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

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Abstract: More than 80 percent of the decline in the variance of aggregate output since 1984 is accounted for by a decline in the covariance (and correlation) of output among industries that hold inventories. Using a HAVAR macro model (Fratantoni and Schuh 2003) with only two sectors, manufacturing and trade, we show that this decline in comovement – and thus much of the Great Moderation in aggregate and industry-level output – is explained largely by changes in the structural relationships *between* sectors' sales and inventory investment, rather than by "good luck." A small part of the Moderation is explained by structural changes among interest rate parameters, but the case for better monetary policy is complicated by structural changes in the real side of the economy. We also show that the decline in comovement is concentrated in the automobile industry and related industries that are linked by supply and distribution chains. Immediately prior to the Great Moderation, these industries adopted new production and inventory management techniques, which may explain the structural changes.

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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

In the literature striving to explain the substantial decline in the volatility of U.S. real GDP growth since the early 1980s, called the "Great Moderation," the role of comovement – a central feature of business cycles – generally has been overlooked.[1] Relying on aggregate data and macroeconomic models, most research tends to conclude that the Great Moderation is explained by 1) reduced volatility of shocks, termed "good luck", or 2) structural changes associated with monetary policy, final demand, and inventory management, for examples.[2] Even the few studies that rely on disaggregated data focus on similar explanations, and do not examine the importance of comovement.[3] No consensus has emerged yet on which of these ideas best explains the Great Moderation.

This paper provides new evidence that a central empirical feature of the Great Moderation is a decline in comovement, or a decoupling, among industries. Previously (Irvine and Schuh 2005a), we reported that a decline in comovement, as measured by covariance, accounts for 40 percent of the decline in U.S. GDP volatility, as shown in Table 1.[4] Here, we show even greater decoupling among detailed industries in the manufacturing and trade (M&T) sectors, which account for most of the output volatility and inventory-holding in the economy. The decline in covariance (and correlation) among M&T industries accounts for more than 80 percent of the decline in aggregate M&T output volatility – even though the variance of output also declined markedly in virtually every industry.[5]

[1] Kim and Nelson (1999) and McConnell and Perez-Quiros (2000) were the first to document the Great Moderation. On comovement, see Christiano and Fitzgerald (1998).

[2] The literature that focuses on the decline in volatility since the early 1980s also includes: Ahmed, Levin, and Wilson (2004); Blanchard and Simon (2001); Iacoviello, Schiantarelli, and Schuh (2007); Kahn, McConnell, and Perez-Quiros (2002); Kim, Nelson, and Piger (2001); Maccini and Pagan (2007); Ramey and Vine (2006); Stiroh (2005); Stock and Watson (2002, 2003); and Warnock and Warnock (2000).

[3] See Bivin (2003), Herrera and Pesevento (2005), and McCarthy and Zakrajsek (2006) for examples.

[4] If the structures sector, which is linked closely with the goods sector, also is included, goods and structures together account for nearly nine-tenths of the decline in output volatility. The goods and structures sector are the only ones that hold measured inventories.

[5] 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

Although the reduction in covariance (and correlation) was generally widespread, it was concentrated disproportionately in the automobile industry and closely related industries.[6] These industries are linked by extensive and complex supply chains, which provide materials, supplies, and intermediate goods to manufacturers of finished goods, and distribution chains, which transport finished goods from manufacturers to wholesale and retail traders. It is widely acknowledged that these industries adopted new production and inventory management techniques, such as just-in-time production, in the late 1970s and early 1980s – immediately prior to the onset of the Great Moderation. Except for the declining ratio of materials inventories to production in manufacturing industries, the macroeconomic impact of these techniques is not well understood. Our results suggest that this technological change may be manifest in reduced comovement; if so, analyses based on representative-agent models and aggregate data cannot identify this change.[7]

To identify and quantify the role of comovement between industries in a tractable macro-econometric model, we use the heterogeneous-agent VAR (or HAVAR) framework developed by Fratantoni and Schuh (2003).[8] HAVAR models are well-suited for this endeavor because they can incorporate disaggregated of industries within an otherwise standard macroeconomic VAR while imposing all of the necessary aggregation conditions to make the model internally consistent. In fact, standard macroeconomic VARs used in the Great Moderation literature are nested in the HAVAR model, so the homogeneity restrictions imposed by macroeconomic VARs can be tested econometrically.

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improvements in microeconomic innovation and creative destruction. According to Gabaix (2005), change in the size distribution of firms is also a potentially important determinant of the change in aggregate volatility. Rather than offer a grand explanation for all of these facts, we aim to explain the data at intermediate levels of aggregation where volatility and comovement both declined.

[6] This finding affirms the importance of other related research on the automobile industry, such as Blanchard (1983), Kashyap and Wilcox (1993), Ramey and Vine (2006), Hall et al … [TO BE COMPLETED]

[7] Other studies also argue for an important role of inventory management in explaining the Great Moderation. 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."

[8] In a companion study (Irvine and Schuh 2005b, 2007), we show that a standard factor model cannot explain the decline in covariance well. A nonstandard factor model that can explain the decline in covariance suggests that the most important factor in explaining the Great Moderation is one that is closely linked to the automobile industry. 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.

Our HAVAR model parameterizes the contemporaneous and dynamic structural relationships among industries' output (sales and inventory investment), plus the structural relationships among macro variables (inflation and interest rates) and the relationships between the industry and macro variables. Furthermore, the HAVAR model incorporates well-defined roles for aggregate and sector-specific shocks. As a complete macroeconomic framework, the HAVAR model can quantify properly the effects on aggregate output volatility attributable to structural changes, including behavioral relationships among industries that produce comovement, versus changes in the volatility of structural shocks, which the literature terms "good luck."

Using the estimated HAVAR and benchmark macro VAR models, we perform counterfactual experiments patterned after those in Stock and Watson (2003) and Ahmed, Levin, and Wilson (2004) to explore how much of the reduction in output variance can be explained by changes in structural coefficients versus reductions in the variances of shocks. The macro VAR most closely related to the HAVAR model attributes 21 percent of the Great Moderation to structural change – hence 79 percent to "good luck." Our 2-sector HAVAR model of manufacturing and trade attributes 36 percent to structural change. Splitting trade into wholesale and retail components, a 3-sector HAVAR model attributes 73 percent to structural changes. In each case, the most important structural changes occurred in the contemporaneous relationships between the sectors' sales and inventory investment. These results weaken the case for "good luck" without resorting to much disaggregation.

Changes in the dynamic properties of the estimated HAVAR model generally match the empirical decline in sector-specific and aggregate output volatility, as well as the decline in comovement as measured by covariance (and correlation). However, the precise nature of the change in comovement, as reflected in the impulse responses of output, differs significantly across shocks. For example, monetary policy shocks elicit a phase shift in the responses of sectors' output, whereas shocks to trade sales (final demand) primarily reduce the responses of sector-specific and aggregate output in the first period. This finding suggests that a single, or even unified, explanation for the Great Moderation may be unlikely.

A key feature of the change in dynamics is lower correlation between sales and inventory investment – within sectors and between manufacturing and trade – owing to changes in both the contemporaneous and lag coefficient structure. Within sectors, this change smoothes production, primarily in the trade sector, as inventories play more of a buffer stock role since 1984. However, it also reduces the comovement (correlation) between sectors' output and sales. Between manufacturing and trade, the changes in cross-sector correlations among sales and inventory investment may reflect the adoption of new production and inventory management techniques. The HAVAR model suggests that changes in sales persistence, found in the automobile industry by Ramey and Vine (2006), may be less evident and less important in a macroeconomic model with more aggregate data.

Although the HAVAR model results are suggestive, additional theoretical and empirical work is needed to verify the conjecture that the observed structural changes are linked to inventory management along supply and distribution chains. Recent papers by Ramey and Vine (2006), Khan and Thomas (2007), Maccini and Pagan (2007), Wen (2006), and Iacoviello, Schiantarelli, and Schuh (2007) offer models that represent promising steps in this direction. However, these examples do not yet provide a fully specified, data-consistent model of supply and distribution chains in a complete macroeconomic framework that could verify and interpret the economic behavior underpinning our results.

So, in the last section of this paper, we discuss models of inventory management that could be integrated with macroeconomic models to rationalize our findings. We will explain how input-output linkages, emphasized in the comovement literature, can be related to supply and distribution chains, emphasized in the inventory management literature.[9] The organization and operation of these chains (such just-in-time or flexible manufacturing techniques), the management and transmission of information along chains, and other related factors all play a role. We also provide empirical evidence that is consistent with the "bull-whip effect" cited in the management science literature. For example, the volatility of upstream industries (manufacturing) declined more than the volatility of downstream industries (trade).

[9] On the importance of input-output linkages in comovement and business cycles, see Long and Plosser (1983), Cooper and Haltiwanger (1990), Hornstein and Praschnik (1997), Christiano and Fitzgerald (1998), Horvath (1998, 2000), Hornstein (2000), Huang and Liu (2001), Shea (2002), and Conley and Dupor (2003). 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. Firm-level (idiosyncratic) disturbances may also generate large aggregate fluctuations provided the size distribution of firms is "fat-tailed," as argued by Gabaix (2005), but in this case a mechanism such as demand linkages among firms is needed to generate comovement.

2. Automobile Industry Illustration

To preview our ideas and results, consider the U.S. automobile industry, which plays a disproportionately important role in our findings.[10] Figure 1 plots quarterly BEA data on real sales growth for automobile manufacturers (SIC 371) and automobile 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 the sales of automobile manufacturers and retailers moved together before 1984, sales have become almost completely uncorrelated, or decoupled, since.

Table 2 reports the complete set of correlations for automobile 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.[11] Another large decline occurred *within* the retail industry: the correlation between sales and inventories fell from .15 to –.44. Also there are nontrivial changes in the correlation of retailers' inventories with manufacturing sales (–.16) and with manufacturing inventories (.23).

This decoupling of automobile manufacturers and retailers may reflect the adoption of new inventory and production control systems during the industry re-structuring in the late 1970s and early 1980's.[12] But other changes occurred since the early 1980s too and may help explain the intra-industry structural changes. For example, automobile dealerships, once aligned with only one manufacturer, now can sell multiple makes of cars and trucks. In addition, the sales of imported and exported automobiles have increased significantly. Likewise, and foreign automobile manufacturers have built and operated plants in the United States, and U.S. manufacturers are more active in foreign countries.

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 automobile industry, these changes may be responsible for much of the results noted in the

[10] Our finding of an important role for the automobile industry is complementary to Ramey and Vine (2006), who focus exclusively on the automobile industry. We examine the macroeconomic implications of supply and distribution chains, which appear throughout manufacturing and trade and thus influence aggregate behavior.
[11] Data measured in physical units of automobiles yields qualitatively similar results. The analogous correlation between manufacturing auto production and retail auto sales fell from .40 to –.03. Unfortunately, data on physical unit of automobile sales by manufacturers to retailers are unavailable, so we cannot calculate the same correlation.
[12] As is documented in Appendix 2, we investigated another possible explanation, i.e. whether there were major changes in the auto industry input-output structure, and found there were none.

literature and this paper.[13] In fact, our 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.

3. Variance Decomposition of Goods Sector Output

This section reports a complete decomposition of the variance in the output growth of detailed manufacturing and trade (M&T) industries. M&T accounts for most of the output and variance of output in the NIPA goods sector, plus M&T industries hold more than four-fifths of all inventory stocks. In addition, M&T industries have more detailed data at high frequency than the NIPA data. Because output growth contributions are not readily available for M&T industries, they must be constructed from the available data.

3.1 Data

The data are quarterly estimates of real (chain-weighted $2000) sales and inventories for manufacturing and trade (M&T) industries from the Bureau of Economic Analysis (BEA). More than 40 SIC-based industries at the 2- and 3-digit levels offer sufficiently long time series at the industry level. The sample runs from 1967:Q1 through 2001:Q1.[14]

Following NIPA methodology for GDP as closely as possible, we define M&T output as the sum of sales and total inventory investment, $Y_t = S_t + \Delta I_t$. Because GDP is value-added, total inventories include finished goods, work-in-process, and materials and supplies stocks. Unfortunately, however, M&T sales do not net out material input costs, some of which are the sales of upstream industries. So there is double counting of sales among industries and M&T

[13] 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 Kahn, McConnell, and Perez-Quiros (2002) emphasize the importance of durable goods industries, of which the automobile industry is a major part. 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. Studies of the automobile industry, such as Blanchard (1983), Kashyap and Wilcox (1993), Ramey and Vine (2006), and Hall et al provide useful foundations. Other multi-sector or multi-firm inventory studies, such as Cooper and Haltiwanger's (1990), Humphreys, Maccini, and Schuh's (2001), Wen (2006), Khan and Thomas (2007), and Iacoviello, Schiantarelli, and Schuh (2007) may be helpful as well. Changes in markups, as in Bils and Kahn (2000) and Burstein, Eichenbaum, and Rebelo (2004), may also be important, especially for prices charged along supply and distribution chains.

[14] The SIC data were discontinued in the early 2000s, but the new NAICS data are not available far enough back in time to study volatility breaks. Table 12 provides a complete list of SIC industries.

output is gross production rather than value added. Despite this shortcoming, the M&T data appear to provide reliable information about volatility reductions.[15]

The M&T data are constructed as follows.[16] Growth contributions (denoted by a tilde) for real output in industry j are obtained by chain-weighting growth contributions of real industry sales and inventories using a three-variable Tornqvist approximation, $\tilde{y}_{jt} \equiv \tilde{s}_{jt} + \tilde{i}_{jt} - \tilde{i}_{j,t-1}$. Aggregate M&T real output growth is obtained from a Tornqvist approximation using all of the industry-level real output growth contributions, $\tilde{y}_t = \sum_j \tilde{y}_{jt}$. The key advantage of the growth contributions is that they are additive, which facilitates the imposition of the exact aggregation conditions necessary for the variance decompositions and HAVAR model.

Recognizing there may be potentially serious flaws in constructing these M&T data, we used other related data to verify the robustness of our preferred data measure. Our main findings in this section are not sensitive to the data source at all, so we use only our preferred measure of output growth contributions for the remainder of this paper.

3.2 Variance Decompositions

We decompose the variance of aggregate M&T output growth, $\tilde{y}_t$, in terms of the industry-level variance-covariance structure of $\tilde{y}_{jt}$, $\tilde{s}_{jt}$, and $\Delta\tilde{i}_{jt}$, for each sub-sample of the data around the break point identified by McConnell and Perez-Quiros (2000), 1967–1983 and 1984–2001. These variance decompositions are then used to account for the change in variance of aggregate M&T output growth between the periods.

