part of the reason is that the counterfactual simulations do not account for the decline in the proportion of variance explained by the structure within each period. Table 7 shows that the structure accounted for 79 percent of the variance of output growth in the early period but only 64 percent in the late period. Because output variance was much larger in the early period, the reduction in variance explained by the model within the periods (79 to 64 percent) also comprises a significant part of the reduction in output volatility. Put another way, while shocks actually account for more output volatility in the later period (36 versus 21 percent), the shocks account for a much smaller portion of the reduction in output volatility between the periods.

[37] For easier comparison, Table 8 is analogous to Tables 11-13 in Ahmed, Levin, and Wilson (2004).

5.6 HAVAR Model Parameter Estimates

Examination of the estimates of HAVAR contemporaneous parameters provides clearer insights into the nature of the structural changes driving the reduction in aggregate output volatility. Table 9 reports estimates of Γ_0 for each of the macro models plus the coupled HAVAR model. Results are divided into three panels of contemporaneous relationships: 1) the effect of inflation on output, which in the HAVAR model works through real rates; 2) the effects of inflation and output on the federal funds rate (shaded region); and 3) the effects of sales and inventory investment on sales and inventory investment within and between industries. Note that because of the simultaneous nature of Γ_0, the parameter estimates are the opposite sign of the partial contemporaneous correlation between any two variables. The discussion below refers to these contemporaneous correlations, which have the opposite signs as the coefficients in the table.

Inflation exhibits a greater influence on output in the late period. In the Macro 3 model, inflation reduces output ($\hat{\gamma}_{y\pi} > 0$) much more in the late period. Although the effect is not statistically significant, it is economically significant. However, there is stark heterogeneity in the impact of inflation on output apparent in the Macro 4 model. Inflation reduces sales ($\hat{\gamma}_{s\pi} > 0$) but increases inventory investment ($\hat{\gamma}_{\Delta i\pi} < 0$), the latter effect being statistically significant only in the later period. Although the parameter changes are not statistically significant in the Macro 4 model either, their economic importance is greater.

The coupled HAVAR model, which restricts the impact of inflation on output to the real interest rate, reveals further structural changes that vary across industries. In general, sales are positively correlated ($\hat{\gamma}_{sr} < 0$) with the real rate and inventory investment is negatively correlated ($\hat{\gamma}_{\Delta ir} < 0$) with the real rate. Presumably, these results reflect the long-run relationship between consumption and the real rate (positive) and the financing cost relationship between inventory investment and the real rate (negative).[38] In general, most of these individual coefficients are statistically insignificant as well; those on sales in the late period are the most significant. The late-period estimates are larger in absolute value (economic significance) for all parameters.

Strong evidence of structural change also appears in the effects of inflation and output on the federal funds rate. In the Macro 3 model, inflation and output are positively correlated with the federal funds rate ($\hat{\gamma}_{f\pi} < 0$ and $\hat{\gamma}_{fy} < 0$), but both correlations declined in the late period – especially

[38] Apparently, the negative financing cost relationship between fixed investment and the real rate is dominated by the consumption-real rate relationship.

the output effect, which became statistically insignificant in the late period. Consequently, inflation became a relatively more important determinant of the federal funds rate, a finding consistent with the literature on monetary policy reaction functions. However, the Macro 4 model reveals a striking difference in the impact of sales and inventory investment on the federal funds rate. In the early period, sales and the funds rate are positively correlated ($\hat{\gamma}_{fs} < 0$), while inventory investment is negatively correlated ($\hat{\gamma}_{f\Delta i} > 0$, but statistically insignificant). In the late period, the results reverse: inventory investment is significant and positively correlated with the funds rate, while the sales are essentially uncorrelated and statistically insignificant. The structural change in the correlation of inventory investment and the funds rate from negative ($\hat{\gamma}_{f\Delta i} > 0$) to positive ($\hat{\gamma}_{f\Delta i} < 0$) between periods is economically and statistically significant. This change is estimated to be even stronger in the coupled HAVAR model, but it does not depend on industry heterogeneity because it is evident in the Macro 4 model.

Apparently, an important part of understanding changes in monetary policy lies in understanding the effects of inventory investment on the federal funds rate. This novel and robust result is at least tangentially related to the finding by Onatski and Williams (2004) that simple, approximately optimal monetary policy rules may depend heavily on investment, which in their case includes only fixed investment. Our result suggests that structural changes in inventory behavior also may have altered the conduct of monetary policy – actual and possibly optimal too – rather than vice versa. Given the importance of inventory investment in business cycles, these results relating investment and monetary policy would seem to merit further research.[39]

The HAVAR model highlights changes in the importance of relationships between sales and inventory investment among industries. In the Macro 4 model, all interactions between inventory investment and sales are captured in one parameter, ($\hat{\gamma}_{\Delta is} < 0$), which reflects a positive correlation (statistically significant only in the early period). In contrast, the coupled HAVAR model features four parameters that govern explicit linkages between sales and inventory investment among industries. These parameters exhibit much more economic and statistical significance in the relationships between sales and inventory investment among industries than is apparent in the Macro 4 model alone. They also exhibit more evidence of significant structural change.

[39] More research with structural models is needed to disentangle the effects of changes in the conduct of monetary policy (reaction function parameters internalized by rational agents) from the impact of aggregate inventory investment on the federal funds rate (through changes in production and inventory management techniques).

Consider first the parameters that characterize the relationship *within* industries between sales and inventory investment ($\hat{\gamma}^{TT}_{\Delta is}$ and $\hat{\gamma}^{MM}_{\Delta is}$). These parameters were both negative in the early period, signifying a positive relationship (statistically significant only in manufacturing). In the late period, the trade parameter switched dramatically to a positive number, signifying a negative relationship; the manufacturing parameter became essentially zero.[40]

Next consider the parameters that characterize the relationships *between* industries among sales and inventory investment. Sales in the two industries are positively correlated ($\hat{\gamma}_{ss} < 0$) and very statistically significant. However, this correlation declined in the late period by an economically significant margin, especially given the importance of reduced comovement between sales among industries noted in Section 3 and Table 4. Also, the results show that manufacturing sales are very positively correlated with trade inventories ($\hat{\gamma}^{MT}_{s\Delta i} < 0$), and this correlation increased very significantly in the late period – by far, the largest structural change in any contemporaneous parameter estimate. Once again, the coupled HAVAR model draws out economically important differences among industries underlying the parameters of macro models.

Note that the coupled HAVAR results appear to reflect the changes in the auto industry correlations reported in Table 2 and the introduction. The results for $\gamma^{TT}_{\Delta is}$ are related to the reduction in correlation between retailers' sales and retailers' inventories (from .15 to $-.44$ in Table 2), suggesting a greater buffer stock role for inventories in the later period. The results for γ_{ss} are related to the reduction in correlation between manufacturers' sales and retailers' sales (from .63 to .08 in Table 2). Finally, the results for $\gamma^{MT}_{s\Delta i}$ are related to the reduction in correlation between manufacturers' sales and retailers' inventories (from .72 to .56 in Table 2).

As a final check on the potential role of changes in the input-output structure, we report data for the major industrial sectors underlying our M&T HAVAR model in Table 10. The top two panels focus on manufacturing and trade, and the next two panels provide further evidence for the wholesale and retail components of trade. Other represents all sectors besides manufacturing and trade. The input of manufacturing into both manufacturing and trade has declined modestly (-5.5 and -7.1 percentage points, respectively), but these inputs have been offset by greater inputs from other sectors, not from trade. Nevertheless, the changes are not very large. Within the trade sector,

[40] These results may seem odd in light of standard target-stock theories of inventory behavior, which specify a positive relationship between *expected* sales and the *level* of inventories. However, in the HAVAR model, $\gamma_{\Delta is}$ reflects the relationship between the growth contributions of sales and inventory investment. The switch in sign may reflect more use of inventories as a buffer stock in the late period.

however, there is somewhat greater evidence of change in the input-output structure. For example, manufacturing input to retail trade fell by 9.9 percentage points and other input rose 11.0 percentage points. These changes may be large enough to help account for some of the changes in the structural coefficients of the HAVAR model, but a more detailed analysis is needed.

5.7 HAVAR Impulse Response Functions

This section examines the dynamic properties of the M&T HAVAR model in the early and late periods. We consider two aggregate shocks, 1 percentage point increases each in the federal funds rate and inflation, and two sector-specific shocks, 1 percentage point increases in sales growth of one industry only.[41] Shocks to trade sales pertain to final ("downstream") demand, and shocks to manufacturing sales pertain to intermediate ("upstream") demand. In each simulation, the focus is on responses of output growth in each sector and in the aggregate (sum of the industry growth contributions) for 12 quarters. Figures 6 and 7 plot the impulse responses; Tables 11 (volatility ratios) and 12 (correlations) report summary statistics for the impulse responses.

Two key results emerge from the dynamic analysis, which clarify the structural change. First, output is less volatile throughout the HAVAR system. The impulse response of aggregate output to each of the four shocks is much less volatile in the late period (see Figures 6 and 7 and the first row of Table 11), with declines running from 59 percent for the fed funds shock to 31 percent for the manufacturing sales shock. Moreover, the impulse responses of industry-level output are less volatile in both industries to each shock except for the trade output response to an inflation shock. Volatility also declined generally for the sales responses, except for the inflation shock.

In contrast, the volatility of the inventory investment responses increased significantly. The volatility of aggregate inventory investment responses in the HAVAR system more than doubled, and the volatility of trade inventory investment responses to inflation and manufacturing sales shocks increased by an order of magnitude. The only evidence of reduced volatility in inventory investment is in the responses of manufacturing inventories to all shocks except the fed funds shock. This result implies that the reduction in output volatility occurred through changes in the relationships among sales and inventory investment (more on this later).

Finally, the volatility of the shocks themselves also declined significantly, especially the aggregate shocks (fed funds and inflation). The last panel of Table 11, which reports the volatility ratios for the HAVAR shocks, indicates that the volatility of the shocks declined by a factor of four or more for all but the trade sales shock – which is the least variable shock in both periods. This result indicates that the HAVAR model attributes significant reductions in output volatility both to changes in dynamic structure (impulse responses) and to reductions in shock variances.

