



## Interest Sensitivity and Volatility Reductions: Cross-Section Evidence

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### Abstract:

As has been widely observed, the volatility of GDP has declined since the mid-1980s compared with prior years. One leading explanation for this decline is that monetary policy improved significantly in the later period. We utilize a cross-section of 2-digit manufacturing and trade industries to further investigate this explanation. Since a major channel through which monetary policy operates is variation in the federal funds rate, we hypothesized that industries that are more interest sensitive should have experienced larger declines in the variance of their outputs in the post-1983 period. We estimate interest-sensitivity measures for each industry from a variety of VAR models and then run cross-sectional regressions explaining industry volatility ratios as a function of their interest-sensitivity measures. These regressions reveal little evidence of a statistically significant relationship between industry volatility reductions and our measures of industry interest sensitivity. This result poses challenges for the hypothesis that improved monetary policy explains the decline in GDP volatility.

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## 1. Introduction

The observation that the volatility of GDP has declined since the mid-1980's has spawned a substantial number of papers seeking to explain the decline.<sup>1</sup> The explanations suggested include: (1) good luck, in the sense that the economy has experienced smaller shocks since 1985,

(2) changes in the structure of industry, including the use of better production and inventory control systems and the adoption of modern information systems, and (3) better monetary policy.<sup>2</sup> Clarida, Gali, and Gertler (2000), Stock and Watson (2002), and Boivin and Giannoni (2002, 2003) attribute a substantial amount of the reduction in GDP volatility to improved monetary policy. No consensus has emerged yet among these explanations.

Most of the initial studies investigating volatility reduction examined aggregate data. More recent contributions, however, have used disaggregated data, which offer the opportunity to exploit cross-sectional variation for better identification of hypothesized explanations.<sup>3</sup> In Irvine and Schuh (2005a), we found for a cross section of 2-digit SIC manufacturing and trade industries that the amount of variance reduction varied considerably across industries. In this paper, using this cross-section of industries, we investigate whether this reduction in volatility can be explained by better monetary policy in the post-1983 period.

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<sup>1</sup> The decline was first observed by Kim and Nelson (1999), Blanchard and Simon (2001), and McConnell and Perez-Quiros (2000). Blanchard and Simon (2001) believe that GDP volatility has been declining since the 1950s.

<sup>2</sup> Ahmed, Levin, and Wilson (2002) attribute most of the reduction to "good luck" in the sense of smaller shocks. The explanations of McConnell and Perez-Quiros (2000), Blanchard and Simon (2001), Kahn, McConnell, and Gabriel Perez-Quiros (2002), center on the adoption of better production and inventory control systems. Our other papers on this topic (Irvine and Schuh (2005a and 2005b) suggest that these systems have reduced the co-movement between industries. Ramey and Vine (2003) argue that changes in sales persistence help explain the reduction in GDP volatility. Please refer to our earlier papers for a more extensive review of the literature.

<sup>3</sup> See Bivin (2003), Herrera and Pesavento (2003), McCarthy and Zakrajsek (2003), and Irvine and Schuh (2005a, 2005b).

A major channel through which monetary policy affects the economy is variation in interest rates.<sup>4</sup> Hence, if improved monetary policy after 1983 was a major reason for the reduction in GDP volatility, then theoretically one should observe, on average, that the more interest-sensitive sectors experienced the largest reductions in the volatility of their output. In Irvine and Schuh (2005a) we reported general results that are broadly consistent with this hypothesis: namely, the output variances of the interest-sensitive NIPA Goods Sector and Structures Sector declined by about the same percentage as GDP in the post-1983 period, whereas the variance of the output of the much less interest-sensitive Service Sector barely changed. We further investigate this hypothesis in this paper using the same cross-section of 2-digit manufacturing and trade industries. Although the estimated coefficients in the cross-section regression are generally of the expected sign, we find little evidence of a statistically significant relationship between output volatility reductions and our measures of interest sensitivity. This result raises questions about the validity of the hypothesis that improved monetary policy has been a major factor in the reduction of GDP volatility.

In the next section, we briefly review the monetary policy literature which has addressed the volatility reduction. The data we utilize and the relationship of these data to GDP are summarized in Section 3. In Section 4, we calculate interest sensitivities from a variety of relatively simple versions of standard VAR models like those described in Christiano, Eichenbaum, and Evans (1999). We use three measures of interest sensitivity: the standard deviation of the impulse-response function (IRF) of sales to a shock to the federal funds rate, the cumulative IRF of sales to a change in the federal funds rate, and the sum of the lagged

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<sup>4</sup> While the Federal Reserve's operating procedure has varied over the last four decades, many authors have argued that the federal funds rate has been the key policy instrument in the U.S. over most of the last 45 years (see, for example, Bernanke and Blinder (1992), and Bernanke and Mihov (1998) ).

coefficients on the federal funds rate in the sales equation of the VAR. In Section 5 we report the results of cross-section regressions of output volatility ratios on these interest-sensitivity measures. Section 6 concludes.