Table 3 reports results for M&T, and Table 4 reports results for the two sectors separately to facilitate comparison with our HAVAR model. The first panel of each table reports the decomposition by output:

$$\mathrm{Var}(\tilde{y}) = \sum_{j=1}^{\mathrm{J}} \mathrm{Var}(\tilde{y}_j) + 2\sum_{\mathrm{j>k}} \mathrm{Cov}(\tilde{y}_j, \tilde{y}_k) \ .$$

The remaining panels report the decomposition by sales and inventory investment:

[15] The correlation between growth rates of NIPA goods-sector value-added and M&T sector gross production is about 0.7 despite the fact that the NIPA goods sector includes several highly volatile industries (agriculture, mining, and utilities) that M&T does not. Importantly, the qualitative properties of variance, and change in variance, are very similar between the two output measures. For more details, see Irvine and Schuh (2005a).

[16] See the Data Appendix to this paper and Irvine and Schuh (2005a) for more details.

$$\text{Var}(\tilde{y}) = \sum_{j=1}^{J} \left[\text{Var}(\tilde{s}_j) + \text{Var}(\Delta \tilde{i}_j) + 2\text{Cov}(\tilde{s}_j, \Delta \tilde{i}_j) \right]$$

$$+2\sum_{j>k} \left[\text{Cov}(\tilde{s}_j, \tilde{s}_k) + \text{Cov}(\Delta \tilde{i}_j, \Delta \tilde{i}_k) \right] + 2\sum_{j \neq k} \text{Cov}(\tilde{s}_j, \Delta \tilde{i}_k) \quad .$$

In both cases, we refer to the individual variances as the *within*-industry component and the covariance terms as the *between*-industry component. The first two columns of each table report the variance-covariance values in each period, and the third column reports their ratio (late period to early period). The final two columns report the shares of each component in the variance decomposition of aggregate M&T output growth.

Our central empirical result is that the vast majority of the decline in volatility associated with the Great Moderation occurred through a reduction in covariance – a decoupling – among industries. Table 3 shows that the variance of aggregate M&T output growth declined by 82 percent (a variance ratio of .18).[17] The reduction was slightly higher for covariance among industries (84 percent), and slightly smaller for industry variances (73 percent). More importantly, however, the reduction in covariance among industries accounts for 82 percent of the decline in aggregate M&T output variance.[18] Alternative measures of output, and of factor inputs, yield strikingly similar results.[19]

In absolute terms, covariance had to play a larger role in the Great Moderation simply because it accounted for most of the variance in aggregate output initially (4.11 of the 5.12 variance in the early period). So, for robustness, we also report statistics on correlation between industries (fourth row). The mean correlation among pairs of industry output growth contributions declined from by about half, from .19 to .09 (or 52 percent, correlation ratio of

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[17] The comparable estimate for the NIPA goods sector is 74 percent (variance ratio of .26), as reported in Irvine and Schuh (2005a).

[18] The comparable estimate for the NIPA goods sector is 64 percent, as reported in Irvine and Schuh (2005a). To relate the M&T results to GDP, assume that M&T is roughly representative of the NIPA goods sector. Then the reduction in covariance between industries in the goods sector would account for 52 percent ($.64 \times .82$) of the decline in GDP volatility. Adding in the contribution of the decline in covariance between the three NIPA sectors from Table 1 (27 percent), the total covariance reduction would account for at least 79 percent of the decline in GDP volatility. This estimate likely would be even higher if the NIPA structures and services sectors could be disaggregated into detailed industries as well.

[19] We performed analogous decompositions of aggregate M&T growth using three alternative data sources: 1) a measure of chain-weighted BEA real output growth using a "residual" method (see the Data Appendix); 2) industrial production data from the Federal Reserve; and 3) hours data from the Bureau of Labor Statistics establishment survey. Each alternative data source yields virtually identical results to those in Table X. That is, the variance of

.48). This result reaffirms that the large reduction of covariance characterizing the Great Moderation reflects changes in comovement, rather than an artifact of the decline in industry variances and covariances.

The variance decomposition results for sales, inventory investment, and their covariance (remaining panels of Table 3) are qualitatively similar to those for output in at least two respects. First, the variance of all three aggregate M&T variables each declined by roughly 80 percent (variance ratios from .18 to .23). Second, most of the decline in the aggregate variance is attributable to a decline in covariance among industries (shares of 82 percent for sales and 89 percent for sales-inventory investment covariance), although the within-industry component is relatively large for inventory investment (49 percent share).

The disaggregated data paint a different picture of the Great Moderation than the aggregate data do. The decline in sales variance actually accounts for most (73 percent) of the decline in output variance, a fact pointed out by Stock and Watson (2003), among others, using aggregate data. However, the vast majority of this decline in sales variance (and thus in output variance) occurred in the between-industry covariance component. Convincing explanations of the Great Moderation must explain this reduction in comovement among industries' sales and output. Although inventory investment variance declined, it cannot explain much of the decline in output volatility directly (13 percent). Thus, to explain more of the Great Moderation, inventory investment would have had to play a more nuanced role in contributing to reduced comovement among industries' sales.

Perhaps the most intriguing example of this point is seen in the results on covariance between sales and inventory investment in the last panel of Table 3. As Blanchard and Simon (2001) first noted, covariance between sales and inventory investment did decline significantly (covariance ratio of .23). However, the variance decomposition reveals that this change only accounts for 14 percent of the decline in aggregate output variance. Moreover, nearly all (89 percent) of the change in covariance occurred between industries – that is, between the sales of industry j and the inventory investment of industry k (and vice versa).

By itself, this last result is suggestive of behavioral changes along supply and distribution chains. However, only a formal model can to verify this conjecture properly by allowing us to

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aggregate M&T growth declined by about 81 to 85 percent from the early to late period, and changes in industry-level covariance accounted for about 81 to 87 percent of this decline in aggregate variance.

test whether such changes could be related to the much larger change in covariance among industries' sales.

Because the remainder of this paper is based primarily on a two-sector HAVAR model, Table 4 reports the variance decomposition partitioned into manufacturing and trade sectors separately.[20] The shaded rows in Table 4 are repeated from Table 3 for convenience. The decline in the variance of output growth is somewhat larger for manufacturing (83 percent, variance ratio of .17) than trade (77 percent, variance ratio of .23). However, covariance between these sectors' output accounts for much less of the decline in aggregate output variance (only 42 percent) than the total contribution of covariance between industries (82 percent, Table 3). Changes in covariance between industries within M&T sectors account for the remainder (27 percent within manufacturing and 13 percent within trade), but this covariance is not reflected in the sector-level data used to estimate the HAVAR model. Industry variances in the M&T sectors each account for close to half of the change in this variance component (43 percent and 58 percent, respectively).

3.3 Industry-Level Changes in Variance and Covariance

The decline in variance and covariance was pervasive across industries. Irvine and Schuh (2005a) report that nearly every industry experienced a decline in variance of at least XX percent, and only X industries did not experience a material decline in variance. Likewise, in an earlier version of this paper (Irvine and Schuh 2005b), we showed that pair-wise covariance between industries and industry-wide covariance (the sum of an industry's covariance with all other industries) also declined widely. Thus, a few outliers cannot account for the results in Tables 3 and 4.

However, a relatively small group of industries – which are related by supply and distribution chains – account for a disproportionately large part of the decline in output covariance among industries, and thus for the Great Moderation. Figure 2 plots the relationship between industry size and the reduction in covariance among industries' sales. Industry size is measured as the average nominal share of industry sales in the early period (1967–1983). The reduction in total sales covariance for industry j with all other industries is

[20] See Appendix Table 1 for the complete set of variance decompositions into the M&T sales and inventory investment components of aggregate output.

$$\theta_j = \left[\frac{\sum_{k \neq j} \Delta \mathrm{Cov}(\tilde{s}_j, \tilde{s}_k)}{\sum_{k > j} \Delta \mathrm{Cov}(\tilde{s}_j, \tilde{s}_k)} \right],$$

where Δ denotes the change from the early period to the late period. The numerator sums all the individual covariance terms for industry j, and the denominator is the total change in covariance among all industries. The 45-degree line indicates where the covariance reduction is proportional to size.

Figure 2 begins to reveal why the two industries highlighted in Figure 1 are so important. Automobile manufacturers (SIC 371) and automobile retailers (SIC 551) each accounts for about 8 percent of the decline in aggregate sales covariance, or roughly twice their size. Furthermore, several other industries that account for disproportionately large shares of the covariance reduction (SIC 28, 29 30, 33, 34, 35, 36 505, and 517) make products (chemicals, rubber, metals, machinery, and petroleum) that are closely related to the automobile industry through supply chains. Together, this group of industries accounts directly for more than two-fifths of the decline in aggregate covariance among the sales of M&T industries.

3.4 Factor Model Interpretation

One way to interpret and explain the important empirical role of changes in comovement in the Great Moderation is to use a factor model. In Irvine and Schuh (2005b, 2007), we do so and find that a typical factor model based on standardized data cannot explain the observed change in comovement (as measured by correlation) well at all. A factor model based on non-standardized data, however, can fit the observed change covariance reasonably well. But to do so, the estimated model identifies a small number of industry-specific factors that account for the bulk of the variance in aggregate M&T output, rather than identifying a common, economy-wide factor that typically emerges from conventional factor models. Perhaps not surprisingly, the covariance-based factor model identifies the following industries (listed in descending order of importance): autos, oil, capital goods, and food.

4. HAVAR Model

To quantify the effects of changes in comovement and the volatility of aggregate output growth since 1983, we use the HAVAR modeling framework developed by Fratantoni and Schuh (2003). Although HAVAR models do not identify preference and technology parameters, they are consistent with the reduced-forms of heterogeneous-agent dynamic optimizing models.[21] These more structural models quickly become intractable for large numbers of agents, and there are "conceptual difficulties inherent in thinking about an economy with many sectors" (Christiano and Fitzgerald 1998, p. 56). Thus, at the cost of some structural identification, the HAVAR framework offers a tractable econometric method of quantifying the potential impact of changes in structural relationships between sectors (or industries) on the volatility of aggregate output.

HAVAR models also exhibit important two advantages over related VAR models used to analyze aggregate output volatility. First, HAVAR models nest macro VARs based on aggregate data, thus they permit direct tests of the strong homogeneity restrictions imposed by macro VARs. If heterogeneity among agents is important in the data, HAVAR models can incorporate it in an econometrically meaningful way, such as allowing for supply- and distribution-chain relationships between sectors or industries. Second, the HAVAR methodology imposes all of the exact aggregation conditions necessary to make the model fully internally consistent, a feature that is lacking in other VAR-based models using data on individual agents.

4.1 General Specification

Our HAVAR framework is a disaggregated type of benchmark macro VAR like those used in Stock and Watson (2002) and Ahmed, Levin, and Wilson (2004). It includes: inflation, π_t; the nominal interest rate (federal funds), f_t; and real output growth (M&T), $\tilde{y}_t$, decomposed into sales and inventory investment, $\tilde{s}_t$ and $\Delta\tilde{i}_t$ (tilde denoting growth contributions).[22] Like Ahmed, Levin, and Wilson, we consider a three-variable aggregate VAR model with $Z_t = \begin{bmatrix}\pi_t & \tilde{y}_t & f_t\end{bmatrix}'$, called Macro3, and a four-variable model with $Z_t = \begin{bmatrix}\pi_t & \tilde{s}_t & \Delta\tilde{i}_t & f_t\end{bmatrix}'$, called Macro4, to identify the importance of disaggregating the components of aggregate output without disaggregating by industry.

The HAVAR model data and innovation vectors are:

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[21] See Abadir and Talmain (2002), for example.

[22] Inflation is measured with the CPI excluding food and energy. Our HAVAR specification differs from the literature as follows: 1) it decomposes output into growth *contributions* (which sum to aggregate output growth and facilitate aggregation); 2) it excludes commodity prices (although our results are robust to their inclusion); and 3) it includes only M&T output growth (which accounts for a large majority of GDP volatility). Although M&T is only a minority of total output in the economy, the goods sector accounts for the vast majority of the volatility of GDP growth (see Irvine and Schuh 2005a).

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

where the lowercase z_t denotes disaggregated data on individual agents (sectors or industries). Subscript $j = \{1, 2, \ldots, J\}$ denotes industries, and the partition separates the macro variables from the industry variables. The structural HAVAR model is

$$\Gamma_0^* \tilde{z}_t^* = \Gamma^* + \sum_{l=1}^{L} \Gamma_l^* \tilde{z}_{t-l}^* + \varepsilon_t^* \;, \tag{1}$$

where Γ_l^* are matrices of structural coefficients on lag l and Γ^* is a vector of constants. Following standard practice, structural parameters can be identified from the OLS estimates of the reduced-form parameters of the unrestricted HAVAR model,

$$\tilde{z}_t^* = \phi^* + \sum_{l=1}^{L} \phi_l^* \tilde{z}_{t-l}^* + u_t^* \;, \tag{2}$$

where $\phi^* = \left(\Gamma_0^*\right)^{-1} \Gamma^*$, $\phi_l^* = \left(\Gamma_0^*\right)^{-1} \Gamma_l^*$, and $u_t = \left(\Gamma_0^*\right)^{-1} \varepsilon_t^*$.

Expanding notation, the contemporaneous part of the structural HAVAR model is

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

where $Z_t^m = \left[\pi_t \; f_t \right]'$ contains the "macro" variables (superscript m) and

$$\tilde{z}_t^a = \left[\tilde{s}_{1t} \; \Delta\tilde{i}_{1t} \; \ldots \; \tilde{s}_{Jt} \; \Delta\tilde{i}_{Jt} \right]'$$

contains variables that are "aggregated" (superscript a) over individual agents. Lagged portions of the model have analogous notation.

We want to consider two polar characterizations of Γ_0^{aa} representing an "uncoupled" (U) and "coupled" (C) HAVAR model economy:

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

As in Fratantoni and Schuh (2003), the uncoupled economy model sets all matrices off the block-diagonal of Γ_0^{aa} to be zero, so there are no contemporaneous structural relationships between agents (though there may be such relationships among variables of the same agent). This model is of interest because it is close to the Macro4 VAR model, except that it allows heterogeneous industry responses to macro variables. In contrast, the coupled economy model captures possible structural relationships among sector-level sales and inventory investment variables. These parameters in the coupled HAVAR model introduce potential comovement among sectors stemming from the existence of supply- and distribution chains, which is distinct from comovement stemming from common responses of sectors to macro variables.[23]

4.2 Relation to Other VAR Models

The HAVAR modeling framework is more general and less restricted than other VAR models based on either aggregate or disaggregated data. For this reason, our HAVAR model nests the VAR models used previously in the literature to evaluate the reduction in GDP volatility. Thus, the HAVAR model permits direct testing of the implicit restrictions in other VAR models that impose homogeneity among agents or prevent direct structural interaction among agents (such as supply- and distribution-chains). Because the HAVAR model does not impose these restrictions, it can identify structural changes that the other VAR-based models cannot. The rest of this subsection briefly explains these points.