A second key result is that comovement declined throughout the HAVAR system. The first two rows of Table 12 reveal significant reductions in the correlation between industries of the output and sales impulse responses. In the early period, the output and sales responses in the trade and manufacturing industries moved nearly one-for-one (left panels of Figures 6 and 7). However, the correlation between industries dropped dramatically in the late period, by about $-.5$ for aggregate shocks and about $-.25$ for sector-specific shocks.[42] In the data, this output correlation declined from .73 to .55 (or $-.18$).

A striking feature of the decline in output volatility is the heterogeneity in the nature of the decline in comovement across shocks. In response to a fed funds shock, there is a phase shift in the impulse responses of trade and manufacturing output (top row, Figure 6). Despite little change in the peak industry responses, aggregate output volatility declined because the industry responses became staggered. In the late period, trade output responds much more quickly to the fed fund shock and is much less persistent. Although the changes are less dramatic, manufacturing output also responds more quickly and is less persistent. As a result, aggregate output growth also responds sooner and recovers more quickly in the late period.

In contrast, the responses of manufacturing output and trade output to other shocks become very negatively correlated without any phase shift. The manufacturing and trade output responses to an inflation shock in the late period are almost perfectly negatively correlated for more than a year after the shock, which greatly dampens the aggregate output response. The general picture conveyed by the inflation shock is that aggregate output was very sensitive to inflation before 1984, but is relatively insensitive since. Likewise, the responses to sector-specific sales shocks are also negatively correlated, but only for one period, so the reduction in comovement is much less.

5.8 Further Economic Interpretations

The HAVAR results portray widespread uncoupling of industry output growth, especially in response to aggregate shocks, and the uncoupling appears to have very different implications for sales

[41] This sales shock represents an increase in demand for the industry's product for any reason other than a change in interest rates or inflation.

[42] Perhaps not surprisingly, the reduction in comovement of industry output in response to sector-specific sales shocks is not entirely robust to identification. For certain identification schemes involving quite different parameters between industries, comovement declines little if at all. However, the reduction of aggregate output volatility is entirely robust to identification, and the reduction of industry output volatility is generally robust to identification.

than for inventory investment. To gain more economic intuition for these results, we examine some of the comovement properties of industry-level sales and inventory investment responses.

Consider the responses to a fed funds rate shock, portrayed in Figure 8. In the early period (top panel), a fed funds rate shock produced little initial response in sales or inventory investment. The modest responses that did occur exhibited substantial positive comovement. By the third period, sales in both industries begin declining significantly. Inventory investment responses lag sales by about one quarter, but are also positively correlated. In the late period, however, most positive comovement disappears. On impact (period 1), the funds rate shock – which acts explicitly as a change in the real interest rate in the HAVAR model – moves sales and inventory investment sharply in opposite directions. Apparently, inventories play a greater buffer-stock role in the late period even though output (production) is not smoothed perfectly. This result is especially evident in trade, where sales plummet in the second period and inventory investment moves in the opposite direction. This negative correlation between trade sales and inventory investment helps stabilize trade output and sales recover much more quickly. In manufacturing, sales and inventory investment move in opposite directions for two periods, but sales eventually decline sharply in the third period and thereafter sales and inventory investment move together positively.

More generally, a decline in correlation between sales and inventory investment was widespread, often with a change in sign from positive to negative. As the remaining rows of Table 12 show, this correlation declined both within industries (last two rows) and between industries (middle rows). Correlations between sales and inventory investment within industries fell dramatically – except for the responses in manufacturing to fed funds shocks and trade sales shocks, which are both final demand shocks and less likely to influence manufacturing directly. In trade, the sign switch of the correlation between sales and inventory investment (from positive to highly negative) in response to all types of shocks suggests the adoption of inventory policies that achieve greater buffering of production from sales shocks. Correlations between sales and inventory investment between industries also fell dramatically in most cases, the primary exception being the responses to the sector-specific sales shocks.

We interpret changes in comovement between industries' sales and inventory investment, manifest in the HAVAR model structure, as likely evidence of changes in production and inventory management techniques along supply and distribution chains. Less comovement between sales and inventory investment within and between industries suggests that some industries might exhibit lower production variance relative to sales variance. The inventory literature has focused on production smoothing in manufacturing induced by convex cost functions and rising marginal cost. But in the data, the ratio of production variance to sales variance declined only for trade (from 1.46 to 1.05), while it was essentially unchanged (about 1.2) in manufacturing and for aggregate M&T sector. This increase in production smoothing (or decrease production bunching) by trade firms really means that deliveries from their suppliers along distribution chains exhibit less variance relative to their sales. We hypothesize that lower variance of deliveries resulted from the adoption of new inventory management techniques, such as improved information and inventory control systems, that enable firms to keep stocks closer to their desired levels.[43]

Our results are related to those of Ramey and Vine (2004) but provide a more complex interpretation of the data. Ramey and Vine emphasize the importance of a reduction in sales persistence in the automobile industry, which they argue brings about a large reduction in output volatility because of non-convexities in production. The HAVAR sales responses to a fed funds shock also exhibit lower persistence of sales, but only for trade and aggregate sales and not for manufacturing sales. However, HAVAR sales responses to other shocks do not exhibit a systematic reduction in the persistence at the industry or aggregate level – and yet output volatility declines in response to all shocks.[44] This result suggests that lower sales persistence is not a necessary condition for lower output volatility, and that the Ramey-Vine hypothesis may not generalize to all shocks, industries, or the macroeconomy.[45]

As a final check on the model, we report the full variance decomposition of aggregate output using the HAVAR impulse responses to a fed funds shock in Table 13 (which is analogous to Table 4).[46] The model is able to broadly replicate most of the qualitative variance-covariance results in the data. First, changes in covariance between industries' output accounts for most of the change in aggregate output variance (61.7 percent). Second, between-industry covariance also is more important for aggregate sales variance (58.6 percent) and the aggregate covariance between sales and

[43] Trade firms may purchase goods from manufacturers via (S,s) ordering policies, which naturally exhibit production bunching. If so, the large decline in output (delivery) volatility would suggest that the new inventory management techniques may have reduced the optimal lot size $(S-s)$ or perhaps even involved a shift away from (S,s) ordering policies, which would occur if the techniques eliminated fixed ordering costs that make (S,s) optimal.

[44] The persistence of HAVAR sales responses does not change uniformly across shocks or industries (and aggregate). In some instances persistence falls, in others it rises, and still others it is unchanged.

[45] The HAVAR model does reveal large changes in the coefficients on lagged interest rates in the sales equations for both industries. Without a more structural model, it is not possible to determine whether those changes are attributable to changes in monetary policy rules or changes in the structure of the real economy associated with the adoption of new inventory and production management techniques. However, there are also large changes in the coefficients on sales and inventory investment from the other industry in the industry sales equations, and these changes are at least as important to the model behavior. In contrast, the coefficients on the own-sales autoregressive parameters are relatively stable in the HAVAR system.

[46] The decompositions for the other three types of shocks are qualitatively similar so we do not report them separately.

inventory investment (56.8 percent), but it is relatively unimportant for aggregate inventory investment variance (32.7 percent). Third, the reduction in variance of aggregate sales accounts for about three-quarters (78.0 percent) of the reduction in variance of aggregate output.

Clearly, one feature of the estimated HAVAR model that is inconsistent with the data is the excess volatility of inventory investment. The variance of HAVAR inventory investment actually increases in the late period, the HAVAR correlations between inventory investment and sales decline too much, and aggregate HAVAR production variance declines relative to sales. These counterfactual results are at least partly attributable to the crude theoretical relationship between inventories and sales at the industry level. The HAVAR model implies a long-run relationship between sales and inventory *investment*, whereas the inventory literature typically specifies a long-run target-stock relationship between sales and the *level* of inventories.

6. Conclusions

The decline in volatility of U.S. GDP growth since 1983 was accompanied by reduced comovement of output among U.S. industries that hold inventories. Our estimates of a standard factor model show that this decline in comovement was not the passive byproduct of a reduction in the volatility of common factors. Rather, estimates of a relatively simple two-sector HAVAR model reveal that the structure of the U.S. economy has undergone important changes in the behavior of sales and inventory investment among goods-producing industries. These structural changes reduced comovement between sales and inventory investment, often turning it negative, both within industries and between industries linked by supply and distribution chains. A greater buffer stock role for inventories led to more production smoothing and less comovement of output among industries for all kinds of economic shocks. As a result of these changes, the volatility of aggregate output growth declined.

Our results significantly weaken the case for the "good luck" hypothesis that the U.S. economy simply has been fortunate to have experienced less volatile shocks since 1983. Although this conclusion appears to be correct using small macroeconomic models and aggregate data only, it not robust to even minimal disaggregation. When the goods-producing sector is broken up into just two industries (manufacturing and trade), structural changes in the relationships among the sales, inventory investment, and output behavior among industries become quite clear. Drawing this conclusion required disaggregated data and an integrated macroeconomic framework, and underscores the importance of heterogeneity in macroeconomic analysis. Further disaggregation may be redundant for demonstrating the importance of structural change but it would provide a more refined economic explanation for the changes in relationships among industries.

Our results do not rule out changes in monetary policy or sales persistence as contributing factors in the decline in aggregate output volatility, but the evidence does suggest that changes in production and inventory management techniques likely played a central role. The fact that output volatility and comovement between industries both declined in response to all kinds of shocks (not just monetary policy shocks) suggests that something probably changed in the structure of the real side of the economy. Nevertheless, the economy's dynamic responses to monetary policy shocks did change and these changes are different from the responses to other types of shocks. This fact, along with apparent changes in the monetary policy rule, suggests that something associated with monetary policy changed. Whether it was a change in the policies and preferences of the Federal Reserve, or a change in the private sector's ability to perceive and respond to monetary policy, or both, is not identifiable from our analysis.