## **2. Monetary Policy Literature**

A vast literature has established that monetary policy significantly influences the short-run course of the real economy and has examined how best to conduct monetary policy.<sup>5</sup> Most of this literature uses small macroeconomic models with monetary policy approximated by an interest-rate rule, such as the Taylor rule, to evaluate the optimality of monetary policy. The quality of monetary policy is typically evaluated by how closely the observed (estimated) rule conforms to the theoretically optimal rule that is designed to minimize deviations of inflation from its target and output from potential output. Improvements in monetary policy, then, are characterized by movements in the observed rule toward the optimal rule over time, for example, before and after 1979.

The literature focuses on two possible manifestations of improved policy: 1) whether the monetary authority (Federal Reserve) has become more aggressive in adjusting the nominal federal funds rate to increases in expected inflation; and 2) whether monetary policy shocks – the portion of the funds rate unexplained by the policy rule – have become less volatile. For example, Clarida, Gali, and Gertler (2000) compared the pre-Volker (1960-1979) and Volker-Greenspan (since 1979) eras using a small New Keynesian macro model with a forward-looking monetary policy reaction function. They estimated the coefficient on expected inflation in their monetary policy interest-rate rule to be significantly larger since 1979. Their simulations suggest that both the variance of inflation and the variance of output have been reduced substantially

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<sup>5</sup> Clarida, Gali, and Gertler (1999) summarize the recent literature through 1999.

under the Volker-Greenspan rule, since it has been more effective than the previous policy at mitigating demand and supply shocks that hit the economy.<sup>6</sup>

Other papers use small structural VAR macro models to investigate the possible role of improved monetary policy. Stock and Watson (2002) used a four-variable model with a priori calibration of three key parameters fixed over their entire sample: the slope of the IS function, the slope of the Phillips curve, and a parameter governing the forward-looking nature of the Phillips curve. They estimated the parameters of a forward-looking Taylor rule for two periods divided in 1984 and used counterfactual experiments to determine the reduction in output variance attributable to shocks and to changes in the structural parameters. Acknowledging considerable uncertainty, Stock and Watson “attribute perhaps 20 percent to 30 percent of the reduction in the variance of four-quarter GDP growth to improved monetary policy.”

Boivin and Giannoni (2002) also used a four-variable structural VAR to document changes in the impulse-response functions (IRF) of output and inflation to monetary policy (federal funds rate) shocks. They found that: 1) monetary policy shocks were much smaller in periods starting in 1980 or 1984 compared with 1963-1979; and 2) the response of output to a funds-rate shock was much smaller in the later periods. A variance decomposition (their Table 4) shows that the reduction in the size of monetary shocks during the later periods can account for at most 16 percent of the reduction of output variance in the post-1983 period. Investigating the smaller response of output to monetary shocks in the later period using counterfactual simulations, Boivin and Giannoni also found that output volatility declined mainly as a result of changes in the structural coefficients in the federal funds rate VAR equation. However, as Boivin and Giannoni acknowledge, their structural VAR is unable to distinguish between the use

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<sup>6</sup> In addition, the Volker-Greenspan policy eliminated sunspot fluctuations that could arise under the pre-Volker rule (from self-fulfilling changes in inflation expectations).

by the Federal Reserve of an improved monetary reaction function and the alternative hypothesis that private agents in the economy changed their behavior and the organization of markets in ways that reduced the effect of shocks on output and inflation.

More recently, Boivin and Giannoni (2003) further investigated these questions using a small-scale structural New Keynesian macro model with a forward-looking Taylor rule reaction function. They estimated this model using impulse responses from their structural VAR model and a minimum distance estimator and found changes in the Taylor rule coefficients between the pre-1979 and post-1979 samples similar to those found by Clarida, Gali, and Gertler (2000). Output became more sensitive to the real interest rate in the post-1979 period, and counterfactual experiments showed that the changes in the private sector coefficients imply a larger response to monetary shocks in the later period. These experiments also showed “that the observed reduction in the magnitude of the impulse responses is almost entirely attributable to monetary policy” as measured by changes in the reaction-function coefficients.<sup>7</sup>

### **3. Data and Methodological Issues**

Most papers to date have used aggregate data from the National Income and Product Accounts (NIPA). In Irvine and Schuh (2005a), we found through a variance decomposition that reductions in the volatility of the NIPA Goods Sector output accounted for nearly two-thirds of the reduction in GDP volatility and the NIPA Structures accounted for 9 percent of GDP volatility reduction, while the NIPA Services Sector accounted for basically none of the GDP volatility reduction.<sup>8</sup> In this paper, we use quarterly data from the Bureau of Economic Analysis

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<sup>7</sup> Improved monetary policy also was shown: 1) to have been responsible for removing indeterminacies of the rational expectations equilibrium in the post-1979 period; and 2) to have been the major reason the output response to demand shocks was more moderate in the post-1979 period.