Benchmark macro VAR models based on aggregate data are equivalent to a HAVAR model that imposes three types of implicit homogeneity restrictions on individual agents (industries): 1) $\Gamma_{l,j}^{ma} = \Gamma_l^{ma}$ for all $j = \{1, ..., J\}$, a *representative-agent assumption* that homogenizes the impact of individual agents on macro variables; 2) $\Gamma_{l,j}^{am} = \Gamma_l^{am}$ for all $j = \{1, ..., J\}$, a *homogeneous agent assumption* that forces macro variables to have the same impact on all individual agents; and 3) $\Gamma_l^{aa} = I_{JN}$ (an identity matrix where N is the number of variables in each individual VAR), a *no linkage assumption* that rules out structural relationships between individual agents (and even between variables of the same agent). These restrictions can be tested econometrically.

[23] As we explain in more detail elsewhere (Irvine and Schuh 2005b, 2007), this ability to distinguish between sources of comovement attributable to macro variables (or common factors) and attributable to structural relationships among sectors is a key advantage of the HAVAR model.

Although other disaggregated VARs in the literature allow for some heterogeneity across individual agents, they too impose restrictions that the more general HAVAR framework does not. For example, McCarthy and Zakrajsek (2007) restrict $\Gamma_{l,j}^{ma} = 0 \quad j = \{1,...,J\}$. This restriction prevents their industry variables from having a direct effect on any aggregate variables – neither macro variables (such as inflation and the interest rate) nor aggregated variables (such as sales and inventories).[24] While this restriction may be relatively innocuous for the feedback from industry sales and inventories to inflation and interest rates – a hypothesis better tested than assumed, of course – it is incorrect by definition for aggregate sales and aggregate inventories. Thus, the McCarthy-Zakrajsek model does not incorporate the aggregation conditions necessary to make the system internally consistent in the way the HAVAR framework does.[25]

4.3 Identification

Identification issues are similar to those in macro VAR models, but the HAVAR model poses more identification challenges because estimation is considerably more difficult. In its most general form, as reflected in equation (4), the HAVAR model is generally impossible to estimate for large J because the number of unrestricted parameters in Γ_0^{aa} is too large relative to the degrees of freedom in the available data. Fratantoni and Schuh (2003) dealt with this problem using a two-step estimation approach, in which the structural parameters of each geographic region were estimated independently.

Here we take a potentially better approach by constructing a two-sector ($J = 2$) HAVAR model for manufacturing (M) and trade (T), the latter containing wholesale and retail industries. This specification choice has several advantages. It allows for potential supply- and distribution-chain relationships that exist naturally among the industries of these sectors. However, it remains relatively aggregate and close enough to the macro VAR models to limit potential small-sample problems such as over-fitting, spurious correlation, and insignificance. Furthermore, the two-sector specification allows us to estimate all structural parameters simultaneously.

[24] Herrera and Pesavento (2005) also use industry-level VARs in their study of break points. Because their models do not include any aggregate data or interactions between industries, they implicitly assume that $\Gamma_l^{mm} = \Gamma_l^{ma} = \Gamma_l^{am} = 0$ and that the off-diagonal elements of Γ_l^{aa} are zero.

[25] In addition, the McCarthy-Zakrajsek model assumes that the off-diagonal elements of Γ_l^{aa} are zero, an assumption that rules out direct structural linkage relationships between industries. This assumption is particularly problematic for sectors or industries linked by input-output and supply-chain relationships.

The contemporaneous portion of the M&T structural HAVAR model, with output disaggregated into sales and inventory investment, is

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

Impact matrix Γ_0^* contains $N^2 = (2J+2)^2 = 36$ potential parameters, where N is the dimension of $\tilde{z}_t^*$, and 30 off-diagonal parameters after normalization. However, only $N(N-1)/2 = 15$ unique parameters may be identified and estimated (Christiano, Eichenbaum and Evans 1999), so we must make some additional identifying restrictions.

Following the general identification strategy advocated by Fratantoni and Schuh (2003), we impose the following restrictions on three of the quadrants in Γ_0^*:

- An ordering between π and f in Γ_0^{mm} (upper left quadrant) analogous to that used in many macro VARs, which appeals to short-run price stickiness and inflation persistence. Thus, $\gamma_{\pi f} = 0$ and the contemporaneous effect of f on π is zero.
- Representative agent behavior in macro variables, $\Gamma_{0,j}^{ma} = \Gamma_0^{ma} \;\; \forall \; j$ (upper right quadrant), so only aggregate sales and aggregate inventory investment affect inflation and the federal funds rate contemporaneously. For sales, this implies $\gamma_{\pi s}^{T} = \gamma_{\pi s}^{M} = \gamma_{\pi s}$ and $\gamma_{fs}^{T} = \gamma_{fs}^{M} = \gamma_{fs}$ (and likewise for the analogous inventory parameters). Thus, the federal funds 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. This representative agent assumption is justified because the monetary authority only targets aggregate variables. In addition, we impose the common ordering of π and y, again appealing to short-run price stickiness and inflation persistence ($\gamma_{\pi s} = \gamma_{\pi\Delta i} = 0$).[26]

[26] 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.

- Heterogeneous effects of *ex post* real rates on sector-level output variables in $\Gamma_{0,j}^{am}$ (lower left quadrant).[27] For example, $\gamma_{sf}^{T} = -\gamma_{s\pi}^{T}$ (and likewise for the other parameters).

Together, these 11 restrictions reduce the number of parameters from 30 to 19, so we still need at least 4 additional restrictions on the remaining quadrant of Γ_0^*.

Although difficult to identify, Γ_0^{aa} (lower right quadrant) is precisely where the HAVAR model exhibits its greatest advantage over macro VARs – the opportunity to characterize and quantify potential structural relationships among sectors. Unfortunately, there is little theoretical or empirical guidance in the literature on which to rely for this part of identification. One possibility, common in the VAR literature, would be to order the sectors by location along the supply chain (Γ_0^{aa} lower triangular). However, this strong assumption is sensible only if all manufactured goods are distributed to the trade sector before going to final customers, and if the only source of output fluctuations along the chain is changes in final demand. So this ordering easily could be violated for many reasons.[28]

Instead, to identify the parameters of $\Gamma_{0,C}^{aa}$, we imposed the following restriction, which is suggested loosely by existing inventory theories:

- An ordering of Δi and s *within* each sector, so inventory investment does not affect sales contemporaneously ($\gamma_{s\Delta i}^{TT} = \gamma_{s\Delta i}^{MM} = 0$). Sales do affect inventory investment contemporaneously ($\gamma_{\Delta is}^{TT}, \gamma_{\Delta is}^{MM} \neq 0$), and the effect is allowed to differ across sectors. These parameters should be negative (hence a positive contemporaneous correlation between inventory investment and sales), reflecting the long-run relationship between inventories and sales. However, because we must use growth contributions data to facilitate aggregation, this relationship differs from the standard theoretical long-run

[27] For examples, see Carlino and DeFina (1998) and Fratantoni and Schuh (2003). 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.

[28] 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

relationship between sales and the *level* of inventories, rather than inventory investment.[29]

This ordering restriction is imposed on each of the two block diagonal matrices in $\Gamma_{0,C}^{aa}$, reducing the number of parameters remaining to identify from 19 to 17.

Finally, the off-diagonal matrices in $\Gamma_{0,C}^{aa}$ represent the key structural relationships *between* sectors that would reflect the influence of potential supply and distribution chains between manufacturing and trade. Unfortunately, there are few data-consistent theories of these chain relationships on which to rely for guidance in identification.[30] Thus, we use intuition and statistical tests to settle on the following remaining restrictions:

- Manufacturing and trade sales are linked by a distribution chain, so $\gamma_{ss}^{TM} = \gamma_{ss}^{MT} = \gamma_{ss}$. We assume that $\gamma_{ss} < 0$ (a positive long-run correlation between manufacturing sales and trade sales). An implication of this restriction is a symmetric effect on sales in each sector: final demand shocks that hit trade sales raise manufacturing sales, and supply shocks that hit manufacturing sales raise trade sales. *A priori* it is not entirely clear that this symmetry is warranted, but this restriction turns out to be very strongly supported by the data.
- Inventories in one sector might plausibly affect sales in the other sector, or vice versa, so we allowed both $\gamma_{s\Delta i}^{MT}$ and $\gamma_{s\Delta i}^{TM}$ to be non-zero. These effects might arise from strong corporate relationships, like those in the auto industry documented by Blanchard (1983) and Ramey and Vine (2006). Another possible explanation is price flexibility or information sharing along supply and distribution chains. However, we cannot reject the hypothesis that $\gamma_{s\Delta i}^{MT}$ is the only significant parameter among those remaining, so we restrict the rest to zero.

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intermediate goods to manufacturers. These are a few examples of how a strict ordering may break down. In any case, sector ordering has very little effect on the aggregate dynamics of our M&T HAVAR model.

[29] For example, see Kashyap and Wilcox (1993), which emphasizes the cointegrating relationship between the levels of sales and inventories.

[30] Khan and Thomas (2007) and Wen (2006) are the closest theoretical models to provide some underlying intuition regarding input-output and supply chains, but neither one is estimated to fit actual data. The estimated two-sector model in Iacoviello, Schiantarelli, and Schuh (2007) has a goods sector, which holds inventories, and a services sector, which does not, but it does not have stage-of-fabrication linkages between industries like manufacturing and trade within the goods sector as in the M&T HAVAR model.

These restrictions reduce the number of parameters to be estimated to 11. Thus, the identified contemporaneous HAVAR matrix reduces to:

$$\Gamma_0^* \tilde{z}_t^* \equiv \left[\begin{array}{cc|cccc} 1 & 0 & 0 & 0 & 0 & 0 \\ \gamma_{f\pi} & 1 & \gamma_{fs} & \gamma_{f\Delta i} & \gamma_{fs} & \gamma_{f\Delta i} \\ \hline -\gamma_{sr}^{T} & \gamma_{sr}^{T} & 1 & 0 & \gamma_{ss} & 0 \\ -\gamma_{\Delta ir}^{T} & \gamma_{\Delta ir}^{T} & \gamma_{\Delta is}^{TT} & 1 & 0 & 0 \\ -\gamma_{sr}^{M} & \gamma_{sr}^{M} & \gamma_{ss} & \gamma_{s\Delta i}^{MT} & 1 & 0 \\ -\gamma_{\Delta ir}^{M} & \gamma_{\Delta ir}^{M} & 0 & 0 & \gamma_{\Delta is}^{MM} & 1 \end{array}\right] \left[\begin{array}{c} \pi_t \\ f_t \\ \hline \tilde{s}_t^T \\ \Delta\tilde{i}_t^T \\ \tilde{s}_t^M \\ \Delta\tilde{i}_t^M \end{array}\right].$$

With only 11 parameters to estimate, the model is over-identified, and these over-identifying restrictions are testable.[31]

4.4 Estimation

All models are estimated using standard VAR estimation methods. Reduced-form coefficients are obtained from OLS estimation over the periods 1967:4–1983:4 and 1984:1–2001:4. Based on pre-testing, the models include two lags of data ($L = 2$). For the Macro3 and Macro4 models, we obtain the estimated structure (Γ_0 and ε_t) from the Cholesky decomposition of the reduced-form residuals, with variables ordered as shown earlier in the text. For the HAVAR models, we obtain the estimated structure using maximum likelihood estimation of the variance-covariance relationships implied by $u_t = \left(\Gamma_0^*\right)^{-1} \varepsilon_t^*$.

5. Results

This section contains our main analysis of the Great Moderation using the estimated M&T HAVAR model, and a comparison of those results with a similar analysis using standard macro VAR models. First, we describe the results of counterfactual simulations that quantify the

[31] We have explored numerous identification schemes and found the qualitative dynamics of the model to be quite robust. To obtain results comparable to the literature, especially Ahmed, Levin, and Wilson (2004) and Stock and Watson (2003), we explored a HAVAR model using a variable ordering scheme $\left[\pi_t \quad \tilde{s}_t \quad \Delta\tilde{i}_t \quad f_t\right]$ that is close to the Cholesky decomposition. The only qualitative difference is that the HAVAR model allows a contemporaneous effect of real rates on output while the ordered model does not. From the ordered HAVAR model are qualitatively similar to those from our identified HAVAR model. However, the ordering identification poses a problem for the HAVAR model because it orders agents, which may not be warranted. It is unlikely that these large, interrelated M&T sectors do not respond to shocks in the other for an entire quarter (the frequency of our data). Alternative orderings and restrictions on $\Gamma_{0,C}^{aa}$ have very little effect on the aggregate dynamics of the model, although they do alter the sector dynamics somewhat, but our focus is on aggregate dynamics.

roles of changes in economic structure versus shocks in explaining the observed decline in aggregate output variance. Second, we analyze the structural parameter estimates of the HAVAR model to gain better economic interpretation of the most important structural changes in the model. And third, we examine the dynamic properties of the entire HAVAR model.

5.1 Counterfactual Simulations

First, we examine the properties of the HAVAR model using the kind of regime-change counterfactual experiment conducted by Stock and Watson (2003) and Ahmed, Levin, and Wilson (2004), among others, to gauge the impact of structural change on output volatility.[32] This counterfactual experiment involves substituting the estimated parameters, or structure, from the late period (1984-2001) into the estimated model of the early period and comparing the model's estimated decline in output variance with the actual decline in variance observed in the data. Similar experiments can be conducted with the residuals. Although there is not universal agreement about the ability of such exercises to reveal changes in the "deep" structure using VAR-based models, we report results for comparison with the literature.

From equations (1) and (2), the estimated structural HAVAR model can be written as

$$z_t^* = \left[\Gamma_0^{*-1}\Gamma^* + \Gamma_0^{*-1}\Gamma_1^* z_{t-1}^* + \Gamma_0^{*-1}\Gamma_2^* z_{t-2}^*\right] + \Gamma_0^{*-1}\varepsilon_t^* \ ; \qquad (3)$$

the Macro VAR models can be written similarly. Following Stock and Watson, we refer to the first three terms (in brackets) on the right-hand-side of equation (3) as the lagged coefficients, or *lagged structure*, of the reduced-form model defined in equation (2). The counterfactual simulation for the lagged structure is to substitute the late-period (L) estimates of the lagged structure, $\phi_{l,L}^*$, for the early-period (E) estimates, $\phi_{l,E}^*$, and then to simulate the new time series of z_t^* using the early-period reduced-form residuals, $u_{t,E}^*$ and the actual data. We define Γ_0^* as the *contemporaneous structure* to examine the independent contribution of this part of the structure on change in volatility of the reduced-form residuals. The counterfactual exercise for the contemporaneous structure is to substitute $\Gamma_{0,L}^*$ for $\Gamma_{0,E}^*$ only in the reduced-form residual, $u_{t,E}^*$, and then to simulate the new time series of z_t^* using the early-period lagged structure, the actual data, and the early period innovations, $\varepsilon_{t,E}^*$. Because the structural changes in Γ_0^* are so important, we also report a counterfactual simulation based on the *"real" contemporaneous* *structure* in which only the portion of Γ_0^* associated with sales and inventory investment, Γ_0^{aa}, is changed. This reveals the importance of the changes in structural relationships between sectors.