This last point underscores a limitation of our empirical approach. The HAVAR model proved useful for revealing structural changes associated with the covariance structure of industries' sales, inventory investment, and output that played a significant role in reducing aggregate volatility. However, the relatively weak identification in a HAVAR model (like VAR models) obscures a full explanation of exactly how the structure of the economy changed in terms of fundamental preference and technology parameters. Instead, more theoretical and empirical research is needed to develop more structural, dynamic optimizing models of inventory behavior in a multi-sector environment with supply and distribution chains among firms. Such models are needed to understand the precise nature of the structural changes in production and inventory management techniques and their implications for aggregate behavior and policy.

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Table 1
Contributions to the Reduction in Variance of Real GDP Growth

	Share (%) of the reduction in GDP variance
Real GDP	**100**
Variance terms	**60**
Goods sector output	51
Final sales	20
Inventory investment	31
Services sector output	0
Structures sector output	9
Covariance terms	**40**
Goods sales and inventory investment	13
Goods output and services output	6
Goods output and structures output	19
Services output and structures output	2

NOTE: Table shows the percentage contribution of each variable to the change in the variance of real GDP growth from the period 1959-1983 to the period 1984-2002. Variables other than GDP are chain-weighted growth contributions, as defined in the National Income and Product Accounts. Shares of variance reductions may not add due to rounding.

SOURCES: Haver Analytics, Inc., Bureau of Economic Analysis.

Table 2
Correlation Among Sales and Inventories in the Automobile Industry

			SIC 371 Manufacturing		SIC 551 Retailers	
			s_t	Δi_t	s_t	Δi_t
Early Period (1967:Q2-1983:Q4)	**SIC 371**	s_t	1			
		Δi_t	.01	1		
	SIC 551	s_t	.63	-.04	1	
		Δi_t	.72	-.13	.15	1
Late Period (1984:Q1-2001:Q1)	**SIC 371**	s_t	1			
		Δi_t	.06	1		
	SIC 551	s_t	.08	.04	1	
		Δi_t	.56	.10	-.44	1
Correlation Change (Late-Early)	**SIC 371**	s_t	1			
		Δi_t	**.05**	1		
	SIC 551	s_t	**-.55**	**.08**	1	
		Δi_t	**-.16**	**.23**	**-.60**	1

NOTES: Table shows the correlation of the growth contributions of real sales and real inventory investment to real output growth.

SOURCES: Haver Analytics, Inc., Bureau of Economic Analysis.

Table 3

Input and Output Use Data

Motor Vehicles and Retail Trade

Industry	Input	1977-82 Rank	1977-82 Share	1987-92 Rank	1987-92 Share	Change
Motor vehicles	Motor vehicle parts	1	36.1	1	34.1	-2.1
	Automotive stampings	2	10.5	3	8.8	-1.7
	Wholesale trade	3	9.3	2	9.7	.5
	Motor vehicles	4	5.4	20	1.0	-4.4
	Automotive & apparel trimmings	5	2.8	7	2.2	-.6
	Tires and inner tubes	6	2.6	12	1.7	-.9
	Electrical equipment for engines	9	2.0	6	2.5	.5
	Plastics products	10	2.0	4	3.9	1.9
	Retail trade ex. eating & drinking	35	.3	67	.1	-.2
	Automotive repair shops	74	.1	5	3.8	3.8
Retail trade	Real estate	1	18.5	1	20.7	2.2
	Advertising	2	15.7	2	16.3	0.7
	Electric services (utilities)	3	8.1	3	7.6	-0.6
	Petroleum refining	4	5.5	14	1.6	-3.9
	Legal services	5	5.2	4	5.8	0.6
	Eating and drinking places	6	4.4	9	2.8	-1.6
	Banking	8	2.7	6	3.5	0.8
	Other repair and maintenance	9	2.5	5	3.8	1.3
	Wholesale trade	12	1.9	16	1.4	-0.5
	Retail trade ex. eating & drinking	24	0.7	20	0.9	0.3
	Other business services	25	0.7	8	2.9	2.2
	Motor vehicles		0		0	0

Note: Inputs listed for each industry are among the top six inputs in either the 1977-82 and 1987-92 time periods in addition to Motor Vehicles, Wholesale Trade, and Retail Trade.

Table 4

Variance Decomposition of Manufacturing and Trade Output Growth

	Values: Early	Values: Late	Ratio (Late/ Early)	Percent Share of the Change in Aggregate Variance/Covariance: Output	Percent Share of the Change in Aggregate Variance/Covariance: Component
$\mathrm{Var}(\tilde{y})$	5.15	.92	.18	100	
$\sum_j \mathrm{Var}(\tilde{y}_j)$	1.03	.27	.27	17.8	
$2\sum_{j>k} \mathrm{Cov}(\tilde{y}_j, \tilde{y}_k)$	4.12	.65	.16	82.2	
Mean correlation (standard deviation) *	.20 (.23)	.11 (.09)	.53		
$\mathrm{Var}(\tilde{s})$	3.81	.72	.19	73.0	
$\sum_j \mathrm{Var}(\tilde{s}_j)$	.65	.22	.34	10.1	13.9
$2\sum_{j>k} \mathrm{Cov}(\tilde{s}_j, \tilde{s}_k)$	3.15	.50	.16	62.8	86.1
$\mathrm{Var}(\Delta\tilde{i})$	.67	.12	.18	13.0	
$\sum_j \mathrm{Var}(\Delta\tilde{i}_j)$	.36	.10	.28	6.1	47.4
$2\sum_{j>k} \mathrm{Cov}(\Delta\tilde{i}_j, \Delta\tilde{i}_k)$	.31	.02	.07	6.8	52.6
$2\mathrm{Cov}(\tilde{s}, \Delta\tilde{i})$	.67	.08	.23	14.1	
$2\sum_j \mathrm{Cov}(\tilde{s}_j, \Delta\tilde{i}_j)$	.02	-.05	-3.30	1.6	11.1
$2\sum_{j\neq k} \mathrm{Cov}(\tilde{s}_j, \Delta\tilde{i}_k)$	.66	.13	.19	12.5	88.9

Notes: Data are constructed using Tornqvist measure of growth contributions (see text for details). $\tilde{y}$ is the growth rate of output. $\tilde{s}$ and $\Delta\tilde{i}$ are the growth rate contributions of aggregate sales and inventory investment. $\tilde{y}_j$ $\tilde{s}_j$, and $\Delta\tilde{i}_j$ are the industry-level growth contributions of output, sales, and inventory investment, respectively. The early period runs from 1967:Q2 to 1983:Q4. The late period runs from 1984:Q1 to 2001:Q1. Shares do not add to 100 due to rounding.

* The values columns in this row contain the average pairwise correlation between industries' output growth in each period (standard deviation in parentheses).

Sources: Haver Analytics Inc., BEA NIPA data

Table 5

Cross-Section Correlation Regressions: R-squared Statistics

Factor	**Early**	**Late (Predicted)**
#1	.40	.12
#2	.04	.00
#3	.30	.03
#4	.06	.00
#5	.02	.00
#1-5	.78	.11
#1 and 3	.63	.13

Table 6
Reduced-Form Model Contributions to Unconditional Variance

Model	Variable	Unconditional Variances Early	Unconditional Variances Late	Unconditional Variances Change	Structure (Φ, z_{t-l}) Early	Structure (Φ, z_{t-l}) Late	Structure (Φ, z_{t-l}) Change	Residuals (u_t) Early	Residuals (u_t) Late	Residuals (u_t) Change
Macro 3	π	10.39	1.18	-9.21	65	80	63	35	20	37
	f	13.12	3.73	-9.38	89	96	86	11	4	14
	y	**4.99**	**.91**	**-4.08**	**38**	**31**	**39**	**62**	**69**	**61**
Macro 4	π	10.39	1.18	-9.21	66	80	64	34	20	36
	f	13.12	3.73	-9.38	89	96	87	11	4	13
	y	**4.99**	**.91**	**-4.08**	**42**	**34**	**44**	**58**	**66**	**56**
	s	3.87	.72	-3.15	44	30	47	56	70	53
	Δi	.51	.12	-.40	48	38	51	52	62	49
Coupled HAVAR	π	10.39	1.18	-9.21	66	80	64	34	20	36
	f	13.12	3.73	-9.38	89	96	87	11	4	13
	y	**4.99**	**.91**	**-4.08**	**43**	**34**	**45**	**57**	**66**	**55**
	s	3.87	.72	-3.15	45	31	48	55	69	52
	Δi	.51	.12	-.40	51	47	52	49	53	48

Notes: The early sample runs from 1967:Q2 to 1983:Q4 and the late sample runs from 1984:Q1 to 2001:Q1. Because the models are estimated with two lags, the first complete observation of the early period is in 1967:Q4, and the output variance in this table (4.99) differs from Table 4's calculation (5.15).

Table 7

Identified Model Contributions to Unconditional Variance

		Unconditional Variances			Structure (Γ, z_{t-l})			Residuals (ε_t)		
		Early	**Late**	**Change**	**Early**	**Late**	**Change**	**Early**	**Late**	**Change**
Macro 3	π	10.39	1.18	-9.21	65	80	63	35	20	37
	f	13.12	3.73	-9.38	92	96	90	8	4	10
	y	**4.99**	**.91**	**-4.08**	**38**	**31**	**39**	**62**	**69**	**61**
Macro 4	π	10.39	1.18	-9.21	66	80	64	34	20	36
	f	13.12	3.73	-9.38	93	96	91	7	4	9
	y	**4.99**	**.91**	**-4.08**	**52**	**39**	**54**	**48**	**61**	**46**
	s	3.87	.72	-3.15	44	33	46	56	67	54
	Δi	.51	.12	-.40	54	42	58	46	58	42
Coupled HAVAR	π	10.39	1.18	-9.21	66	80	64	34	20	36
	f	13.12	3.73	-9.38	92	96	91	8	4	9
	y	**4.99**	**.91**	**-4.08**	**79**	**64**	**82**	**21**	**36**	**18**
	s	3.87	.72	-3.15	78	62	82	22	38	18
	Δi	.51	.12	-.40	56	43	60	44	57	40
	$\bar{y}$ (s.d.)				*79* *(1)*	*37* *(20)*	*88* *(4)*	*21* *(1)*	*63* *(20)*	*12* *(4)*

Notes: $\bar{y}$ is the mean of the y contributions under different orderings of the microvariables in the HAVAR model and s.d is the standard deviation of the contributions across orderings. The early sample runs from 1967:Q2 to 1983:Q4 and the late sample runs from 1984:Q1 to 2001:Q1. Because the models are estimated with two lags, the first complete observation of the early period is in 1967:Q4, and the output variance in this table (4.99) differs from Table 4's calculation (5.15).