<sup>8</sup> The remainder of the decline in GDP variance was accounted for by the reduction in covariance between these three sectors.

for the manufacturing and trade (M&T) sector, which represents the bulk of the NIPA Goods Sector.<sup>9</sup> Our sample runs from 1959:Q1 through 2001:Q1. For this analysis, we divided the sector into 27 2-digit SIC manufacturing, retail, and merchant wholesale trade industries. NIPA value-added data are not available at this level of industry detail and frequency. In the VAR models we estimate in Section 4 to derive measures of an industry's sensitivity to monetary policy, we utilized log levels of chain-weighted industry sales and inventory level (and alternatively, their first differences).

Following the practice of previous researchers, we constructed each industry's output,  $Y_j$ , as the sum of its chain-weighted sales and the change in its inventories.<sup>10</sup> Then we constructed its quarterly output growth rate as  $y_{jt} = (\Delta Y_{jt}/Y_{j,t-1})$ .<sup>11</sup> For each M&T industry, we constructed the ratio of the variance of its output growth rate over the post-1983 period (1984:Q1 through 2001:Q1) to its variance in the pre-1984 period (1959:Q1 through 1983:Q4), using our constructed  $y_{jt}$  series.<sup>12</sup> These output "volatility ratios,"  $\left[ \text{Var}(y^L) / \text{Var}(y^E) \right]$ , are plotted in Figure 1. As one can see, nearly all the M&T industries experienced dramatic reductions in

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<sup>9</sup> See our earlier discussion in Irvine and Schuh (2005a). The variance properties of M&T gross production are very similar to those of NIPA Goods value added, and the growth rates of the two aggregate measures have a correlation of about 0.7. Overall, M&T gross production varies less than the NIPA Goods value added output, most likely because the M&T sector excludes relatively high-variance sectors (for example, agriculture and mining). However, the relative variance reduction from the pre-1984 period to the post-1983 period is virtually identical for the two output measures. See also our discussion of the important differences between NIPA data and M&T data.

<sup>10</sup> Inventories are total inventories, reflecting the fact that NIPA output is defined to include stocks in all stages of processing: manufacturing materials, work-in-process, and finished goods, as well as retail and wholesale stocks.

<sup>11</sup> For reasons related to chain-weighted deflation, this approach introduces some measurement error (see Whelan, 2000). Hence, we constructed an alternative measure of each industry's output growth rate even though data to do so were only available starting in 1967. Ideally, one would like the Commerce Department to provide growth contributions for each industry, but they do not. However, growth contributions can be approximated by weighting the chain-weighted variables by their nominal share; for example, the growth contribution of sales (denoted by a tilde) would be approximated by  $\tilde{s}_t = \theta_t^s s_t$ . Using this approach, we constructed a three-variable Tornqvist approximation to each industry's output growth rate,  $\tilde{y}_t = \tilde{s}_t + \tilde{i}_t - \tilde{i}_{t-1}$ . See Appendix of Irvine and Schuh (2005b) for a detailed discussion of this issue.

<sup>12</sup> The 1984:Q1 break point corresponds to that found by McConnell and Perez-Quiros (2000) for GDP.

output variance, with the vast majority declining by over 50 percent.<sup>13</sup> To investigate the relationship between monetary policy and output volatility, we want to estimate the relationship between these industry volatility ratios and the interest sensitivities of the industries.

#### **4. Measuring the Interest Sensitivity of Industries**

For each industry, we calculated interest sensitivity using relatively simple versions of standard VAR models as described in Christiano, Eichenbaum, and Evans (1999). Our cross-sectional hypothesis is that improvements in monetary policy should produce a disproportionately greater reduction in output volatility in industries that are relatively more interest sensitive.

Two caveats are immediately obvious. First, it is challenging to identify an industry's interest sensitivity separately from its sensitivity to aggregate activity. Second, an industry's reduction in its output variance is endogenous, and it is possible that the direction of causation could run from volatility to interest sensitivity rather than vice versa. Highly interest-sensitive sectors may have greater profit incentive to insulate themselves from fluctuations caused by monetary policy actions.<sup>14</sup> If so, those industries may respond to poor monetary policy by investing in improved inventory and production techniques, for example.<sup>15</sup>

To generate robust results for this exercise, we used a variety of VAR models to measure sensitivity to monetary policy. One reason VAR models have been widely criticized is that their dynamic characteristics can be quite dependent on model specification and identification. The base VAR specification includes inflation, real GDP, industry sales, industry inventories, the

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<sup>13</sup> The volatility ratios of only two industries (tobacco manufacturers and petroleum) increased.