Results of the counterfactual simulations are reported in Table 5. The table contains the percentages of the actual decline in variance accounted for by changes in the lagged and contemporaneous structure, as measured by each macro VAR and HAVAR model. Results are reported for the variance of aggregate M&T output growth, which fell from 5.13 to .92, and the variance of inflation, which fell from 10.45 to 1.18. The table also includes a three-sector HAVAR model, with trade disaggregated into retail and wholesale industries, to illustrate the crucial importance of disaggregation and comovement in fully explaining the Great Moderation.

Structural change and comovement become more important in explaining the Great Moderation with only modest disaggregation, as seen in the first column of Table 5. Simply by disaggregating aggregate M&T output into sales and inventory investment, the contribution of total structural change rises from 4.5 percent in Macro3 to 21 percent in Macro4.[33] By relaxing the homogeneity restrictions on agents imposed by Macro4, the contribution rises to 29.9 percent in the uncoupled 2-sector HAVAR model. And by introducing structural relationships between industries, the contribution rises to 35.5 percent in the coupled HAVAR model.

Disaggregating the aggregate economy into two coupled sectors increases the importance of structural changes a nontrivial amount (from 21 to 36 percent), and motivates further investigation into the role played by comovement between these sectors. Nevertheless, using the 2-sector HAVAR model, one might still conclude that "good luck" – a reduction in the variances of the structural innovations, ε_t^* – remains the primary explanation for the Great Moderation. However, the final row of Table 5 suggests this conclusion may be tenuous. The 3-sector HAVAR model, which features independent roles for wholesale and retail trade, reveals that nearly three-fourths (73.1 percent) of the Great Moderation can be explained by structural change.[34] This result appears to weaken the case for the "good luck" explanation.

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[32] These kind of regime-change counterfactual experiments have been used in VAR-based analyses at least back to Sims (1998), especially in testing for changes in monetary policy reaction functions.
[33] This result is qualitatively similar to the one found by Ahmed, Levin, and Wilson (2004) in their macro VAR.
[34] Although we believe it is important to disaggregate the trade sector into wholesale and retail components, we want to focus on the most aggregate HAVAR results here to minimize skepticism about the results from disaggregated models. In future research, we plan to explore the roles of supply and distribution chains in more detail, both within trade and within manufacturing, as well as the roles different types of inventories play in those chains.

The second and third columns of Table 5 indicate that most of the structural change occurred in the contemporaneous, rather than lagged, portion of the model. The contribution of changes in contemporaneous structure to the Great Moderation ranges from 4 percent in the Macro3 model to 49 percent in the 3-sector HAVAR model. For the 2-sector HAVAR model, 25.7 percent out of the 35.5 percent contribution (nearly three-fourths) is attributable to changes in the contemporaneous structure. And nearly all (24.1 percent) of that 25.7 percent is attributable to changes in the real structure – the relationships governing sales and inventory investment behavior among sectors – rather than in the nominal structure – inflation and the federal funds rate – or in the interaction between real and nominal variables.

This last result not only illustrates the critical importance of comovement in explaining the Great Moderation, it also reduces the likelihood that changes in monetary policy played a central role in reducing volatility. Once the linkages between sectors are taken into account, the HAVAR model attributes essentially all of the contemporaneous structural change to the real structure. This result emerges despite evidence of structural changes in contemporaneous coefficients on the federal funds rate, as shown in the next sub-section. Only a minor, though nontrivial, portion of structural change is attributed to the lagged structure. Even if the lagged structure associated with inflation and the federal funds rate explained all of the lagged structural change (which it does not), the lagged structure cannot account for most of the Great Moderation.

The remaining columns of Table 5 show the results for inflation. Comovement is not very important for understanding the role of total structural change in explaining the decline in inflation volatility. The coupled 2-sector HAVAR model only attributes 6 percentage points more than the Macro3 model to total structural change (40.9 versus 34.9 percent). The 3-sector HAVAR model estimate of 53.3 percent suggests the additional disaggregation may alter this finding significantly. Moreover, as in the case output, most of the structural changes that reduced inflation volatility occurred in the contemporaneous structure. In contrast, comovement does influence the importance of contemporaneous versus lagged structural changes. The Macro3 model only attributes 14.7 percent (out of 34.9 percent) of the decline in inflation variance to contemporaneous structural change, whereas the 2-sector HAVAR model attributes 34.3 percent (out of 40.9 percent). Apparently, changes in the lagged structure are more important in aggregate models.

5.2 Econometric Estimates and Tests

The econometric estimates and tests of the 2-sector HAVAR model can provide additional insight into the counterfactual simulation results. This sub-section examines estimates of the contemporaneous structural coefficients, over-identifying restrictions tests of the models, and selected estimates of the lag coefficients.

5.2.1 Contemporaneous Coefficients

Table 6 reports estimates of Γ_0 (Macro3 and Macro4 models) and Γ_0^* (2-sector coupled HAVAR model) for the early (1967-1983) and late (1984-2001) periods, and their changes between periods. Results are divided into three panels of coefficients: 1) the effects of inflation on output (which occurs through *ex post* real rates in the HAVAR model); 2) the effects of inflation and output on the federal funds rate (shaded region); and 3) the effects of real variables (sales and inventory investment) on real variables (within and between industries). Note that because Γ_0 represents the simultaneous relationships, parameter estimates are the opposite sign as the contemporaneous correlation between variables.

The most statistically and economically significant changes in coefficients occurred in the real-variable quadrant of the HAVAR model, Γ_0^{aa}, that governs the relationships between sales and inventory investment within and between industries (lower right corner of Table 6). Three main findings emerge:

- *The contemporaneous correlation between manufacturing and trade sales is very significant and it declined modestly (coefficient increased).* The estimate of $\hat{\gamma}_{ss}$ rose from –.35 to –.27); although both sub-sample estimates are very statistically significant, the change is not quite. This result is qualitatively consistent with the decline in correlation between automobile manufacturing sales and retail sales reported in Table 2 (from .63 to .08). The hypothesis that $\hat{\gamma}_{ss}^{MT} = \hat{\gamma}_{ss}^{TM} = \hat{\gamma}_{ss}$ is strongly supported by the data.
- *Within industries, the contemporaneous correlation between sales and inventory investment declined (coefficients increased).* This change is most evident in trade, where $\hat{\gamma}_{\Delta is}^{TT}$ increased from –.07 to .16 (statistically significant change); thus, the correlation between sales and inventory investment changed from positive in the early

period to negative in the late period.[35] This result is qualitatively similar to the decline in retail automobile sales and inventory investment reported in Table 2 (from .15 to –.44). In manufacturing, $\hat{\gamma}_{\Delta is}^{MM}$ increased from –.08 to 0, but the change is not significant. This decline in correlation between sales and inventory investment is evident in the Macro4 model, where $\hat{\gamma}_{\Delta is}$ increased from –.11 to –.05, but the change is not significant and the model cannot capture the large differences in this coefficient between identified by the HAVAR model in the late period.

- *Between industries, the correlation between sales and inventory investment increased (coefficients decreased).* In particular, $\hat{\gamma}_{s\Delta i}^{MT}$ declined from –.40 to –.98 (statistically significant change). Trade inventory investment is now even more positively with correlated with manufacturing sales.

Each of these results pertains to the structural relationships between sectors. Because these sectors are linked by supply and distribution chains, structural changes in the design and operation of these chains may help account for these results. We discuss this possibility in more detail in the last section of the paper.

Statistically significant changes also occurred in coefficients related to the federal funds rate, $\gamma_{f\pi}$ and γ_{fy}. These macro coefficients, which appear in all three models, are related to the parameters of a Taylor rule, but given the legitimate concerns about identification in structural VARs, we do not want to push this interpretation hard here.[36]

Nevertheless, as one might expect, inflation and output are positively correlated with the federal funds rate ($\hat{\gamma}_{f\pi} < 0$ and $\hat{\gamma}_{fy} < 0$), and the coefficient on inflation is larger in both periods. However, both coefficients increased (correlations declined) in the late period – especially the output effect, which became statistically insignificant in the late period in the Macro3 model. This finding is not consistent with the literature on monetary policy reaction functions, but the

[35] 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.

[36] This HAVAR model is not suitable to represent a typical Taylor rule for reasons other than identification. In particular, the model contains growth rates of output, whereas most monetary reaction functions depend on a measure of capacity, such as an output gap.

inflation coefficients in the macro VAR and HAVAR models did become relatively more important, and this result is consistent with the literature.

The most intriguing results pertaining to the federal funds rate coefficients are found in the estimates of the Macro4 and 2-sector coupled HAVAR model, which reveal 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 significantly 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 positively correlated with the funds rate, while the sales are essentially uncorrelated. 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 larger in the HAVAR model.

Apparently, an important part of understanding changes in monetary policy lies in understanding the relationship of inventory investment to 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.[37]

The remaining coefficient estimates in the Macro4 and HAVAR models pertaining to inflation and the real interest rate are generally statistically insignificant and do not offer evidence of important structural changes. Real rates are negatively correlated (positive coefficients) with inventory investment, but oddly positively correlated with sales. For this reason, one can reject the hypothesis $\gamma_{sr} = \gamma_{\Delta ir} = \gamma_{yr}$ in most cases, but the sales result remains a puzzle.

5.2.2 Over-identifying Restrictions Tests

[37] More structural models are 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).

While the contemporaneous coefficient estimates are interesting, we want to test formally the viability of the entire VAR-based model to determine whether the disaggregation of the data in the HAVAR model is warranted. Table 7 reports the results of tests of the models' over-identifying restrictions (p-values of the χ^2 distribution, with appropriate degrees of freedom). We test the baseline models without homogeneity restrictions on the coefficients on sales and inventory investment (denoted as output restrictions "none" because these coefficients allow separate influences of sales and inventory investment). We also test models that impose these homogeneity restrictions on coefficients relating to output. In particular, the output restriction is the null hypothesis that the coefficients on sales and inventory investment are the same in the real rate block (YR: $\gamma_{sr} = \gamma_{\Delta ir} = \gamma_{yr}$) and in the federal funds rate equation (FY: $\gamma_{fs} = \gamma_{f\Delta i} = \gamma_{fy}$).

The coupled HAVAR model is the only one for which the over-identifying restrictions of its most unrestricted version cannot be rejected in both the early and late periods (p-values of .21 and .26). The uncoupled model's restrictions are easily rejected (p-values < .01) and the Macro4 model does not have any inherent over-identifying restrictions. The output restrictions, YR and FY, made on the Macro4 and coupled HAVAR model generally cannot be rejected in the early period, but are rejected in the late period with only one exception (Macro4 FY). Clearly, coupling of sectors is crucial for the HAVAR model – the uncoupled HAVAR model's over-identifying restrictions are soundly rejected.

Although one cannot reject the over-identifying restrictions of the Macro4 model with the FY restrictions, the Macro4 model is soundly rejected in favor of the HAVAR model. The addendum to Table 7 reports the results of the homogeneity restrictions made implicitly by the Macro4 model on the coupled HAVAR model. These restrictions are soundly rejected too.

5.2.3 Lag Coefficients: Sales Persistence

Ramey and Vine (2006) advance the intriguing idea that a reduction in the persistence of sales may explain the reduction in output volatility, and they provide evidence in support of this idea from data on the automobile industry. In addition to our common interest in the automobile industry, we want to examine the Ramey-Vine hypothesis more generally in a macroeconomic model such as our coupled HAVAR model.

Table 8 reports the econometric estimates of the sales equations in the HAVAR model, and compares them to more restricted equations that are closer to those Ramey and Vine used to motivate their analysis. Within each sector, the top panel of the table contains the sums of coefficients on two lags of sales – a univariate measure of persistence – in each equation; the bottom panel indicates (with an X) which other explanatory variables were included in the regressions. Column 1 reports results from a simple AR(1) equation, column 7 reports the results from the 2-sector coupled HAVAR model, and the columns in between report results from intermediate related equations to illuminate the differences between the AR(1) and HAVAR results.

Column 1 reveals that sales persistence declined in the simple AR(1) equations for trade and manufacturing. However, this result is not robust. Column 7 shows that when the lagged effects of all variables in the HAVAR model are taken into account, this univariate measure of persistence is not consistent with the Ramey-Vine results. Not only does the sales equation in both sectors display negative autocorrelation in the early period (perhaps related to the use of growth rates), persistence actually increases in the late period – by at least as much as the estimated decline in the simple AR(1) equation. Apparently, the autoregressive persistence of sales is sensitive to system dynamics.

Columns 2 through 6 of Table 8 suggest that most of the sensitivity of sales persistence is attributable to the presence of lags of the federal funds rate, but also to the presence of lags of cross-sector real variables. Columns 2 and 3 show that sales persistence increases when only the funds rate is added to lagged sales, and when inflation and the funds rate are added together. This finding suggests that the persistence phenomenon may be related to monetary policy, or to the interaction between monetary policy and the real economy. Column 6 shows that adding lags of sales, and especially inventory investment, in the *other* sector also has an ameliorating effect on sales persistence.

Based the results in Table 8, together with the counterfactual simulation results in Table 5, we conclude that changes in sales persistence are unlikely to explain a large portion the observed reduction in aggregate output volatility. However, two caveats are in order. First, our results pertain to the entire M&T sector, not the automobile industry, so we are not disputing the Ramey-Vine industry-level results. Second, and more importantly, the persistence of an individual variable in a dynamic macroeconomic model depends not just on the own lags but on the eigenvalues of the system, which depend on all coefficient matrices. Thus, the issue of persistence is better understood from the impulse response dynamics of the HAVAR model.

5.3 HAVAR Model Dynamics

This section examines the dynamic properties of the 2-sector HAVAR model in the early and late periods. We consider two aggregate shocks – a 1 percentage point increase in the federal funds rate and inflation – and two sector-specific shocks – a 1 percentage point increase in each sector's sales. The latter are catch-all, sector-specific shocks to final demand (trade) and intermediate demand (manufacturing) that are not caused by shocks to other model variables.

5.3.1 Output Responses

Figures 3 and 4 plot the impulse responses of output in each sector, and of aggregate M&T output (the sum of sector growth contributions), to the aggregate shocks. Summary statistics for all impulse response functions are found in Table 9, which reports variance ratios of impulse responses (late-period response relative to early-period response), and Table 10, which reports correlation among responses in the early and late periods (and the change in correlation).

Clearly, the impulse responses reflect a Great Moderation of output occurred throughout the HAVAR system. Aggregate output responses to each of the four shocks are much less volatile in the late period. The "peak" (most negative) output response to the fed funds shock moderated from –0.5 to –0.3; the response to the inflation shock also moderated. The actual decline in the variance of the impulse response runs from 61 percent for the fed funds shock to 27 percent for the inflation shock (see Table 9, first row) – similar to, but somewhat less than, the actual decline in output variance in the data. Most sector-specific output responses also are much less volatile in the late period, with the notable except of the trade response to the inflation shock (see Table 9, fourth and seventh rows). However, the declines in sector-specific output variance are generally smaller than the declines in aggregate M&T output variance – a result consistent with the data as reported in Tables 3 and 4.