Table 8

Counterfactual Simulations with Coupled HAVAR model

Coefficients (Γ)	Shocks (ε)	Unconditional Variances								
		π	f	y	s	s,m	s,t	Δi	$\Delta i,m$	$\Delta i,t$
Early Period	Early Period	10.02	11.88	**5.01**	3.81	1.44	.77	.46	.06	.30
Late Period	Late Period	1.41	2.68	**.77**	.65	.21	.26	.10	.03	.09
Early Period	Late Period	1.21	2.83	**1.39**	1.11	.32	.33	.12	.03	.07
Late Period	Early Period	6.30	6.61	**3.36**	2.70	1.01	.90	.49	.08	.46

Notes: The Early Period runs from 1967:Q2 to 1983:Q4, and the Late Period runs from 1984:Q1 to 2001:Q1. Variables are initially set to their early-period mean values in every simulation.

Table 9

HAVAR Contemporaneous Model Coefficient Estimates (Γ_0)

	Macro 3			Macro 4			Coupled HAVAR		
	Early	Late	Change	Early	Late	Change	Early	Late	Change
$\gamma_{y\pi}$	-.03 (.12)	.13 (.20)	.16 (.23)						
$\gamma_{s\pi}$				.03 (.10)	.26 (.17)	.23 (.20)			
$\gamma_{\Delta i\pi}$				-.05 (.03)	-.15** (.07)	-.10 (.07)			
γ_{sr}^{M}							-.06 (.07)	-.17** (.09)	-.12 (.11)
γ_{sr}^{T}							.00 (.04)	-.18 (.11)	-.18 (.12)
$\gamma_{\Delta ir}^{M}$							.03** (.01)	.05 (.04)	.02 (.04)
$\gamma_{\Delta ir}^{T}$							.03 (.04)	.09 (.06)	.05 (.07)
$\gamma_{f\pi}$	-.30** (.07)	-.23** (.10)	.07 (.12)	-.33** (.07)	-.21* (.09)	.14 (.12)	-.32** (.07)	-.09 (.10)	.23* (.13)
γ_{fy}	-.15** (.07)	-.08 (.06)	.07 (.09)						
γ_{fs}				-.21** (.09)	-.03 (.06)	.18 (.12)	-.11 (.12)	.10 (.09)	.21 (.15)
$\gamma_{f\Delta i}$				.25 (.27)	-.28* (.17)	-.54* (.33)	-.10 (.33)	-.82** (.27)	-.72* (.42)
$\gamma_{\Delta is}$				-.10** (.04)	-.04 (.05)	.06 (.06)			
$\gamma_{\Delta is}^{MM}$							-.07** (.02)	-.01 (.04)	.07 (.05)
$\gamma_{\Delta is}^{TT}$							-.06 (.09)	.13** (.06)	.20* (.11)
γ_{ss}							-.35** (.05)	-.26** (.06)	.09 (.08)
$\gamma_{s\Delta i}^{MT}$							-.37 (.25)	-.99** (.22)	-.63* (.34)

Note: Coefficients significant at the 5% and 10% level are denoted by ** and *, respectively.

Table 10

Input and Output Use Data

Industry	Input	1977-82 Share	1987-97 Share	Change
Manufacturing	Manufacturing	61.4	55.9	-5.5
	Trade	7.8	8.6	.8
	Other	30.8	35.5	4.7
Trade	Manufacturing	19.4	12.3	-7.1
	Trade	6.0	5.9	-.1
	Other	74.6	81.9	7.2
Wholesale trade	Manufacturing	21.0	16.3	-4.7
	Wholesale trade	7.6	8.1	.5
	Retail trade	.9	1.0	.1
	Other	70.3	74.6	4.4
Retail trade	Manufacturing	18.3	8.4	-9.9
	Wholesale trade	2.9	1.4	-1.5
	Retail trade	.9	1.3	.4
	Other	78.0	89.0	11.0

Source: Bureau of Labor Statistics

Table 11
Volatility Ratios of HAVAR Impulse Responses

Sector	Variable	Volatility			
		Fed Funds Shock	Inflation Shock	Sales Shock	
				Trade	Manufacturing
Total	Output	.41	.66	.49	.69
	Sales	.47	1.25	.55	.67
	Inventories	3.15	2.74	2.37	3.12
Manufacturing	Output	.59	.26	.57	.71
	Sales	.39	.37	.53	.82
	Inventories	3.61	.88	.55	.69
Trade	Output	.51	2.21	.55	.96
	Sales	.91	3.41	.75	.89
	Inventories	3.98	10.22	4.99	15.30

Shock Variances	Early	1.00	3.53	.025	.61
	Late	.13	.24	.018	.15
	Ratio	.13	.07	.72	.25

Note: Table entries are the ratio of impulse response variance in the late period (1984-2001) to variance in the early period (1967-1983).

Table 12
Correlations of Impulse Responses

	Inflation Shock			Fed Funds Shock			Manufacturing Sales Shock			Trade Sales Shock		
Correlation	Early	Late	Change	Early	Late	Change	Early	Late	Change	Early	Late	Change
y_m, y_t	.99	.48	-.52	.98	.43	-.55	.96	.70	-.26	.74	.51	-.23
s_m, s_t	.98	.94	-.05	.96	.56	-.40	.97	.48	-.49	.78	.38	-.41
$s_m, \Delta i_t$	.37	-.57	-.94	.29	-.01	-.30	.25	.27	.02	.35	.39	.04
$\Delta i_m, s_t$	.47	-.43	-.89	.17	-.52	-.69	.66	.86	.20	.25	.31	.05
$\Delta i_m, \Delta i_t$	.89	-.24	-1.13	.93	.61	-.33	.79	-.55	-1.33	.46	.25	-.22
$s_m, \Delta i_m$	.51	-.32	-.83	.33	.37	.04	.72	.03	-.69	.62	.87	.26
$s_t, \Delta i_t$	.27	-.43	-.70	.12	-.61	-.73	.20	-.40	-.60	.58	-.51	-1.09