<sup>14</sup> Boivin and Giannoni's (2003) finding that changes in private-sector coefficients suggest that real output has become more sensitive to changes in the federal funds rate since 1979 implies that this has not been the case.

<sup>15</sup> Both caveats indicate the need for a fully specified structural model with disaggregated industries to provide conclusive hypothesis tests, a task we leave for future research.



federal funds rate, and the relative price of oil:  $[\Pi, Y, S_i, I_i, r^f, P^{oil} / P]$ . The baseline identification scheme is the ordering shown in the preceding vector (funds rate fifth). An alternative identification ordering puts the funds rate first. These two alternatives are probably sufficient because the response of sales or output to a funds-rate shock is relatively insensitive to ordering in these types of VAR models. All data are in logs, except the funds rate and the inflation rate,  $\Pi_t$ , which is measured by the change in the log of the consumer price index.<sup>16</sup> An alternative specification differences all the variables.

Using these VAR models, we obtain estimates of industry interest sensitivity measured three ways. The first measure is the scaled standard deviation of the impulse-response function (Std. Dev.) of sales to a change in the federal funds rate, a measure which depends on model identification.<sup>17</sup> We focus on sales, rather than production, to capture the interest sensitivity of demand. The second measure is the cumulative impulse-response function of sales (Cum IRF) over twelve quarters, which also depends on identification. The third measure is the sum of lagged coefficients (Sum Coef.) on the federal funds rate in the sales equation; this measure does not depend on identification.

Figure 2 contains histograms across industries of interest-sensitivity measures for six VAR specifications: level VAR models with the federal funds rate fifth in order and similarly specified differenced VAR models. As one can see from the left-hand panels of Figure 2, the sums of lagged coefficients on the federal funds rate are nearly all negative, as theory would predict. The center panels of Figure 2 contain histograms of the scaled standard deviations of the IRFs to a change in the federal funds rate. All these are positive (by construction) with the

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<sup>16</sup> We estimated VAR(2) models, i.e., with two lags of each variable in each equation, on quarterly data. Conventional lag-length tests suggest shorter lags for industry data than aggregate data.

<sup>17</sup> We scaled each industry's sales IRF standard deviation by the average sales standard deviation across industries, which guards against excessively volatile IRFs due to model misspecification and provides better interpretability.

largest standard deviations corresponding to the most interest-sensitive sectors. The right-hand panels of Figure 2 contain histograms of the cumulative IRF of sales to a change in the federal funds rate. All are negative, as theory would predict. Although each of the estimated interest-sensitivity measures has the expected sign for nearly all industries, the magnitudes of the measures vary considerably across industries.

Not surprisingly for VAR models, the numerical values of interest-sensitivity measures, which are reported in Table 1, also vary across the different VAR model specifications. However, the relative ranking of an industry's interest sensitivity is reasonably close across the different VAR models we estimated. This can be seen by looking at the right-hand columns of Table 1, which report the average interest-sensitivity rank of each industry based on the average of its rankings in the underlying VAR models (with the most sensitive being ranked number one, and so on).<sup>18</sup> The closeness of the industry rankings is confirmed by the high rank correlations reported in Table 2. Generally, one can see from Table 1 that industries ranked high by the Std. Dev. measure were also ranked high by Cum IRF and the Sum of Coef. measures. The most highly interest-sensitive industries are: autos (manufacturing and retail), transportation, lumber, stone-clay-glass, primary metals, rubber, fabricated metals, and textiles. The relatively insensitive industries are: food (manufacturing and retail), paper, leather, nondurable goods wholesalers, instruments, printing and publishing, apparel retailers, and other miscellaneous retail stores. So, on average, the VAR models seem to have ranked the industry interest sensitivities in a manner consistent with a priori assumptions.

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<sup>18</sup> The interest-sensitivity measures were ranked from 1 to 27 for each VAR model. For example, for the scaled IRF std. deviations measure in the "Levels federal funds fifth" VAR, Motor Vehicle Mfrs. were ranked 1 since their std. deviation (3.18) was the largest, Transportation Equipment Mfrs. were ranked 2, and Retail Automotive dealers were ranked 3, etc. Then the average rank across the four VAR models using the Scaled Std. Deviations measure was calculated; these average ranks were in turn ranked from 1 to 27, producing the average rank reported in the right-hand column of Table 1 labeled "Avg. Rank Std. Dev." The average ranks across the Cumulative IRF and Sum of Coefficients measures were calculated analogously.