According to the HAVAR model, the reason aggregate M&T output volatility declined more than sector-specific output volatility is that comovement between the sectors' output also declined – but in very different ways for each shock. In the early period, the sector-specific output responses to each shock were highly synchronized; the correlation was nearly 1.0 in three of the four cases (see Table 10, first row). In the late period, the comovement in the sector-specific output responses changed as follows:

- *Fed funds shock* – The output responses experienced a phase shift in which trade output responds much sooner but manufacturing output does not, so that manufacturing output now lags trade output (see Figure 3, top row). Aggregate M&T output is less volatile primarily because of this staggered timing.

- *Inflation shock* – The output responses remain in phase but now move in opposite direction, as trade output continues to decline initially but manufacturing output does not (see Figure 3, bottom row). Aggregate M&T output is less volatile and the response is smoother.
- *Sector-specific sales shocks* – The output responses differ in magnitude primarily in the first period but remain closely synchronized thereafter (see Figure 4, both rows). Aggregate M&T output is less volatile primarily because of this impact effect, but also because of less "overshooting" in the later periods.

The net result from these changes in impulse responses of output is similar. The correlation between the sectors' output declined, by –.42 and –.51 for the aggregate shocks and by about half that for the sector-specific shocks (see Table 10, first row); in the data, this correlation declined more modestly, from .73 to .55 (or –.18). Although the comovement result is similar, the economic interpretations of these changes in dynamics appear to be quite distinct, suggesting that a single explanation for the entire Great Moderation may be unlikely.

5.3.2 Sales and Inventory Investment Responses

To gain a bit more insight into the changes in output dynamics, we plot the impulse responses of sales and inventory investment to a trade sales shock in Figures 5 and to a federal funds rate shock in Figure 6. Tables 9 and 10 also provide summary statistics for all of the responses for each of the components of output.

Like output, the volatility HAVAR sales declined in the late period, but the volatility of the inventory investment responses did not. In each sector and in the aggregate, the variance ratios in Table 9 show that sales volatility declined in response to all shocks except inflation – generally about the same magnitude decline as output, or less. In contrast, these variance ratios indicate that the volatility of inventory investment generally increased – in most cases, markedly so – with the exception of the manufacturing inventory response to a trades sales shock (ratio of .56). The heightened volatility of inventory investment is the one clear shortcoming of the HAVAR model, probably due to the unusual contemporaneous relationship between sales and inventory *investment* (rather than the inventory *level*), which is necessitated by use of growth contributions for aggregation.

Not withstanding this specification shortcoming, the most striking change evident in the dynamic properties of sales and inventory investment shown in Figures 5 and 6 is the decline in their correlation. In the trade sector especially, but also in manufacturing for some shocks, the correlation between sales and inventory investment within the sector fell sharply – typically moving from positive to negative (see the last two rows of Table 10). An important consequence of this change is that production becomes smoother in both industries, as inventories play more of a conventional buffer stock role. Less evident from the figures, but equally important in Table 10, is a decline in the correlations of sales and inventory investment between sectors (the sales of one sector and inventory investment of the other, or vice versa). This last result suggests that even a simple 2-sector coupled HAVAR model can capture whatever structural changes may be occurring in the relationships among sectors and industries. To reiterate, however, a more structural theoretical model is needed to obtain a sound economic interpretation of these changes.

5.2.3 Sales Persistence, Again

The HAVAR model dynamics are related to Ramey and Vine (2006) hypothesis, they but provide a more complex interpretation of the data. The HAVAR responses of trade and aggregate sales to a fed funds shock do exhibit lower persistence, but the manufacturing sales responses do not. However, the HAVAR sales responses to all other shocks do not exhibit a systematic reduction in the persistence at the industry or aggregate level – yet output volatility declines in response to all shocks.[38] This result suggests that lower sales persistence is not a necessary condition for lower output volatility, at least not at more aggregate levels within the macroeconomy, and not for all types of shocks.

5.2.4 Impulse Response Variance Decompositions

As a final measure of the success of the HAVAR model, we decompose the variance of the model's aggregate output responses in a manner analogous to the empirical variance decompositions reported in Tables 3 and 4. The results of this decomposition for the case of a federal funds rate shock, as an example, appear in Table 11. Decompositions for other shocks produce qualitatively similar results.

The HAVAR model responses approximately replicate most of the qualitative properties of the empirical variance decompositions. The variance ratios of the impulse responses reflect

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

moderation in most variables, albeit somewhat less than in the data and inventory investment volatility rises counterfactually. Covariance between the sectors' output and sales account for about 60 percent of the decline in aggregate M&T output variance – a majority but not quite as much as in the data. The covariance share for inventory investment is much smaller than the industry variance component, as it is in the data. But the covariance share for the sales-inventory investment relationship is smaller than in the data.

6. Inventory Management

[TO BE COMPLETED. Table 12 will be explained here.]

7. Conclusion

A 2-sector HAVAR model of U.S. manufacturing and trade appears to provide a better characterization of the data than conventional macro VARs relying solely on aggregate data and offers a unique interpretation of the decline in comovement that characterizes the Great Moderation. In addition, the HAVAR model boasts the added advantage of being able to provide a structural specification that could reasonably be associated with the potentially complex and important relationships among sectors and industries in U.S. economy. Because these relationships are most likely characterized supply and distribution chains, the structural changes identified by the HAVAR model suggest that the adoption of new production and inventory management techniques in the late 1970s and early 1980s may be associated with the structural changes observed in the data. For sure, further research is warranted to verify this conjecture; we hope that the evidence in this paper provides sufficient motivation.

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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.[39] 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.[40]

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

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[39] This section relies heavily on the work of Landefeld and Parker (1997) and Whelan (2002).

[40] Adding nominal sales and inventory investment data is correct, however.

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 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),

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

where $\theta_{jt}^{y} = (1/2)\sum_{\tau=0}^{1}(\hat{Y}_{j,t-\tau} / \hat{Y}_{t-\tau})$ 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.[41]

B. Input-Output Structure

An alternative potential explanation for changes in comovement and structural coefficients between industries is a change in the input-output structure of the economy rather than a change in the economic relationships between sectors and industries. We investigated this hypothesis using the data on input-output tables, which are made available every five years. We use data for 1977 to 1992, with the average of 1977 and 1982 representing the early period and the average of 1987 and 1992 the late period. The results appear in Appendix Table 2. The top panel is for the manufacturing, wholesale trade, and retail trade sectors; the bottom panel is for the detailed industries associated with motor vehicle manufacturers and automobile retailers.[42]

[41] 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.
[42] Unfortunately, separate data for retail automobile dealers were unavailable.

For each sector or industry, the columns contain percentages of total intermediate inputs used by the sector or industry.

The data do not reveal large, obvious changes in the input-output structure of the economy that could explain our results. At the sector level, the largest changes occurred in the manufacturing and other industry inputs into the trade sector, both of which declined by around 7 percentage points. By dividing trade into wholesale and retail components, the largest share rises to about 10 percentage points or so. While this change is nontrivial and may partly explain the change in coefficients between sectors in the HAVAR model, it is unlikely that changes this modest can account for the kinds of changes observed in the model, especially the dynamic properties.

Changes in the inputs to the motor vehicles industry are even smaller. The table reports the inputs with one of the six largest shares in either the early or late period. Here the change in shares is less than 5 percentage points in each case. 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 the input-output tables; 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.

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

NOTES: Table shows the percentage contribution of each variable to the reduction in the variance of real GDP growth from the period 1959:Q1-1983:Q4 to the period 1984:Q1-2002:Q4. Variables other than GDP are chain-weighted growth contributions, as defined in the National Income and Product Accounts (NIPA). Shares of variance reductions may not add due to rounding.

SOURCES: Haver Analytics, Inc., Bureau of Economic Analysis, authors' calculations.

Table 2

Correlation among Sales and Inventory Investment in the U.S. Automobile Industry

			Manufacturers (SIC 371)		**Retailers (SIC 551)**	
			$\tilde{s}_t$	$\Delta\tilde{i}_t$	$\tilde{s}_t$	$\Delta\tilde{i}_t$
Early Period	**Mfg.**	$\tilde{s}_t$	1			
		$\Delta\tilde{i}_t$	.01	1		
	Retail	$\tilde{s}_t$	.63	-.04	1	
		$\Delta\tilde{i}_t$	.72	-.13	.15	1
Late Period	**Mfg.**	$\tilde{s}_t$	1			
		$\Delta\tilde{i}_t$	.06	1		
	Retail	$\tilde{s}_t$	.08	.04	1	
		$\Delta\tilde{i}_t$	.56	.10	-.44	1
Correlation Change (Late-Early)	**Mfg.**	$\tilde{s}_t$	1			
		$\Delta\tilde{i}_t$	**.05**	1		
	Retail	$\tilde{s}_t$	**-.55**	**.08**	1	
		$\Delta\tilde{i}_t$	**-.16**	**.23**	**-.60**	1

NOTES: Table shows the correlation of growth contributions of real sales ($\tilde{s}_t$) and real inventory investment ($\Delta\tilde{i}_t$) to real output growth. The early period runs from 1967:Q3 to 1983:Q4. The late period runs from 1984:Q1 to 2001:Q1.

SOURCES: Haver Analytics, Inc., Bureau of Economic Analysis, authors' calculations.

Table 3

Variance Decomposition of Aggregate Manufacturing and Trade (M&T) Output Growth

	Variances			Share (%) of the Change in Variance or Covariance	
	Early	Late	Ratio (Late/ Early)	Aggregate Output	Output Component
$\mathrm{Var}(\tilde{y})$	5.12	.92	.18	100	
$\sum_j \mathrm{Var}(\tilde{y}_j)$	1.01	.26	.26	18	
$2\sum_{j>k} \mathrm{Cov}(\tilde{y}_j, \tilde{y}_k)$	4.11	.66	.16	82	
Mean correlation (standard deviation)	.19 (.20)	.09 (.15)	.48		
$\mathrm{Var}(\tilde{y}) / \mathrm{Var}(\tilde{s})$	1.34	1.28			
$\mathrm{Var}(\tilde{s})$	3.81	.72	.19	73	100
$\sum_j \mathrm{Var}(\tilde{s}_j)$	.64	.22	.34	10	14
$2\sum_{j>k} \mathrm{Cov}(\tilde{s}_j, \tilde{s}_k)$	3.17	.51	.16	63	86
$\mathrm{Var}(\Delta\tilde{i})$	.66	.12	.18	13	100
$\sum_j \mathrm{Var}(\Delta\tilde{i}_j)$	.36	.10	.27	6	49
$2\sum_{j>k} \mathrm{Cov}(\Delta\tilde{i}_j, \Delta\tilde{i}_k)$	.30	.02	.08	7	52
$2\Delta\mathrm{Cov}(\tilde{s}, \Delta\tilde{i})$	.66	.07	.23	14	100
$2\sum_j \Delta\mathrm{Cov}(\tilde{s}_j, \Delta\tilde{i}_j)$	.02	-.05	-3.22	2	11
$2\sum_{j\neq k} \Delta\mathrm{Cov}(\tilde{s}_j, \Delta\tilde{i}_k)$	.64	.12	.19	12	89

NOTES: $\tilde{y}$ is the growth rate of aggregate M&T output constructed from growth contributions; $\tilde{s}$ and $\Delta\tilde{i}$ are the growth rate contributions of aggregate M&T 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:Q3 to 1983:Q4. The late period runs from 1984:Q1 to 2001:Q1. Shares may not add to 100 due to rounding. The values in the "mean correlation" row contain the time series average pairwise correlation between industries' output growth in each period (standard deviation in parentheses).

SOURCES: Haver Analytics, Inc., Bureau of Economic Analysis, authors' calculations.

Table 4

Variance Decomposition of Aggregate Manufacturing and Trade (M&T) Output Growth, by Sector

	Variances			Share (%) of the Change in Variance/Covariance	
	Early	Late	Ratio (Late/ Early)	Aggregate Output	Output Component
$\text{Var}(\tilde{y})$	5.12	.92	.18	100	100
$\text{Var}(\tilde{y}_M)$	1.76	.29	.17	35	35
$\text{Var}(\tilde{y}_T)$	1.27	.29	.23	23	23
$2\sum \text{Cov}(\tilde{y}_M, \tilde{y}_T)$	2.10	.34	.16	42	42
$\text{Var}(\tilde{y}_M) / \text{Var}(\tilde{s}_M)$	1.22	1.21			
$\text{Var}(\tilde{y}_T) / \text{Var}(\tilde{s}_T)$	1.65	1.04			
$\sum_j \text{Var}(\tilde{y}_j)$	1.01	.26	.26	18	100
$\sum_j \text{Var}(\tilde{y}_{Mj})$	.42	.10	.25	8	43
$\sum_j \text{Var}(\tilde{y}_{Tj})$	.59	.16	.27	10	58
$2\sum_{j>k} \text{Cov}(\tilde{y}_j, \tilde{y}_k)$	4.11	.66	.16	82	100
$2\sum_{j>k} \text{Cov}(\tilde{y}_{Mj}, \tilde{y}_{Mk})$	1.33	.19	.14	27	33
$2\sum_{j>k} \text{Cov}(\tilde{y}_{Tj}, \tilde{y}_{Tk})$	.68	.13	.20	13	16
$2\sum_{j>k} \text{Cov}(\tilde{y}_{Mj}, \tilde{y}_{Tk})$	2.10	.34	.16	42	51

NOTES: See notes to Table 3. Subscript M denotes manufacturing, and subscript T denotes trade. Subscripts j and k refer to detailed SIC industries within a sector.

SOURCES: Haver Analytics, Inc., Bureau of Economic Analysis, authors' calculations.

Table 5

HAVAR Model Counterfactual Simulation Results

	Share (%) of the Actual Decline in Variance Explained by the Change in Structural Coefficients					
	Aggregate M&T Output			**Inflation**		
	All Coefficients	Contemporaneous Coefficients Only		All Coefficients	Contemporaneous Coefficients Only	
	Contemporaneous (Γ_0, Γ_0^*) and lagged (Φ_e, Φ_e^*)	All (Γ_0^*)	Real quadrant only (Γ_0^{aa})	Contemporaneous (Γ_0, Γ_0^*) and lagged (Φ_e, Φ_e^*)	All (Γ_0^*)	Real quadrant only (Γ_0^{aa})
Macro 3	4.5	4.0	NA	34.9	14.7	NA
Macro 4	21.0	11.2	NA	38.6	26.2	NA
Uncoupled HAVAR (2 sector)	29.9	19.4	10.7	39.7	31.6	-.6
Coupled HAVAR (2 sector)	35.5	25.7	24.1	40.9	34.3	7.6
Coupled HAVAR (3 sector)	73.1	49.0	58.4	53.3	53.3	34.0

NOTES: Entries in this table are the shares (%) of the actual decline in variance explained by a change in the structural coefficients. Estimates of the coefficients in the late period (1984:Q1-2001:Q1) are used to simulate the data for the early period (1967:Q3-1983:Q4) with the early period structural shocks $(\varepsilon_t, \varepsilon_t^*)$. The variance of the simulated counterfactual series is used to measure the variance reduction attributed to changes in structural coefficients.