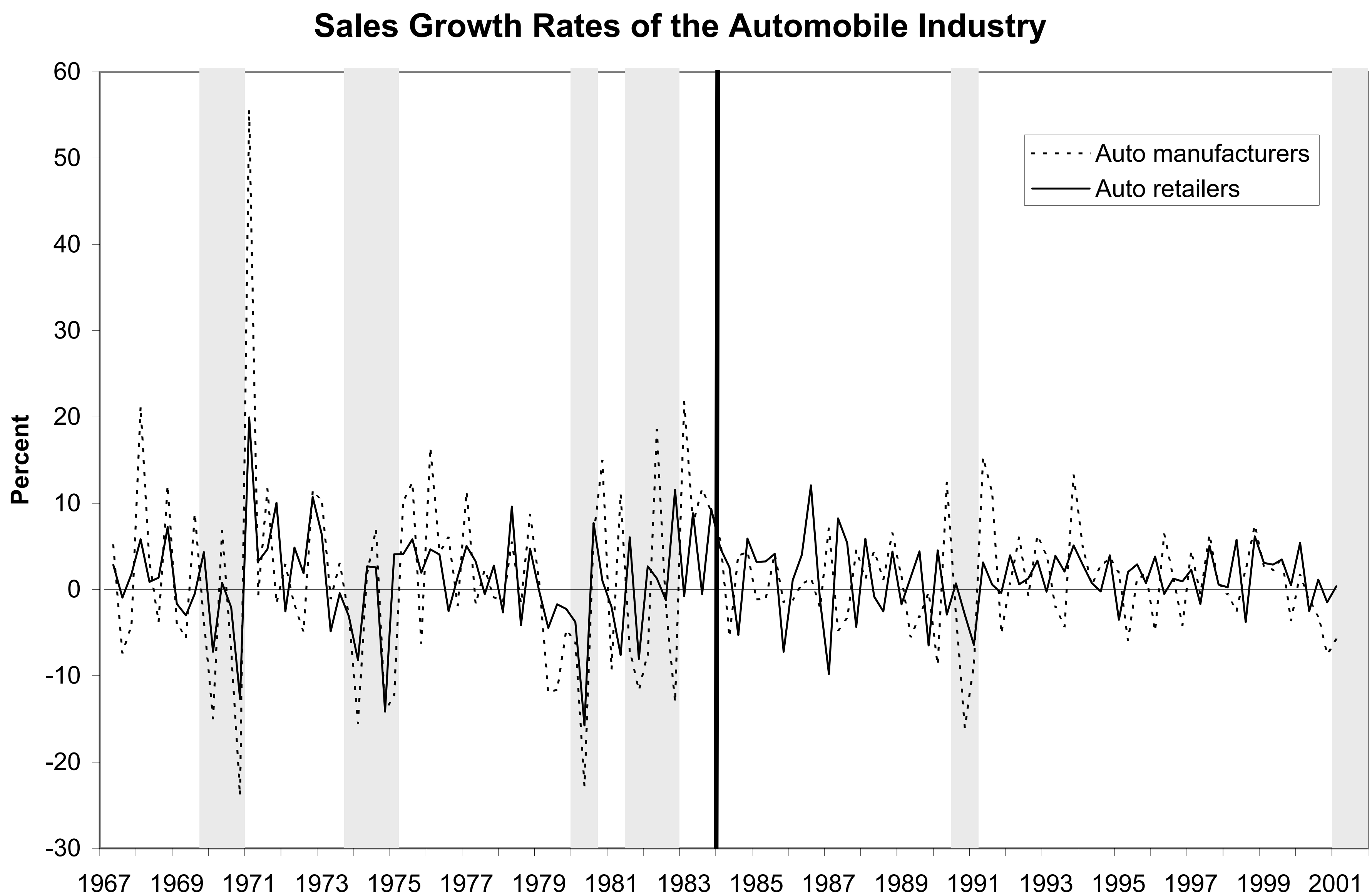
Table 13

Variance Decomposition of Impulse Response to Federal Funds Shock

	Values		Ratio (Late/ Early)	Percent Share of the Change in Aggregate Variance/Covariance	
	Early	Late		Output	Component
$\mathrm{Var}(\tilde{y})$	.0415	.0168	.41	100.0	
$\sum_j \mathrm{Var}(\tilde{y}_j)$	.0215	.0120	.56	38.3	
$2\sum_{j>k} \mathrm{Cov}(\tilde{y}_j, \tilde{y}_k)$	.0200	.0048	.24	61.7	
$\mathrm{Var}(\tilde{s})$	.0360	.0168	.47	78.0	
$\sum_j \mathrm{Var}(\tilde{s}_j)$	.0187	.0108	.57	32.3	41.4
$2\sum_{j>k} \mathrm{Cov}(\tilde{s}_j, \tilde{s}_k)$	.0173	.0060	.35	45.7	58.6
$\mathrm{Var}(\Delta\tilde{i})$	.0017	.0052	3.15	-14.5	
$\sum_j \mathrm{Var}(\Delta\tilde{i}_j)$	.0009	.0033	3.80	-9.7	67.3
$2\sum_{j>k} \mathrm{Cov}(\Delta\tilde{i}_j, \Delta\tilde{i}_k)$	.0008	.0020	2.46	-4.7	32.7
$2\,\mathrm{Cov}(\tilde{s}, \Delta\tilde{i})$	.0038	-.0052	-1.35	36.5	
$2\sum_j \mathrm{Cov}(\tilde{s}_j, \Delta\tilde{i}_j)$	.0019	-.0020	-1.05	15.8	43.2
$2\sum_{j\neq k} \mathrm{Cov}(\tilde{s}_j, \Delta\tilde{i}_k)$	.0019	-.0032	-1.65	20.7	56.8

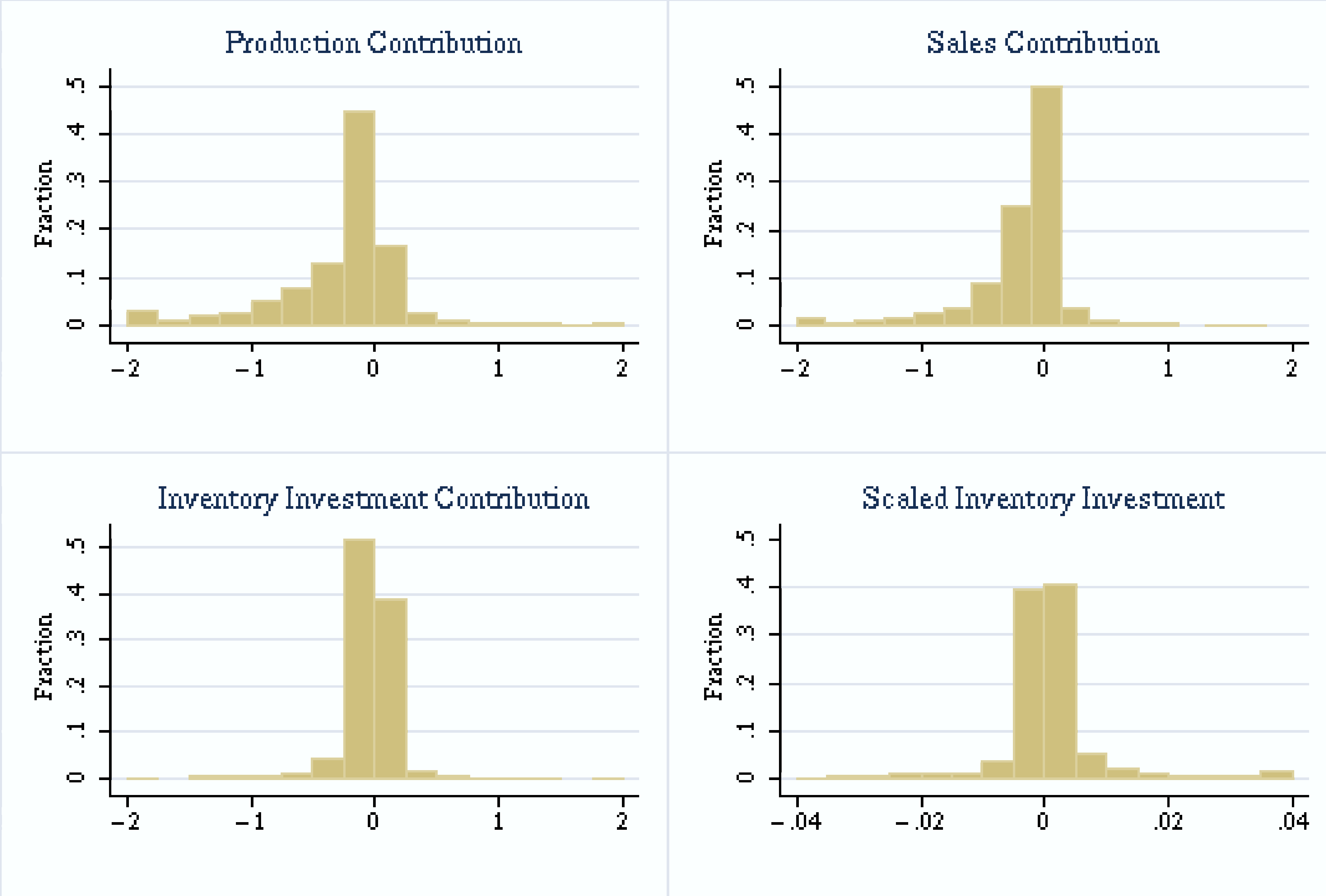
Sources: Haver Analytics Inc., BEA NIPA data

Figure 1



Note: NBER recessions are shaded. The line at 1984 indicates the break in volatility.

Figure 2: Distributions of Scaled Pairwise Covariance Ratio



Note: Figure displays the change in pairwise covariances of industry−level series, scaled by the variance. Contributions were calculated using the 3−variable tornquist method

Figure 3: Distributions of Scaled Industry Covariance Ratios

Note: Figure displays the change in covariances of industry–level series, scaled by the variance and summed by industry. Contributions are calculated using the 3–variable tornquist method.

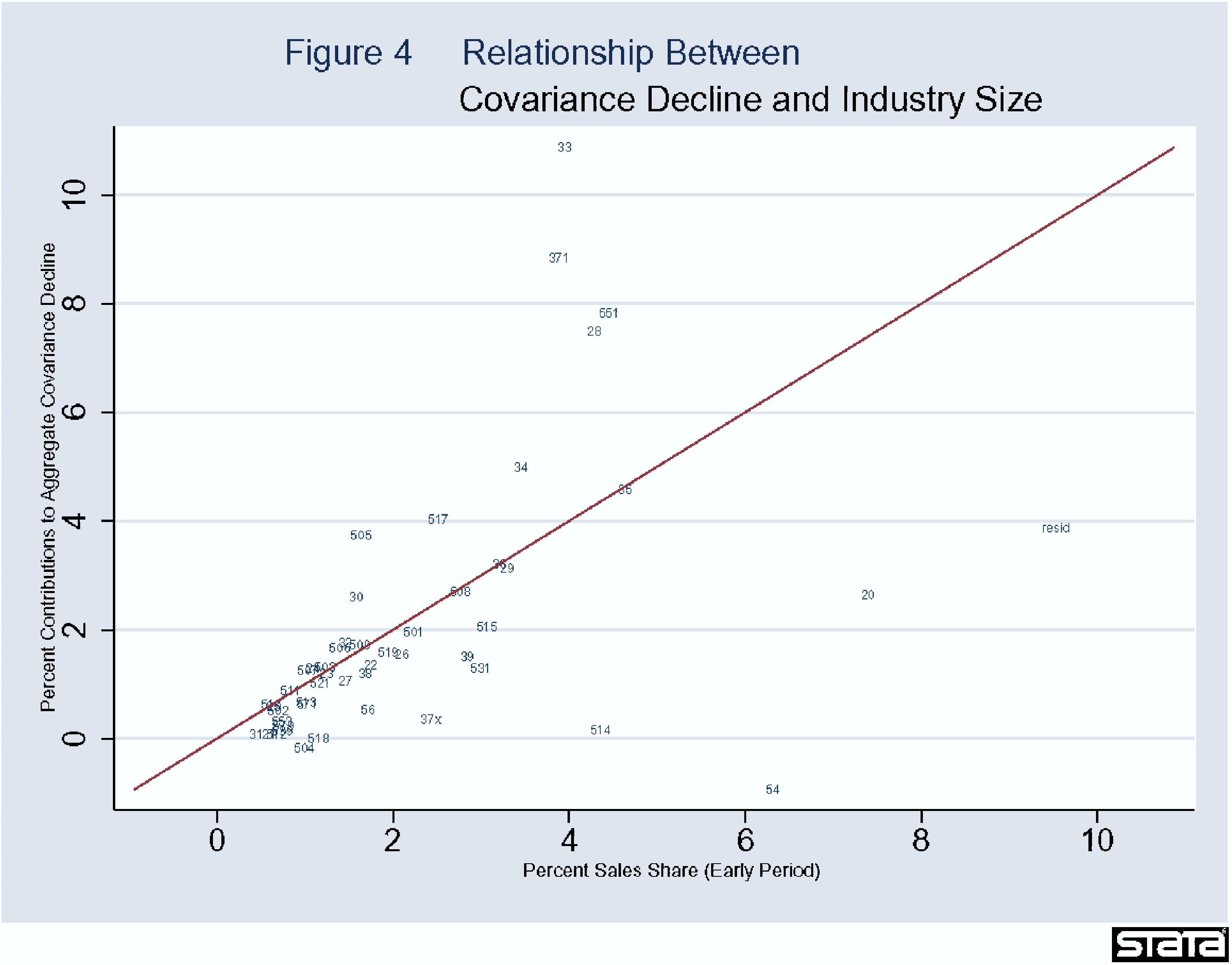


Figure 4 Relationship Between
Covariance Decline and Industry Size
Percent Contributions to Aggregate Covariance Decline
Percent Sales Share (Early Period)
0
2
4
6
8
10
33
371
551
28
34
36
517
505
29
508
30
20
resid
515
501
39
531
22
38
27
521
511
513
56
37x
514
518
504
54