Since many of the most interest-sensitive industries are associated with the auto industry or other transportation industries, they are also likely to be sensitive to energy price shocks. Hence, we also calculated oil-price-sensitivity measures for each different VAR specification. The same three types of measures were constructed: the scaled Std. Dev. of the IRF of sales to an increase in the relative price of oil, a Cumulative IRF of sales to an increase in the relative price of oil, and the sum of lagged coefficients on the relative price of oil in the sales equation. The average oil-price-sensitivity rank of each industry is given in the right-hand column of Table 1. As one can observe, there is a significant positive correlation between the industry interest sensitivity and oil-price-sensitivity ranks (rank correlation is 0.66). These relative oil-price-sensitivity measures are used in the next section as a control variable.

## 5. Are Reductions in Output Volatility Associated with Interest Sensitivity?

To quantify the link between volatility change and monetary policy sensitivity, we ran cross-section regressions of the industry volatility ratios on the three measures of interest-rate sensitivity controlling for the industry's sensitivity to oil price changes:

$$(1) \text{ [Volatility Ratio]}_t = \alpha + \beta \text{ [Interest Sensitivity]}_{t-1} + \gamma \text{ [Oil Price Sensitivity]}_{t-1}$$

where the output variance volatility ratios are  $\left[ \text{Var}(y^L) / \text{Var}(y^E) \right]$ , where  $L$  denotes late period and  $E$  denotes early period.<sup>19</sup> The interest-sensitivity measures and oil price sensitivity measures are based on VAR models estimated only on the early period (dated  $t-1$ ) to minimize potential problems associated with endogeneity.<sup>20</sup> If the larger reductions in variance (lower volatility

<sup>19</sup> We thank Giovanni Olivei for the suggestion to control for energy sensitivity in this regression.

<sup>20</sup> Using interest-sensitivity measures based on pre-1984 data guarantees that the interest-sensitivity measure is a predetermined variable in these OLS regressions. If one were to use post-1983 data to measure interest sensitivity, one could argue that the error term in such a regression equation might be correlated with the interest-sensitivity measure, that is, something that caused the variance reduction could also be influencing the interest-sensitivity measure. However, the regression results are robust to using interest sensitivity measured over the full sample.

ratios) occurred disproportionately in industries with relatively high interest sensitivity, the estimated slope coefficients,  $\beta$ , should be negative for the Std. Dev. measures (larger standard deviations with lower volatility ratios) and positive for both the Cumulative IRF measure (more negative cumulative response to an increase in the federal funds rate associated with larger variance reductions) and the Sum of Coefficients measure (smaller, or more negative, coefficient sums with lower volatility ratios).<sup>21</sup>

Table 3 reports the results of the cross-section regressions. Looking down the estimated coefficients and t-statistics on the interest-sensitivity measures from the 30 different VAR model specifications, one can see that eighty percent have the theoretically expected sign but only one coefficient tests to be statistically significant. Figures 3 and 4 contains representative plots of the variance volatility ratios against each of the three different interest-sensitivity measures.<sup>22</sup> The fitted line reflects the slope estimated in equation (1) on the respective interest-sensitivity measure. The left panel lines slope positively as theoretically expected, but none of the slope coefficients are anywhere near statistically significant. Of the right panel lines only one is negatively sloped as theory would suggest (that is, have bigger variance reductions associated with larger standard deviations).<sup>23</sup>

Figures 3 and 4, however, suggest that the regressions are likely to be heavily affected by the petroleum industry (whose variance-volatility ratio rose substantially from the pre-1984 to the post-1983 period). Dropping the two industries whose volatility ratios rose (petroleum and tobacco manufacturers), we re-ran the regressions. These results are reported in Table 4. The

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<sup>21</sup> We also ran regressions on the sensitivity rank, rather than the sensitivity measure itself, and the results are qualitatively similar.

<sup>22</sup> In the VARs for these figures, the oil-price-sensitivity measure is of the same type as the interest-sensitivity measure.