SOURCES: Haver Analytics, Inc., Bureau of Economic Analysis, authors' calculations.

Table 6

Structural Model Contemporaneous Coefficient Estimates (Γ_0, Γ_0^*)

	Macro 3			Macro 4			Coupled HAVAR		
	Early	Late	Change	Early	Late	Change	Early	Late	Change
$\gamma_{y\pi}$	–.03	.13	.17						
	(.12)	(.20)	(.23)						
$\gamma_{s\pi}$				.03	.26	.23			
				(.10)	(.18)	(.20)			
$\gamma_{\Delta i\pi}$				–.05	–.15**	–.10			
				(.03)	(.07)	(.07)			
γ_{sr}^{M}							–.05	–.17*	–.12
							(.07)	(.09)	(.11)
γ_{sr}^{T}							–.01	–.20*	–.19
							(.04)	(.12)	(.12)
$\gamma_{\Delta ir}^{M}$							.03**	.06*	.03
							(.01)	(.04)	(.04)
$\gamma_{\Delta ir}^{T}$							.04	.08	.05
							(.04)	(.06)	(.07)
$\gamma_{f\pi}$	–.30**	–.23**	.07	–.34**	–.21**	.12	–.32**	–.09	.24*
	(.07)	(.10)	(.12)	(.07)	(.10)	(.11)	(.07)	(.11)	(.13)
γ_{fy}	–.16**	–.08	.08						
	(.07)	(.06)	(.09)						
γ_{fs}				–.21**	–.03	.18*	–.12	.10	.23
				(.09)	(.06)	(.12)	(.12)	(.09)	(.15)
$\gamma_{f\Delta i}$				.34	–.24	–.58*	–.04	–.84**	–.81*
				(.26)	(.17)	(.31)	(.32)	(.26)	(.41)
$\gamma_{\Delta is}$				–.11**	–.05	.07			
				(.04)	(.05)	(.06)			
$\gamma_{\Delta is}^{MM}$							–.08**	–.00	.08
							(.02)	(.04)	(.05)
$\gamma_{\Delta is}^{TT}$							–.07	.16**	.23**
							(.09)	(.07)	(.11)
γ_{ss}							–.35**	–.27**	.09
							(.05)	(.06)	(.08)
$\gamma_{s\Delta i}^{MT}$							–.40	–.98**	–.58*
							(.25)	(.21)	(.33)

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

SOURCES: Haver Analytics, Inc., Bureau of Economic Analysis, authors' calculations.

Table 7
Tests of Model Overidentifying Restrictions

Model	Output Restrictions	Degrees of Freedom	p-values	
			Early	Late
Macro 4	None	0	NA	NA
	YR	1	.46	.03
	FY	1	.12	.17
	YR and FY	2	.23	.04
Uncoupled HAVAR	None	6	<.01	<.01
	YR	9	<.01	<.01
	FY	7	<.01	<.01
	YR and FY	10	<.01	<.01
Coupled HAVAR	None	4	.21	.26
	YR	7	.40	.05
	FY	5	.32	<.01
	YR and FY	8	.47	.01

Addendum:

Macro 4 restrictions on Coupled HAVAR model	——	4	<.01	<.01

NOTES: The Macro 3 model is excluded because there are no overidentifying restrictions imposed. The YR restriction sets $\gamma_{sr} = \gamma_{\Delta ir} = \gamma_{yr}$. The FY restriction sets $\gamma_{fs} = \gamma_{f\Delta i} = \gamma_{fy}$. The early period runs from 1967:Q3 to 1983:Q4. The late period runs from 1984:Q1 to 2001:Q1. Seethe text for more details about the relationship of the HAVAR model to other Macro VAR models.

SOURCES: Haver Analytics, Inc., Bureau of Economic Analysis, authors' calculations.

Table 8

Autoregressive Parameters in the HAVAR Model Sales Equations

		Sums of Lagged Coefficients on Sales						
		1	2	3	4	5	6	7
Trade	Early	.34	.08	-.06	.34	.24	.25	-.07
	Late	.25	.26	.16	.29	.05	.26	.09
	Change	-.09	.18	.22	-.05	-.19	.01	.16
	$\tilde{s}_{Mt}$					X	X	X
	$\Delta\tilde{i}_{Mt}$						X	X
	$\tilde{s}_{Tt}$	X	X	X	X	X	X	X
	$\Delta\tilde{i}_{Tt}$				X		X	X
	f_t		X	X				X
	π_t			X				X
Manufacturing	Early	.31	.10	-.01	.52	-.20	.07	-.14
	Late	.16	.14	.13	.15	-.05	-.02	.00
	Change	-.14	.04	.14	-.38	.15	-.09	.14
	$\tilde{s}_{Mt}$	X	X	X	X	X	X	X
	$\Delta\tilde{i}_{Mt}$				X		X	X
	$\tilde{s}_{Tt}$					X	X	X
	$\Delta\tilde{i}_{Tt}$						X	X
	f_t		X	X				X
	π_t			X				X

NOTES: All regressions included two lags of each explanatory variable and were estimated over the early (1967:Q3-1983:Q4) and late (1984:Q1-2001:Q1) periods. Change is the difference between the late period and early period estimates. An "X" indicates that the explanatory variables were included in the regression.

SOURCES: Haver Analytics, Inc., Bureau of Economic Analysis, authors' calculations.

Table 9

HAVAR Model Impulse Responses: Variance Ratios

Sector	Variable	Variance Ratios: Fed Funds Shock	Inflation Shock	Sales Shock: Trade	Sales Shock: Manufacturing
M&T	Output	.39	.73	.42	.68
	Sales	.46	1.38	.48	.65
	Inventories	2.89	2.77	1.68	3.21
Manufacturing	Output	.54	.25	.45	.69
	Sales	.38	.38	.39	.79
	Inventories	2.52	.86	.56	1.13
Trade	Output	.50	2.40	.49	.98
	Sales	.99	3.90	.71	.81
	Inventories	3.91	10.58	4.00	11.87

Addendum:

Shock Variances	Early	.99	3.59	.26	.57
	Late	.14	.24	.17	.11
	Ratio	.14	.07	.65	.19

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

SOURCES: Haver Analytics, Inc., Bureau of Economic Analysis, authors' calculations.

Table 10

HAVAR Model Impulse Responses: Correlations

Response Correlation	Inflation Shock			Fed Funds Shock			Manufacturing Sales Shock			Trade Sales Shock		
	Early	Late	Change	Early	Late	Change	Early	Late	Change	Early	Late	Change
y_M, y_T	1.00	.57	-.42	.98	.47	-.51	.96	.70	-.27	.72	.50	-.22
s_M, s_T	.99	.95	-.03	.97	.49	-.48	.96	.51	-.45	.75	.35	-.41
$s_M, \Delta i_T$	.42	-.55	-.97	.25	.07	-.18	.24	.26	.02	.39	.38	-.01
$\Delta i_M, s_T$	.41	-.47	-.88	.20	-.53	-.73	.72	.86	.14	.22	.28	.06
$\Delta i_M, \Delta i_T$	.86	-.07	-.93	.92	.74	-.18	.75	-.44	-1.18	.71	.28	-.42
$s_M, \Delta i_M$	.42	-.41	-.83	.34	.40	.05	.81	.04	-.77	.55	.87	.32
$s_T, \Delta i_T$	.35	-.44	-.79	.06	-.68	-.74	.14	-.36	-.50	.55	-.56	-1.11

NOTES: Table entries are the correlations between the impulse responses of the variables listed in the early period (1967:Q3-1983:Q4), the late period (1984:Q1-2001:Q1), and the change in correlation between periods.

SOURCES: Haver Analytics, Inc., Bureau of Economic Analysis, authors' calculations.

Table 11

HAVAR Model Impulse Reponses to a Federal Runds Rate Shock: Variance Decomposition of Output

	Values		Ratio (Late/ Early)	Percent Share of the Change in Aggregate Variance/Covariance	
	Early	Late		Output	Component
$\mathrm{Var}(\tilde{y})$	.0429	.0168	.39	100.0	
$\sum_j \mathrm{Var}(\tilde{y}_j)$	.0222	.0117	.53	40	
$2\sum_{j>k} \mathrm{Cov}(\tilde{y}_j, \tilde{y}_k)$	.0208	.0052	.25	60	
$\mathrm{Var}(\tilde{y}) / \mathrm{Var}(\tilde{s})$	1.153	.9767			
$\mathrm{Var}(\tilde{s})$	.0372	.0172	.46	77	
$\sum_j \mathrm{Var}(\tilde{s}_j)$	.0193	.0116	.60	29	38
$2\sum_{j>k} \mathrm{Cov}(\tilde{s}_j, \tilde{s}_k)$	.0179	.0056	.31	47	62
$\mathrm{Var}(\Delta\tilde{i})$	.0019	.0054	2.89	–14	
$\sum_j \mathrm{Var}(\Delta\tilde{i}_j)$	.0010	.0032	3.23	–8	62
$2\sum_{j>k} \mathrm{Cov}(\Delta\tilde{i}_j, \Delta\tilde{i}_k)$	.0009	.0023	2.52	–5	38
$2\Delta\mathrm{Cov}(\tilde{s}, \Delta\tilde{i})$	.0039	–.0057	–1.49	37	
$2\sum_j \Delta\mathrm{Cov}(\tilde{s}_j, \Delta\tilde{i}_j)$	.0019	–.0031	–1.64	19	52
$2\sum_{j\neq k} \Delta\mathrm{Cov}(\tilde{s}_j, \Delta\tilde{i}_k)$	.0020	–.0026	–1.34	18	48

NOTES: Table entries are the variances and covariances of the HAVAR model output responses to a 100 basis point shock to the Federal Funds Rate, measured over 16 periods. See also the notes to Table 3.

SOURCES: Haver Analytics, Inc., Bureau of Economic Analysis, authors' calculations.

Sources: Haver Analytics Inc., BEA NIPA data

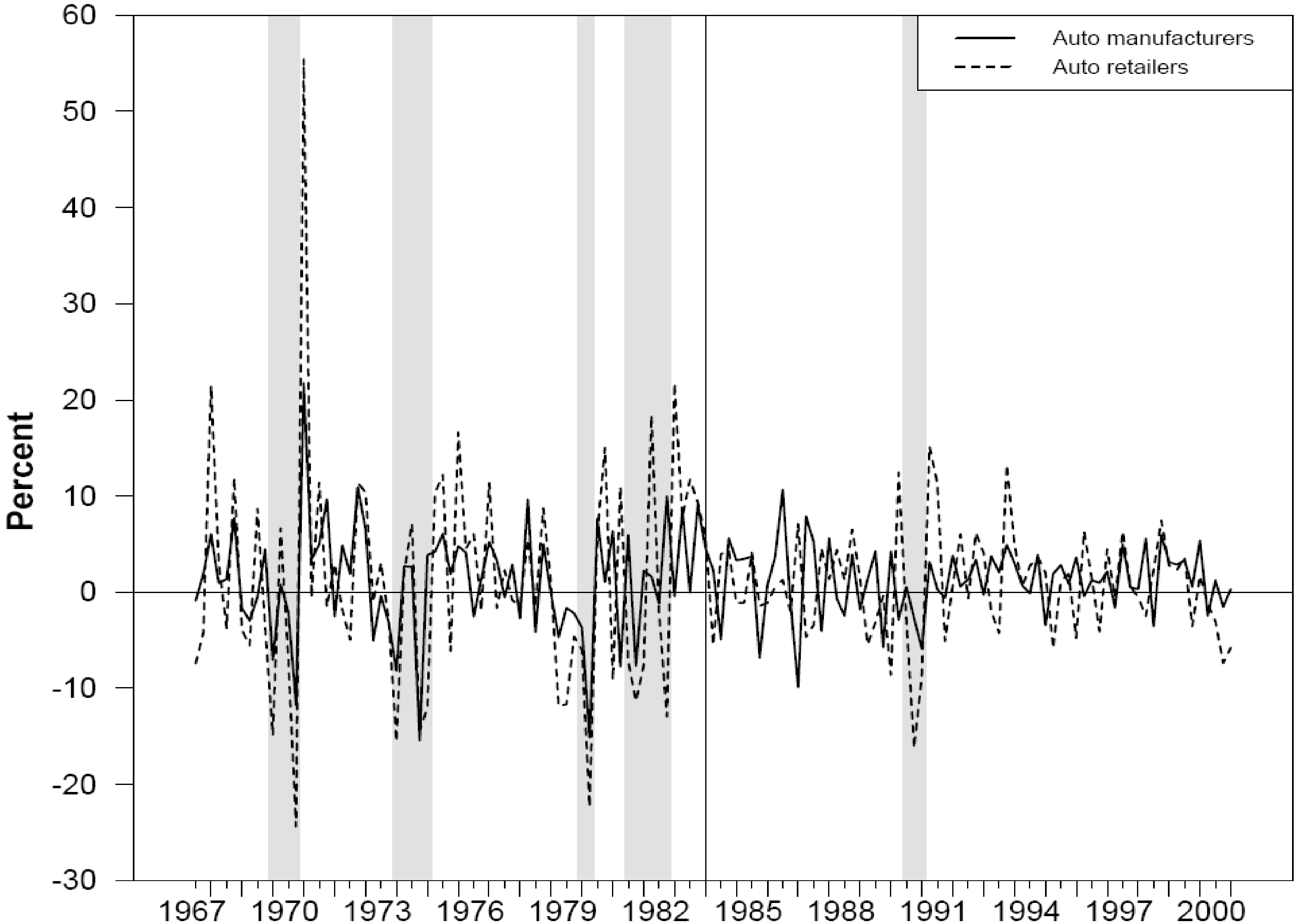
Table 12
Variance Ratios of Sales and Orders in Manufacturing and Trade Industries

	Manufacturing				Trade				
Durability	SIC	Industry	Variance ratio			SIC	Industry	Variance ratio	
			Sales	Orders			Sales	Sales	Orders
Non-Durable Goods	20	Food & Kindred Products	.1	.13	Retail	52-59 (rsd)	Other Durable Goods	.68	.8
	21	Tobacco Products	.67	1.47		52-59(rsnd)	Other Nondurable Goods	.62	.47
	22	Textile Mills Products	.28	.29	Wholesale	511	Paper Products	.86	.77
	23	Apparel & Related Products	.13	.1		512	Drugs and Sundries	4.4	2.34
	26	Paper & Allied Products	.33	.4		513	Apparel and Piece Goods	1.4	.56
	27	Printing & Publishing	.63	.49		514	Groceries	.63	.42
	28	Chemicals & Allied Products	.17	.15		515	Farm Products	.22	.24
	29	Petroleum Refining	.69	.41		516	Chemicals and Allied Products	1.01	.86
	30	Rubber & Plastic Products	.27	.32		517	Petroleum Products	.28	.08
	31	Leather & Leather Products	.16	.21		518	Alcoholic Beverages	.98	.21
						519	Other Non-durable Goods	.88	.86
Durable Goods	24	Lumber & Wood Products	.39	.39	Retail	54	Food Stores	.19	.19
	25	Furniture & Fixtures	.36	.32		55	Automotives	.56	.3
	32	Stone, Clay & Glass Products	.32	.38		56	Apparel Stores	.69	.45
	33	Primary Metal Products	.06	.04	Wholesale	501	Motor Vehicles	1.17	.49
	34	Fabricated Metal Products	.17	.18		502	Furniture/Home-furnishings	1.74	1.42
	35	Industrial Machinery, Computer Equipment	.41	.53		503	Lumber/Construction Materials	.58	.47
	36	Electric & Electronic Machinery	.53	.68		504	Professional/Commercial Equipment	9.31	.82
	37x	Transportation Ex. Motor Vehicles	.41	.72		505	Metals & Minerals excluding Petroleum	.13	.08
	371	Motor Vehicles and Parts	.22	.22		506	Electrical Goods	1.69	1.23
	38	Instruments	.79	.44		507	Hardware and Plumbing	.45	.37
	39	Miscellaneous Manufacturing Products	.24	.25		508	Machinery/Equipment/Supplies	.37	.19
						509	Other Durable Goods	.43	.5
All		Median	.32	.32	Retail	Median	.62	.45	
		Mean	.35	.39		Mean	.55	.44	
					Wholesale	Median	.87	.5	
						Mean	1.47	.66	

NOTES: Table entries are the ratios of variance in the late period (1984:Q1-2001:Q1) to variance in the early period (1967:Q3-1983:Q4).