Figure 5

Changes in Industry Level Output Variance and Covariance

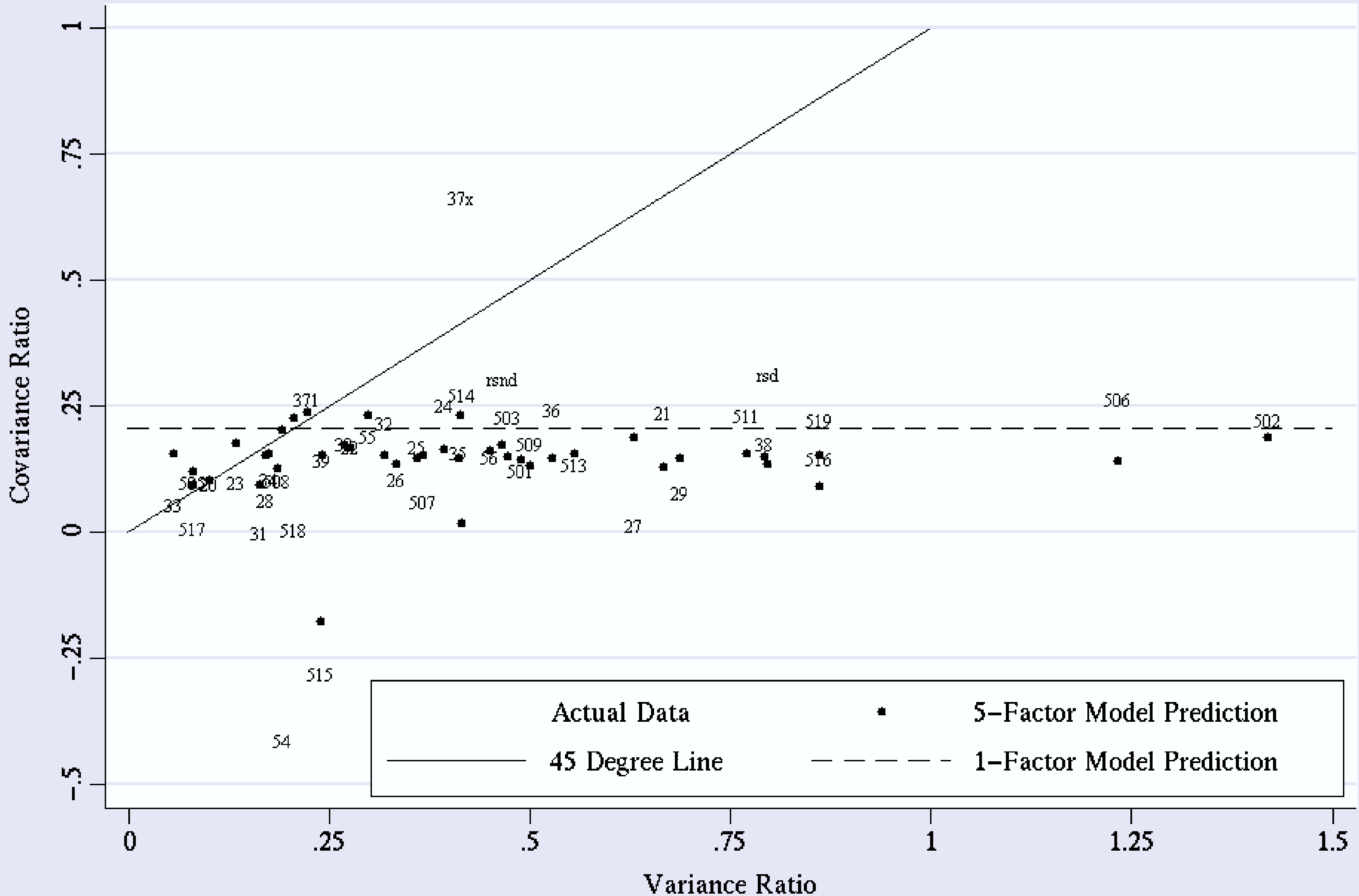


Figure 6

HAVAR Output Growth Impulse Responses

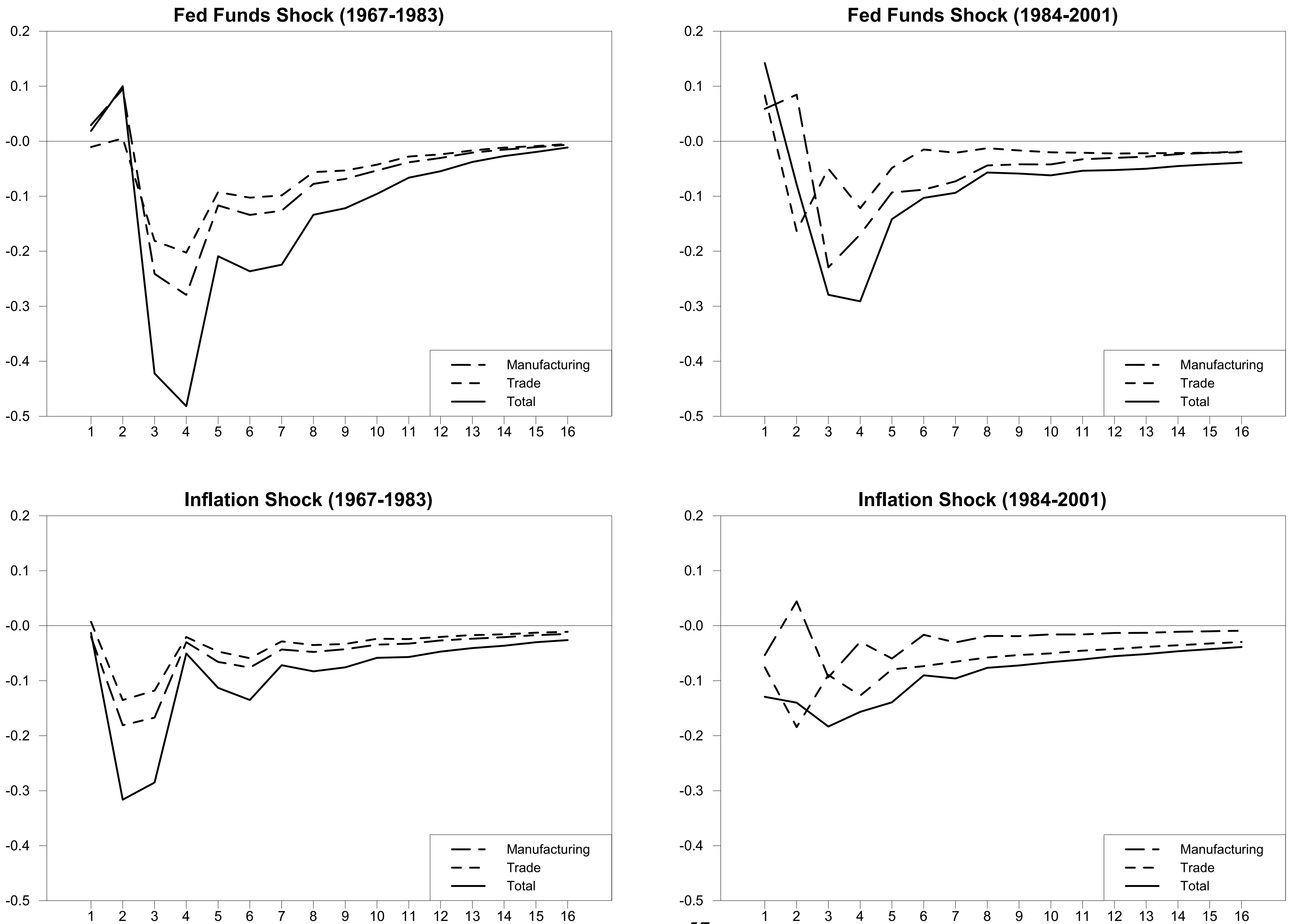


Figure 7

HAVAR Output Growth Impulse Responses

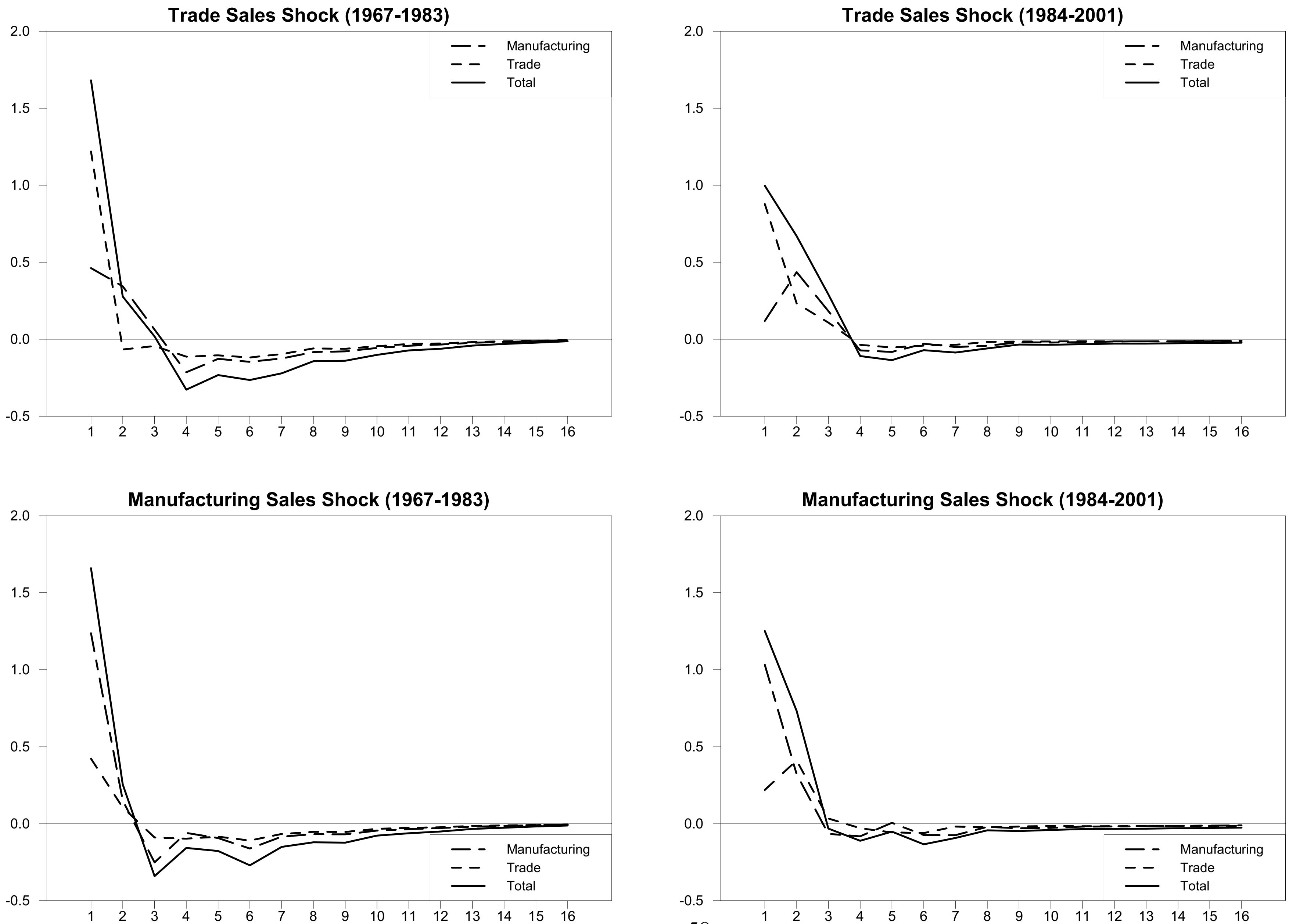
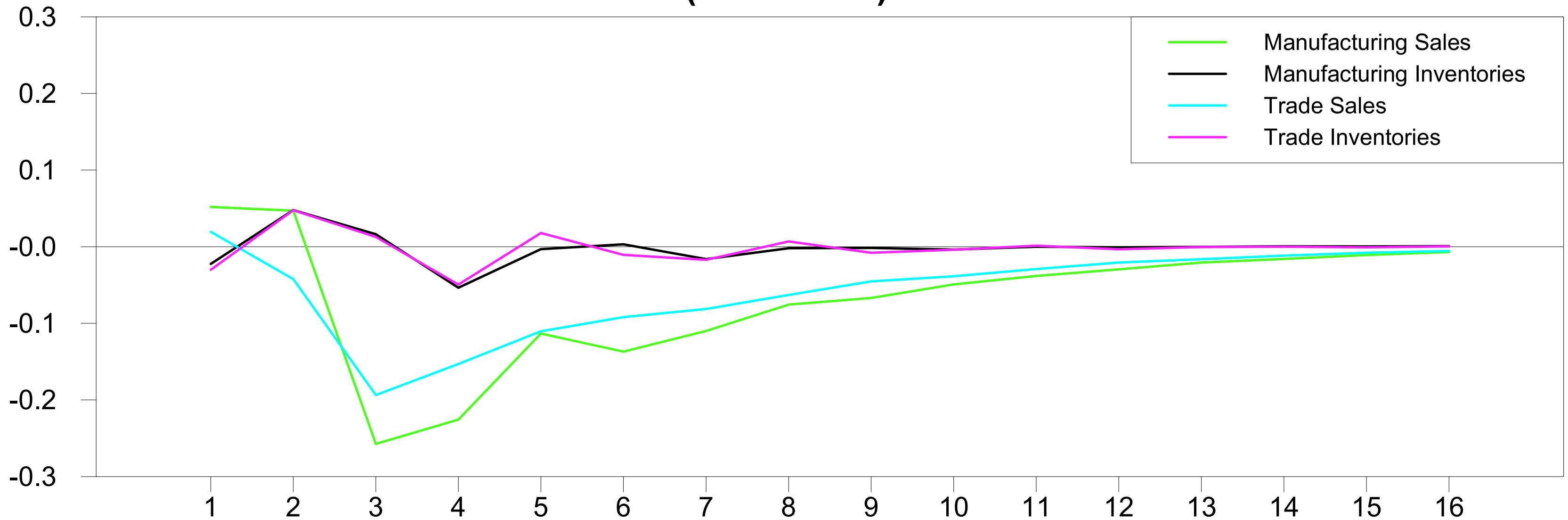


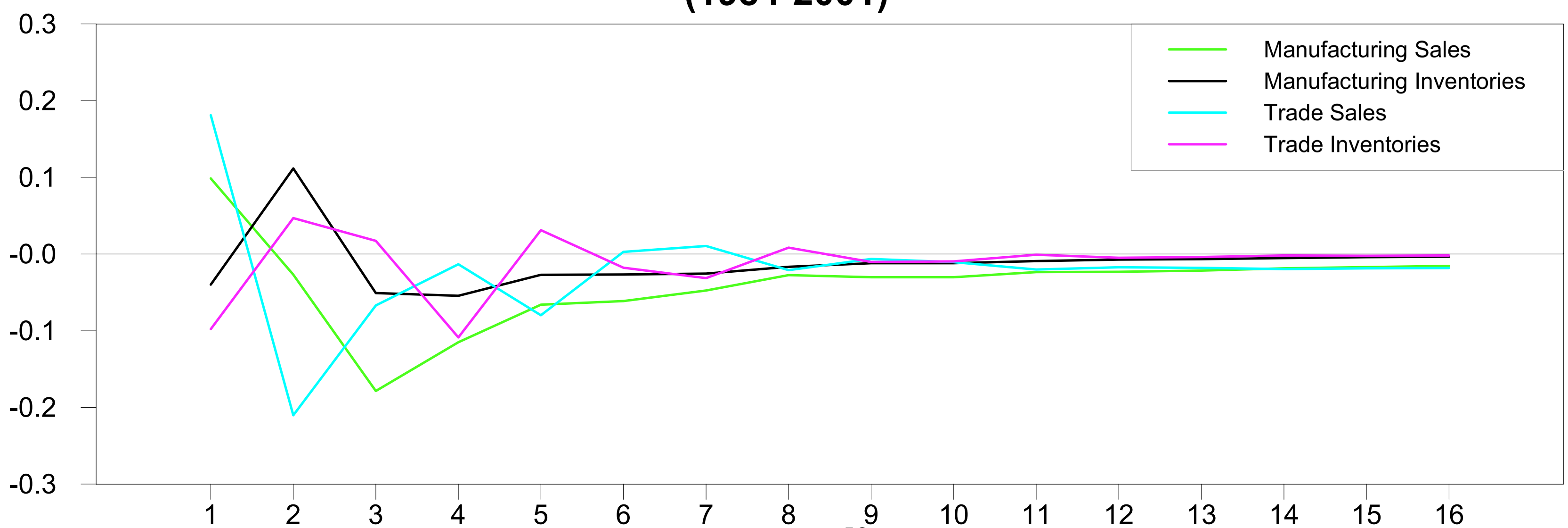
Figure 8

HAVAR Impulse Responses: Fed Funds Shock

(1967-1983)



(1984-2001)



Appendix A: Data Details

This section describes the various methods of calculating gross output, and the contributions of sales and inventory investment to the growth of output using manufacturing and trade real sales (or shipments) and inventory data from the Bureau of Economic Analysis.[46] Lowercase letters denote growth rates, and tilde (~) denotes an output growth contribution.

The *level method* involves adding the real values of sales and inventory investment, $Y_t = S_t + \Delta I_t$, and deriving a standard output growth rate, $y_t = (\Delta Y_t / Y_{t-1})$, where $I_t = I_t^M + I_t^W + I_t^F$ denotes the total inventory of materials (M), work-in-process (W), and finished goods (F) stocks. For technical reasons related to the chain-weight deflation procedure, it is incorrect to add real sales and inventory investment data, so this method of constructing an output growth rate contains error.[47]

For this reason, we develop other methods of calculating the growth of output and the growth contributions of sales and inventory investment using a Tornqvist approximation to the chain-weight growth rate. The *Tornqvist method* uses average (current and lagged) shares of nominal sales and inventory investment in production, defined as