<sup>23</sup> These interest-sensitivity slope coefficients are, of course, controlling for the sensitivity of each industry to the relative price of oil. The estimated oil-price-sensitivity slope coefficients reported in Tables 3 and 4 test to be even less statistically significant than the estimated coefficients on the interest-sensitivity measures.

coefficient estimates on the interest-sensitivity measures now all have the theoretically expected signs. Four of the thirty coefficients estimated on the interest-sensitivity measures now have t-statistics that exceed the two-tailed 5-percent critical value of 2.07, indicating a statistically significant relationship. So if one believes that the petroleum refiners and tobacco industry outliers should be dropped (perhaps because of structural changes in those particular industries), then this is weak evidence of some relationship between industry volatility reductions and their interest sensitivities.<sup>24,25</sup>

## 6. Conclusions

These simple regressions suggest that changes in industry output volatilities occurred with little connection to each industry's sensitivity to monetary policy. Although this result does not rule out conclusively the better-monetary-policy hypothesis, it poses challenges. In particular, monetary policy must have improved in such a way as to reduce the output variances of all industries without influencing interest-sensitive sectors relatively more.

Our results using M&T data are only for a subset of the Goods Sector of GDP. It is possible that the major channel by which improved monetary policy lowered the volatility of GDP was through reducing the variance of the Structures Sector and the covariance of the

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<sup>24</sup> To further test the robustness of these results, we also estimated similar equations with output volatility growth rates calculated by a Tornqvist approximation (see footnote 11), with the early period extending from 1967:Q1 through 1983: Q4. Data were not available to construct the Tornqvist output measures before 1967. Interest-sensitivity measures were even less significant in these cross-sectional regressions than those reported in Tables 3 and 4. We ran several other specifications to check the robustness of these results. In one specification, we included just the 14 most interest-sensitive industries. In another, we defined the dependent variable to be the ratio of the standard deviation of output post-1983 to the standard deviation pre-1984; the most statistically significant specification had six coefficients on interest sensitivity whose t-stats exceeded 2.07 in regressions which dropped the tobacco and petroleum industries.

<sup>25</sup> Because our other research (Irvine and Schuh, 2005b) has suggested that covariance reductions are an important component of the GDP volatility decline, we ran similar cross-section regressions with the dependent variable being the change in covariance of each industry (with all other industries) scaled by its early-period variance. The idea was that perhaps the change in covariance was a function of industry interest sensitivity. The estimated coefficients on the interest-sensitivity measures in these covariance regressions are often of the incorrect sign and even less statistically significant.

Structures Sector with the Goods Sector. However, by our decomposition of variance (Irvine and Schuh, 2005a), this channel accounts for at most about 28 percent of the reduction in GDP volatility.

In any case, these results suggest that, at best, improved monetary policy is only part of the explanation for reduced GDP volatility. Even then, the influence of monetary policy will have to be shown through more nuanced channels. Ultimately, we will probably find that the volatility of GDP declined for a number of different reasons. Sorting out their contributions to the GDP volatility decline will require much more careful structural modeling, an obvious avenue for future research.

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Figure 1: Distribution of Output Growth Volatility Ratio