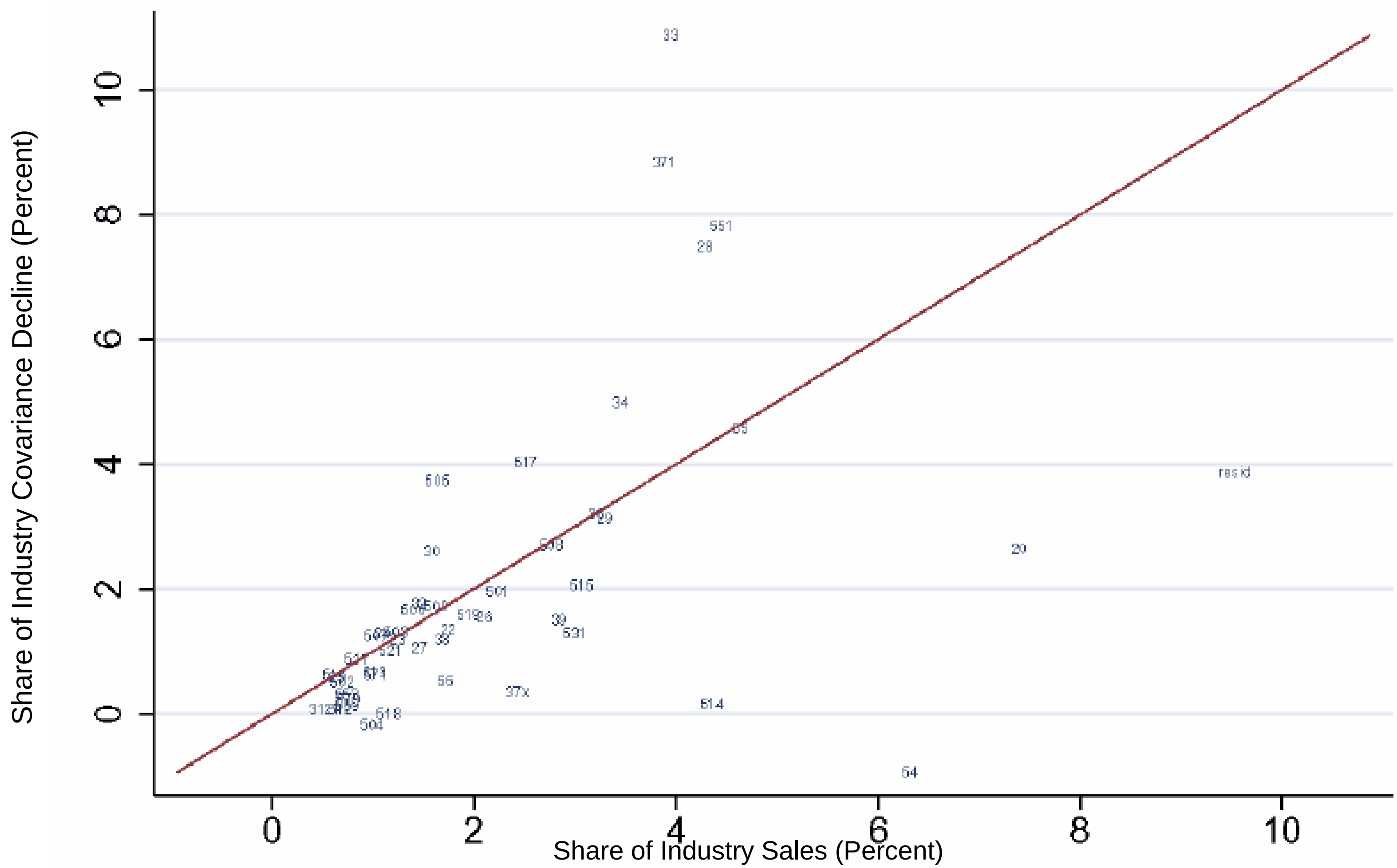
SOURCES: Haver Analytics, Inc., Bureau of Economic Analysis, authors' calculations.

Figure 1
Growth Rates of Sales in the Automobile Industry



SOURCES: Haver Analytics, Bureau of Economic Analysis.
NOTES: NBER recessions are shaded. The line at 1984 indicates the trend break in volatility.

Figure 2
Relationship Between Covariance Decline and Industry Size



SOURCES: Haver Analytics Inc., Bureau of Economic Analysis, authors' calculations.

NOTES: The horizontal axis measures the average nominal share of M&T sales during the period 1967-1983. The vertical axis measures the share of the decline in aggregate M&T covariance accounted for by the covariances of sales in each industry with the sales of all other industries individually. Data points are labeled by SIC industry number. See Table 12 for definitions.

Figure 3

HAVAR Model Impulse Responses: Output Growth

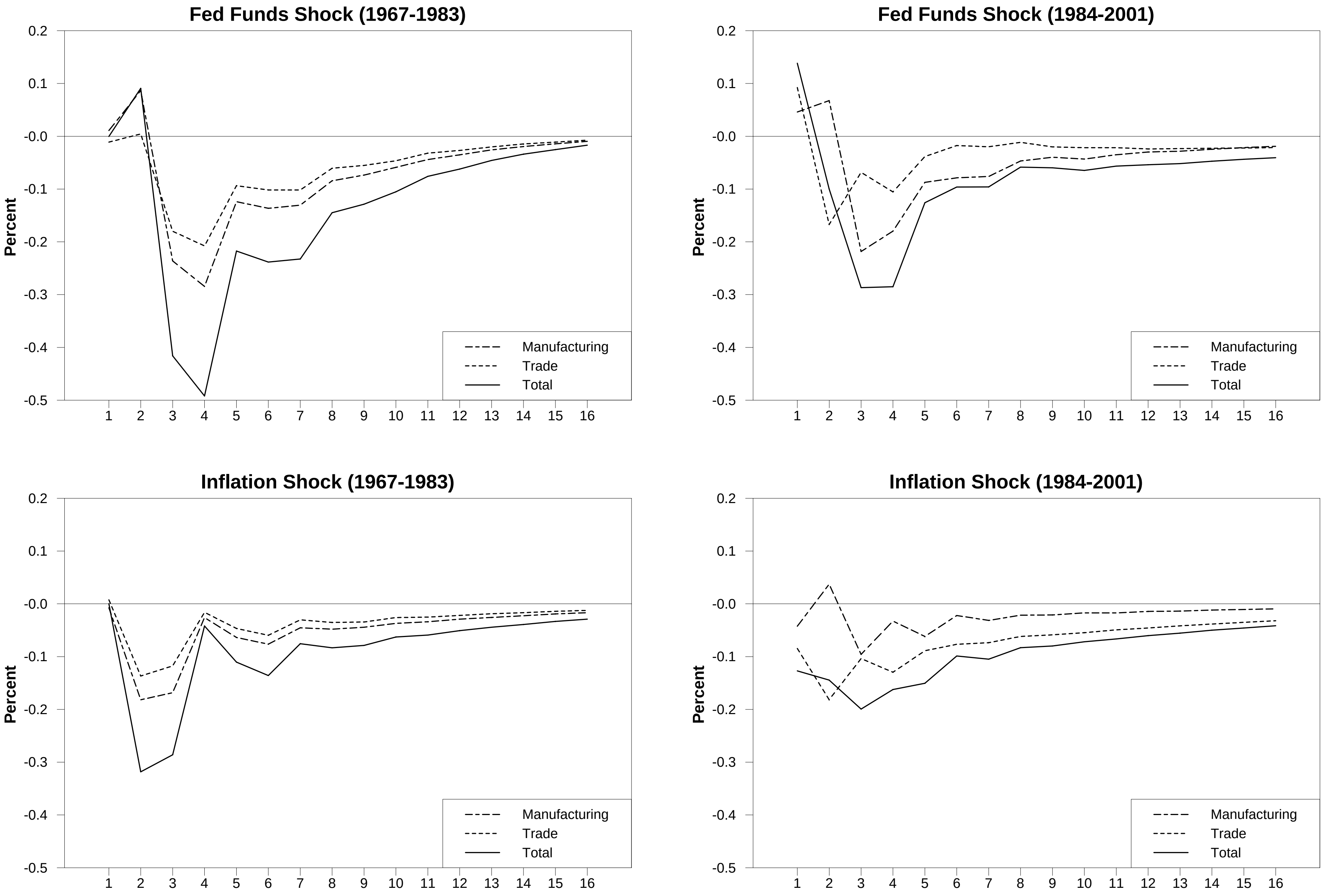


Figure 4

HAVAR Model Impulse Responses: Output Growth

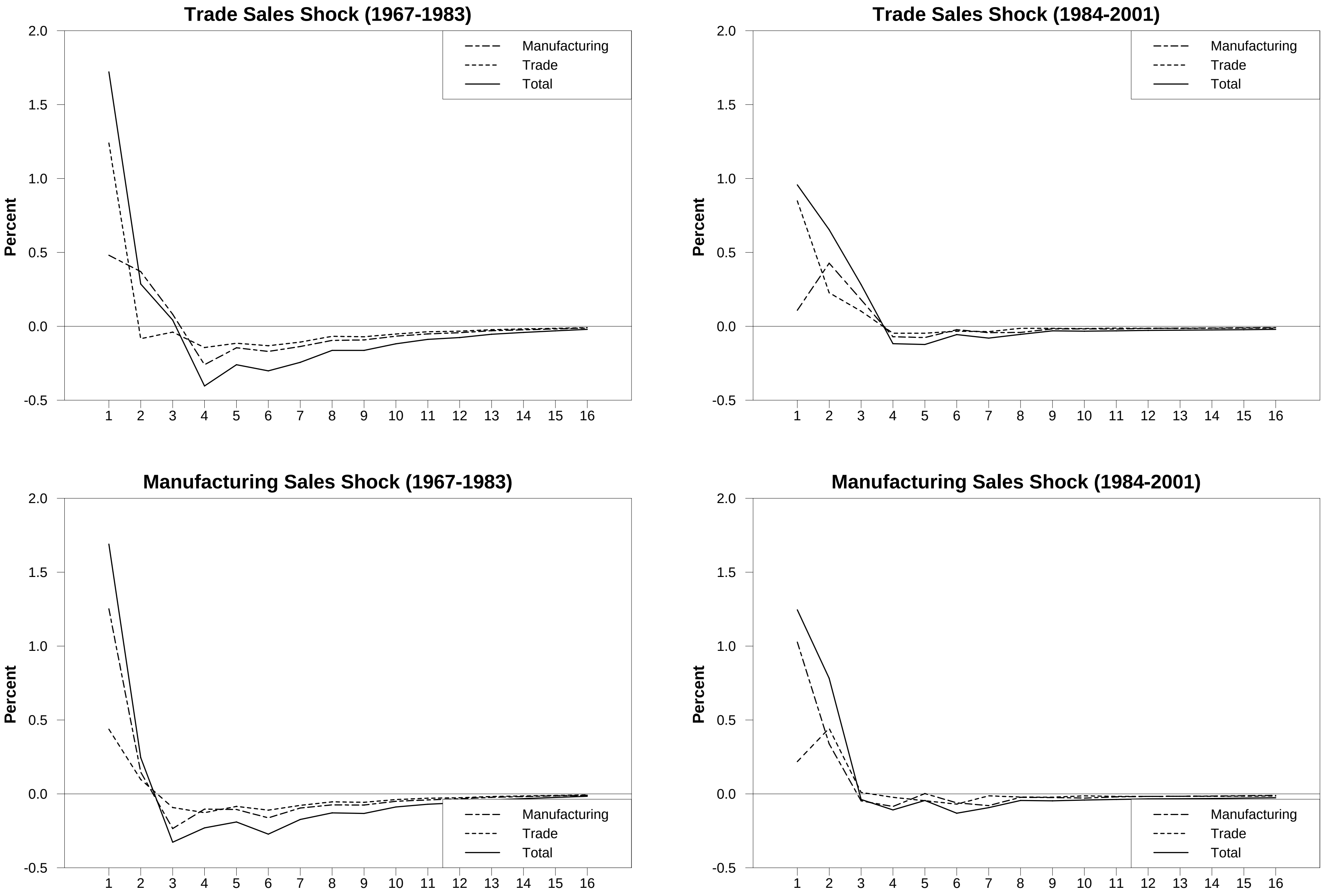
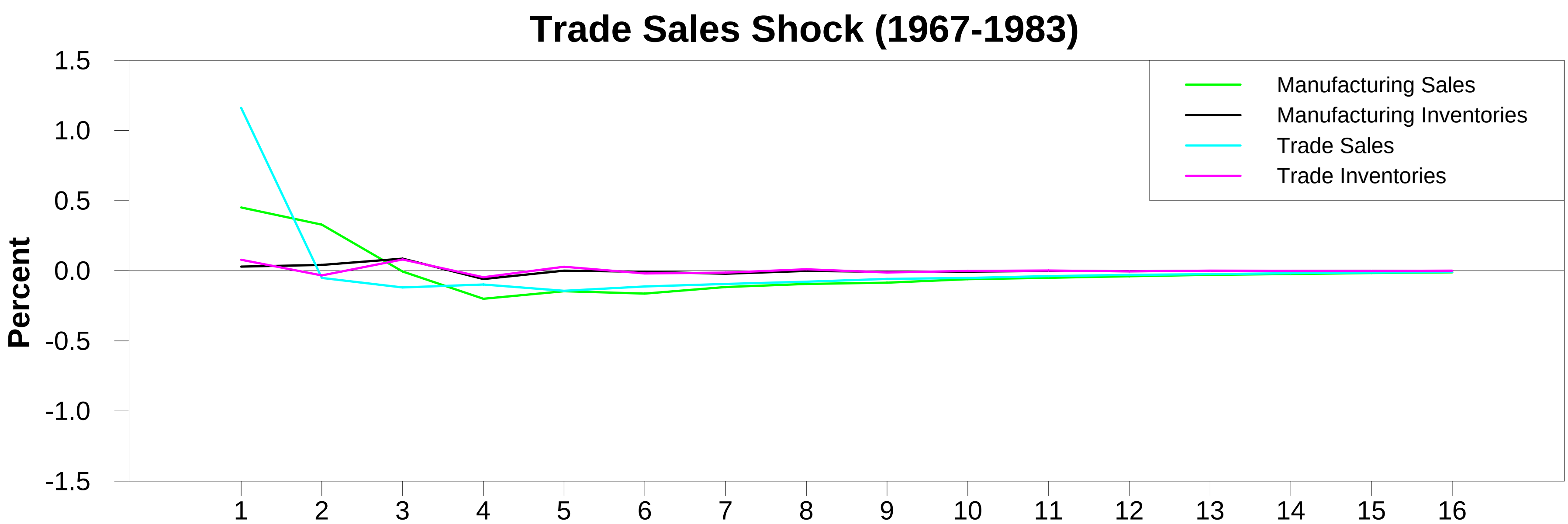