$$\theta_t^s = \sum_{\tau=0}^{1} 0.5(P_{t-\tau}^s S_{t-\tau} / P_{t-\tau}^y Y_{t-\tau}) \qquad \theta_t^i = \sum_{\tau=0}^{1} 0.5(P_{t-\tau}^i I_{t-\tau} / P_{t-\tau}^y Y_{t-\tau}) \ ,$$

where P denotes price. Then using the growth rates of real sales and inventory stocks as $s_t = (\Delta S_t / S_{t-1})$ and $i_t = (\Delta I_t / I_{t-1})$, respectively, the Tornqvist approximation of output growth is

$$\tilde{y}_t^T = \theta_t^s s_t + \left[\theta_t^i i_t - \theta_{t-1}^i i_{t-1}\right] = \tilde{s}_t + \Delta \tilde{i}_t^T \ , \tag{A.1}$$

where the superscript T denotes "Tornqvist." We used this three-variable Tornqvist approximation because it produces less error than the alternative method described next.

A *residual method* also can be used to construct an implicit inventory growth contribution using the growth rate of the level of output and the Tornqvist sales growth contribution as $\Delta \tilde{i}_t^R = y_t - \tilde{s}_t$, where the superscript R denotes "Residual." Kahn, McConnell, and Perez-Quiros (2002) employed this method using real chain-weighted NIPA output data. However, real chain-weighted output data for M&T are not available, so this method also involves error associated with constructing the level of output from real chain-weighted sales and inventory investment. In particular, because it relies on the definition of real output growth constructed from real data levels (y_t), the magnitude of the inventory growth contribution is very sensitive to the relative sizes of sales

[46] This section relies heavily on the work of Landefeld and Parker (1997) and Whelan (2002).
[47] Adding nominal sales and inventory investment data is correct, however.

and inventory investment. The larger is sales relative to inventory investment, the closer are the growth rates of output and sales, and the smaller is the growth contribution of inventories.