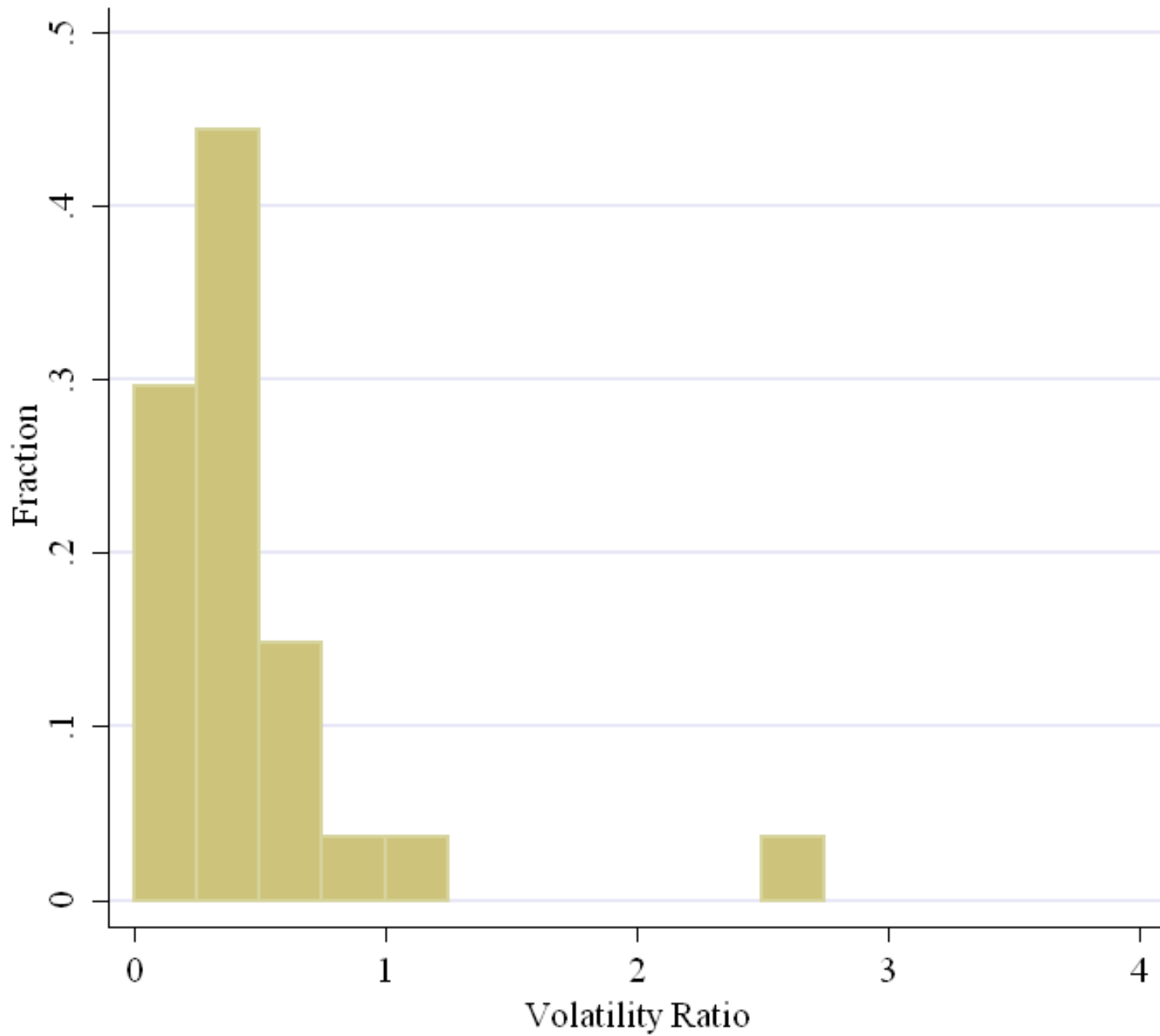
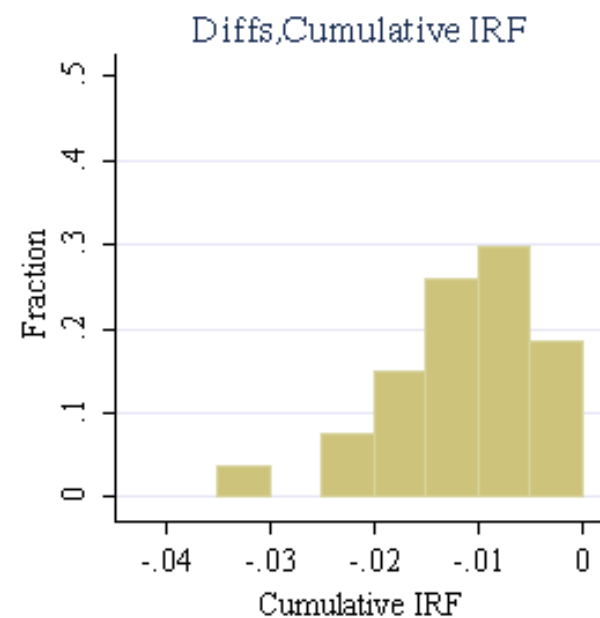
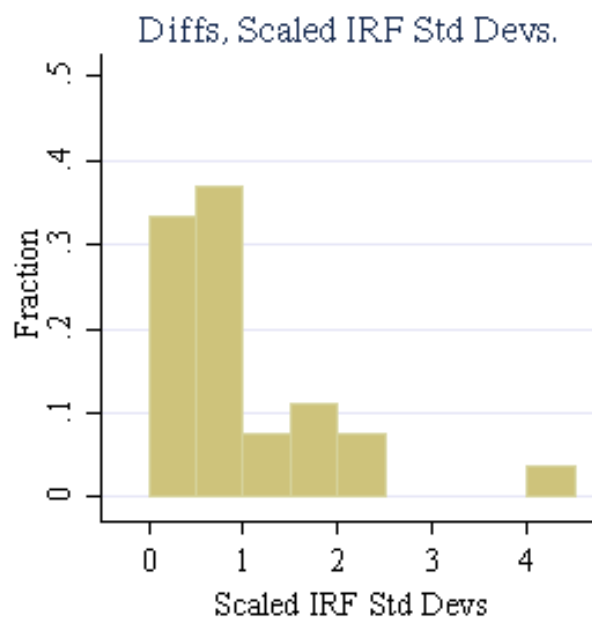