Figure 5

HAVAR Model Impulse Responses: Sales and Inventory Investment



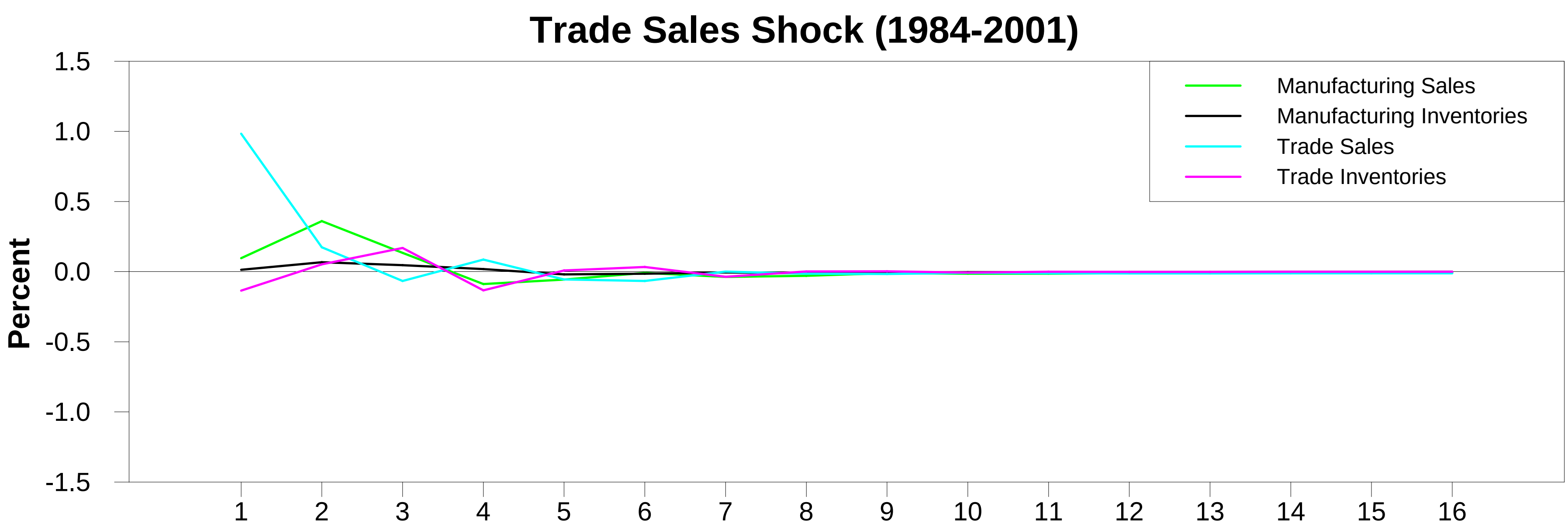
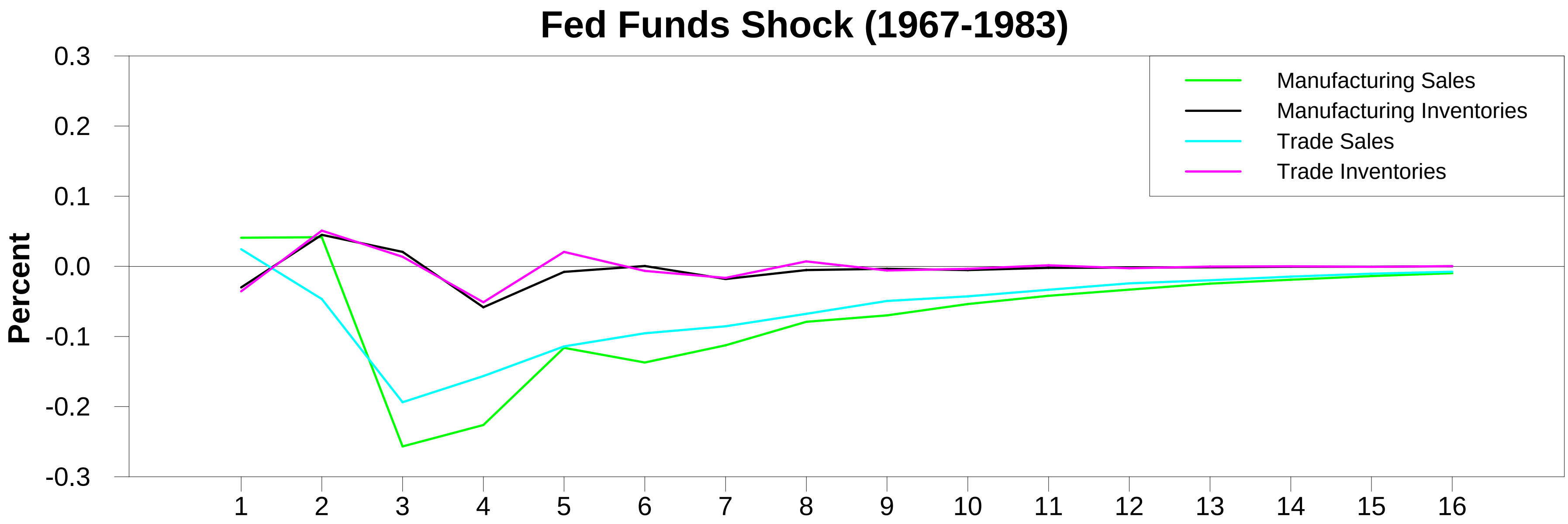
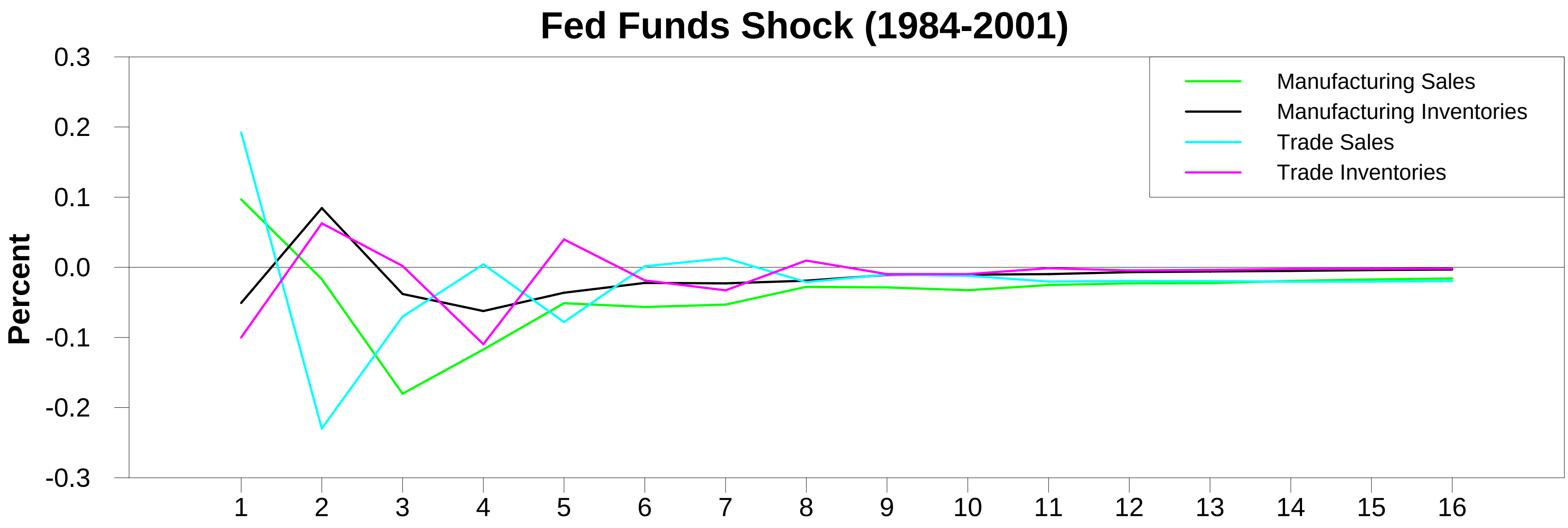


Figure 6

HAVAR Model Impulse Responses: Sales and Inventory Investment





Appendix Table 1

Variance Decomposition of Aggregate Manufacturing and Trade (M&T) Output Growth, by Sector (Components)

	Values		Ratio (Late/ Early)	Percent Share of the Change in Aggregate Variance/Covariance	
	Early	Late		Output	Component
$\mathrm{Var}(\tilde{s})$	3.81	.72	.19	73	100
$\mathrm{Var}(\tilde{s}_M)$	1.44	.24	.16	29	39
$\mathrm{Var}(\tilde{s}_T)$	.77	.28	.36	12	16
$2\sum \mathrm{Cov}(\tilde{s}_M, \tilde{s}_T)$	1.59	.21	.13	33	45
$\sum_j \mathrm{Var}(\tilde{s}_j)$	.64	.22	.34	10	100
$\sum_j \mathrm{Var}(\tilde{s}_{Mj})$	.37	.09	.24	7	67
$\sum_j \mathrm{Var}(\tilde{s}_{Tj})$	.27	.13	.48	3	33
$2\sum_{j>k} \mathrm{Cov}(\tilde{s}_j, \tilde{s}_k)$	3.17	.51	.16	63	100
$2\sum_{j>k} \mathrm{Cov}(\tilde{s}_{Mj}, \tilde{s}_{Mk})$	1.07	.15	.14	22	35
$2\sum_{j>k} \mathrm{Cov}(\tilde{s}_{Tj}, \tilde{s}_{Tk})$	.50	.15	.29	9	13
$2\sum_{j>k} \mathrm{Cov}(\tilde{s}_{Mj}, \tilde{s}_{Tk})$	1.59	.21	.13	33	52
$\mathrm{Var}(\Delta\tilde{i})$	.66	.12	.18	13	100
$\mathrm{Var}(\Delta\tilde{i}_M)$	.06	.03	.45	1	7
$\mathrm{Var}(\Delta\tilde{i}_T)$	.49	.10	.20	9	72
$2\sum \mathrm{Cov}(\Delta\tilde{i}_M, \Delta\tilde{i}_T)$	.11	-.01	-.08	3	21
$\sum_j \mathrm{Var}(\Delta\tilde{i}_j)$	.36	.10	.27	6	100
$\sum_j \mathrm{Var}(\Delta\tilde{i}_{Mj})$	.04	.02	.39	1	10
$\sum_j \mathrm{Var}(\Delta\tilde{i}_{Tj})$	.32	.08	.25	6	90
$2\sum_{j>k} \mathrm{Cov}(\Delta\tilde{i}_j, \Delta\tilde{i}_k)$	.30	.02	.08	7	100
$2\sum_{j>k} \mathrm{Cov}(\Delta\tilde{i}_{Mj}, \Delta\tilde{i}_{Mk})$	.02	.01	.57	0	3
$2\sum_{j>k} \mathrm{Cov}(\Delta\tilde{i}_{Tj}, \Delta\tilde{i}_{Tk})$	.18	.02	.11	4	56
$2\sum_{j>k} \mathrm{Cov}(\Delta\tilde{i}_{Mj}, \Delta\tilde{i}_{Tk})$	.11	-.01	-.08	3	41

NOTES: See notes to Tables 3 and 4.

SOURCES: Haver Analytics, Inc., Bureau of Economic Analysis, authors' calculations.

Appendix Table 1 (continued)

	Values		Ratio (Late/ Early)	Percent Share of the Change in Aggregate Variance/Covariance		
					Component	
	Early	Late		Output	Sectors	Industries
$2\Delta \text{Cov}(\tilde{s}, \Delta\tilde{i})$	.66	.07	.23	13.8	100	
$2\sum \text{Cov}(\tilde{s}_M, \Delta\tilde{i}_M)$	.25	.02	.20	5.4	39	100
$2\sum \text{Cov}(\tilde{s}_{Mj}, \Delta\tilde{i}_{Mj})$	.01	.00	-.12	.2		4
$2\sum_{j>k} \text{Cov}(\tilde{s}_{Mj}, \Delta\tilde{i}_{Mk})$	.24	.03	.11	5.2		97
$2\sum \text{Cov}(\tilde{s}_T, \Delta\tilde{i}_T)$	.01	-.09	-31.65	2.2	16	100
$2\sum \text{Cov}(\tilde{s}_{Tj}, \Delta\tilde{i}_{Tj})$	.01	-.05	-5.85	1.4		64
$2\sum_{j>k} \text{Cov}(\tilde{s}_{Tj}, \Delta\tilde{i}_{Tk})$	.00	-.04	-11.63	.8		36
$2\sum_{j>k} \text{Cov}(\tilde{s}_{Mj}, \Delta\tilde{i}_{Tk})$ $+2\sum_{j>k} \text{Cov}(\tilde{s}_{Tj}, \Delta\tilde{i}_{Mk})$	.40	.13	.34	6.3	46	100.0

NOTES: See notes to Tables 3 and 4.

SOURCES: Haver Analytics, Inc., Bureau of Economic Analysis, authors' calculations.

Appendix Table 2

Input and Output Use Data from Input-Output Tables

Manufacturing and Trade Sectors

Sector	Sector Providing Input	Early Share (%)	Late 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

Motor Vehicle Manufacturing and Retail Trade Industries

Industry	Industry Providing Input	Early		Late		Change
		Rank	Share (%)	Rank	Share (%)	
Motor vehicle manufacturing	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
Motor vehicles 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

NOTES: Table entries are the shares (in percent) of the material inputs used by the sector or industries and produced by the providing sector or industry. Table entries in the motor vehicles panel are early (average of 1977 and 1982) or late (average of 1977 and 1982) period. Inputs listed for each industry were among the top six inputs in either the 1977-82 and 1987-92 time periods.

SOURCES: Bureau of Economic Analysis