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 (2002),

$$y_t = \sum_{j=1}^{J} \theta_{jt}^{y} y_{jt} \quad , \tag{A.2}$$

where $\theta_{jt}^{y} = (1/2)\sum_{\tau=0}^{1}(\hat{Y}_{j,t-\tau\tau}/\hat{Y}_t \quad)$ are industry nominal output shares. 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.[48]

[48] 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.

Appendix B: Characteristics of Common Factors

Several characteristics of the common factors are instructive. First, the variance ratios for each factor, $\mathrm{Var}(C_p^L) \big/ \mathrm{Var}(C_p^E)$, can be compared with the variance ratio of the output data to see which factors' volatility declined more or less than the actual data. Second, the share of aggregate variance accounted for by each factor, $\theta_p = \left(\mathrm{Var}\left(C_{pt}\right) \big/ \sum_j \mathrm{Var}\left(x_{jt}\right)\right)$, reveals which factors are most important for explaining the volatility of aggregate output.[49] Third, the correlation between each factor and aggregate (M&T) output growth, $\mathrm{Corr}(C_{pt}, \tilde{y}_t)$, provides some sense as to whether the factor is macroeconomic (high correlation) or idiosyncratic (low correlation) in nature.

Appendix Table 2 reports summary statistics on the first 10 estimated principal components of industry-level output growth. For the early and late periods, it includes their variance properties (level and share) and their cyclical properties, as measured by their correlation with aggregate output. No single factor accounted for a majority of the aggregate variance of M&T output growth, and only the first five factors each accounted for more than 3 percent of the total variance. The first factor accounted for 34.6 percent of the variance of M&T output growth in the early period and only 27.5 percent in the late period.[50] The next two factors together accounted for about 30 percent of the variance in the early period, but only 11.5 percent in the late period, while the fourth and fifth factors together accounted for about 11 percent in both periods. The proportions of change in variance accounted for by the factors are roughly proportional to the shares. Although no single dominant factor can explain the reduction in aggregate volatility by itself, the first five accounted more than four-fifths of the change in aggregate variance. During the later period, the top 10 factors accounted for much less of aggregate variance, indicating that aggregate variance was explained more evenly by many more factors than in the early period.

The first three factors also exhibit qualitatively different behavior from the rest. They experienced much larger variance reductions. The average variance ratio of .15 is close to the ratio for M&T output growth reported in Table 4 (.18), whereas most of the other ratios are much higher. The first three factors also tend to have much higher positive correlation with aggregate M&T output, as shown in the last two columns. The Factor 1 is aligned most closely to aggregate output, with a correlation greater than .7 in both periods. In the early period, Factors 2 and 3 were very positively

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[49] The denominator of the variance share depends only on the sum of industry sales variances because covariance terms are explained solely in terms of common factor variances.

[50] This result is similar to that from principal component analysis of macroeconomic data variables. Stock and Watson (2002) report that "six factors account for 39 percent of the variance of 215 monthly time series…" (p. 153)

correlated with aggregate output growth too, but their correlation declined significantly in the later period.

Following Stock and Watson (2002), we visually characterize the factors in Appendix Figure 1, which plots their time-series behavior, and Appendix Figure 2, which plots the R^2 statistics from regressions of industry output growth on each of the first five factors. The bar chart in Appendix Figure 2 lists the SIC industry on the horizontal axis, grouped by manufacturing, wholesale, and trade sectors from left to right (see Appendix Table 1 for SIC industry definitions).

Each factor tends to have a particular industrial orientation. Factors 1 and 3 are oriented toward durable goods. Factor 1 is most closely correlated with the automobile industry, the strongest correlation (greater than 0.8) occurring with manufacturers and retailers (SIC 371 and 55). Several industries related to auto manufacturers through input supply relationships also have relatively high correlation, especially rubber (SIC 30), primary and fabricated metals (SIC 33 and 34), and chemicals (SIC 28), but the correlation with auto wholesalers (SIC 501) is low. Factor 3 is closely correlated with industries producing non-auto durable goods in all sectors (manufacturing, wholesale, and retail), especially metal-based machinery industries (SIC 33, 35, 505, and 508).

The other three factors are correlated with narrow nondurable goods industries. Factor 2 is correlated almost exclusively with wholesale petroleum (SIC 517), but oddly not with oil refining (SIC 29) or retail non-durable goods (SIC RSND, which includes gasoline stations). Factors 4 and 5 tend to span the agricultural industries. Factor 4 is correlated almost exclusively with wholesale farm products (SIC 515), and factor 5 is correlated most closely with food manufacturers (SIC 20), wholesale grocers (SIC 514), and retail grocers (SIC RSND).

Factors 1 and 3 together correspond roughly to the interest-sensitive industries and thus might be viewed as being jointly associated with monetary policy, but such an interpretation should be regarded as very loose given the lack of behavioral structure and identification in the factor model. However, it is notable that the principal component methodology identifies these groups of durable goods industries separately, suggesting that there is something potentially different in the structure of autos, an industry with much structural change in production and inventory methods.

Appendix Table 1
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

Appendix Table 2

Principal Components of Output Growth

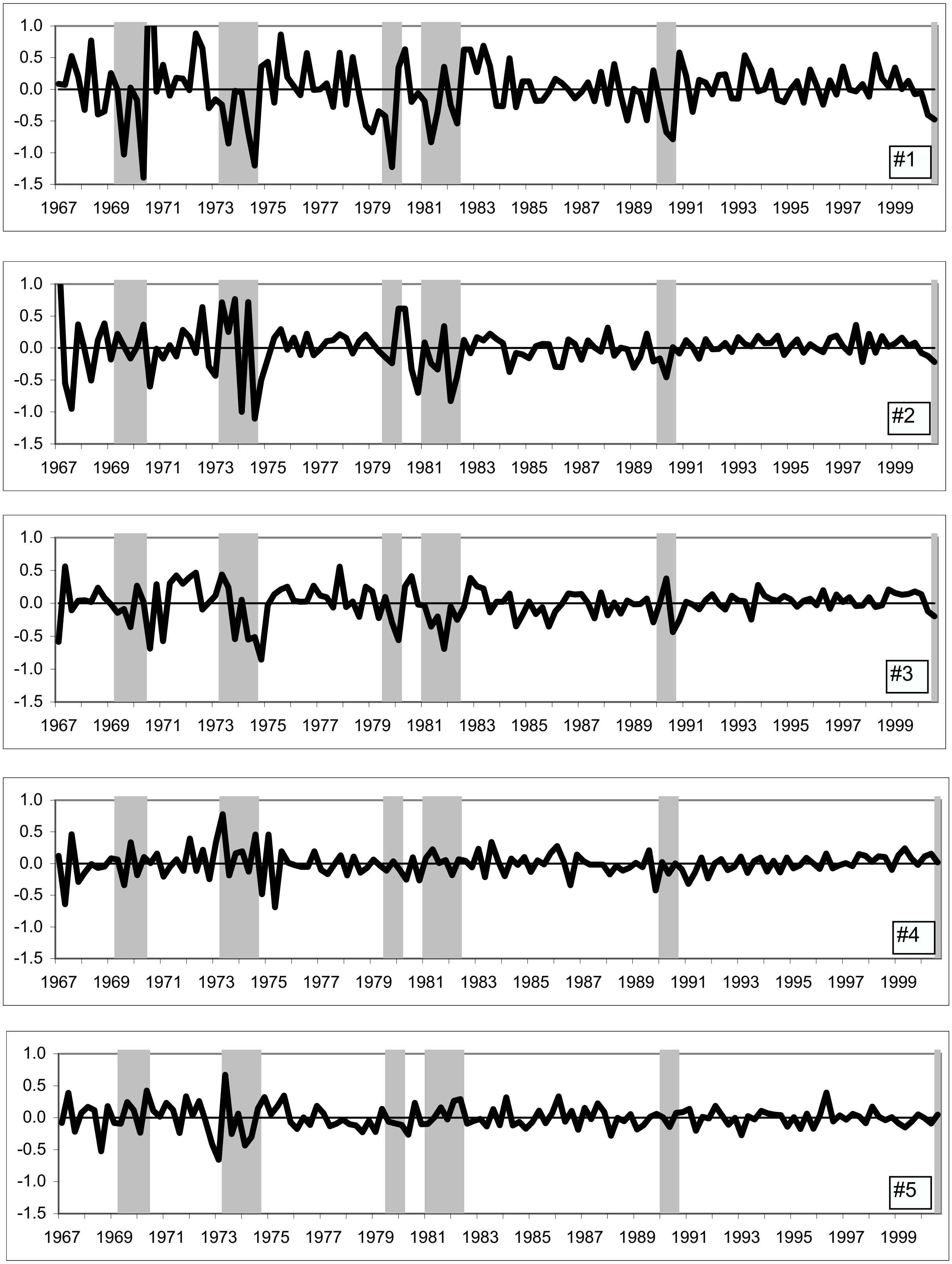
Full Sample Estimates

	Variances			Variance Shares			Correlation (Cp, Yt)	
Component	Early	Late	Ratio	Early	Late	Change	Early	Late
1	.35	.07	.21	34.6	27.5	37.1	.73	.79
2	.20	.01	.07	19.8	5.3	24.8	.52	.19
3	.10	.02	.16	10.2	6.2	11.6	.43	.31
4	.06	.02	.30	5.9	6.7	5.6	.04	.06
5	.05	.01	.21	5.2	4.2	5.6	.10	.22
6	.03	.02	.52	3.0	5.9	1.9	.04	.23
7	.03	.01	.48	2.5	4.6	1.8	-.04	.46
8	.02	.01	.73	1.9	5.3	0.7	-.09	.25
9	.03	.01	.31	2.5	3.0	2.3	-.01	.07
10	.02	.01	.44	1.8	3.1	1.4	.02	.17
Other*	.13	.07	.58	12.6	28.1	7.2	.01	.05

*Other refers to the total for the last 34 components for the variance columns,
and the average of the last 34 compoments in the correlation columns.

Appendix Figure 1

Principal Component Time Series Plots



Note: NBER recessions are shaded.

Appendix Figure 2

R-Squared of Industry Output on Principal Components