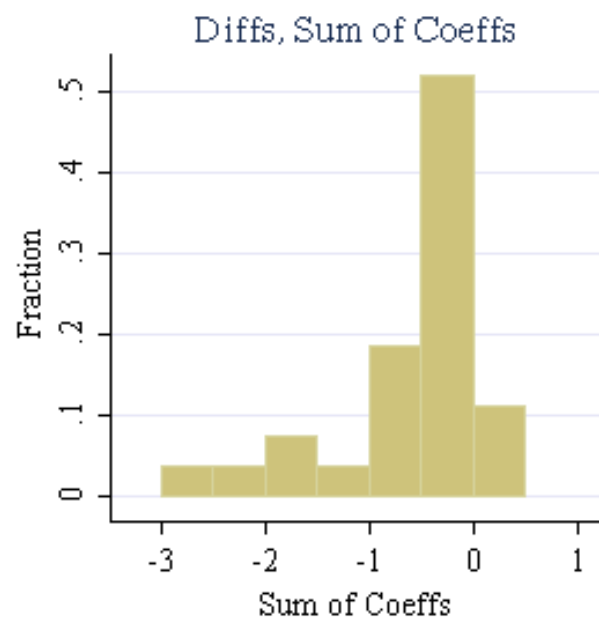
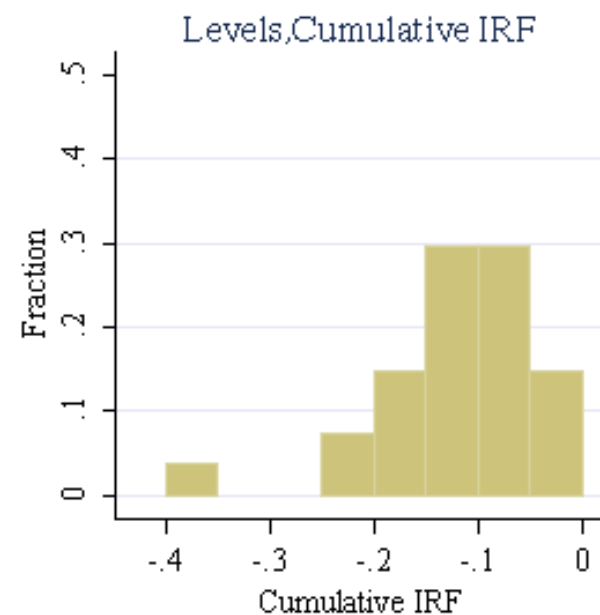
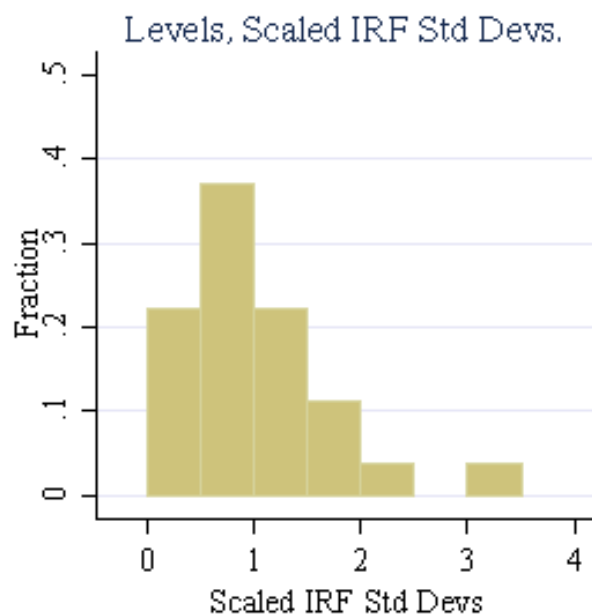
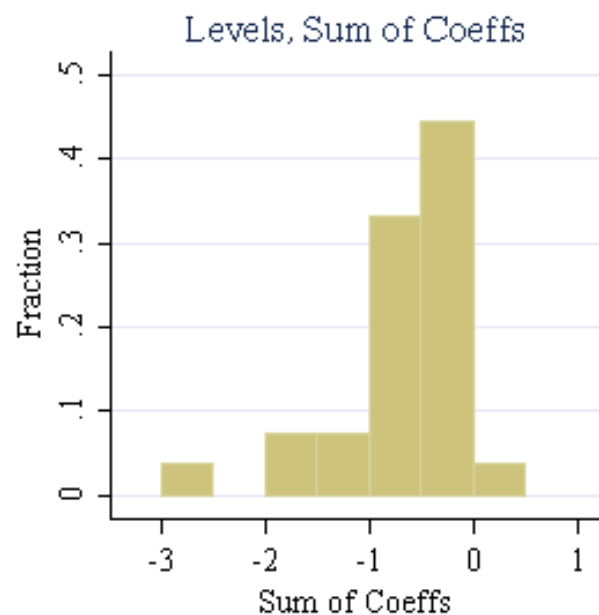
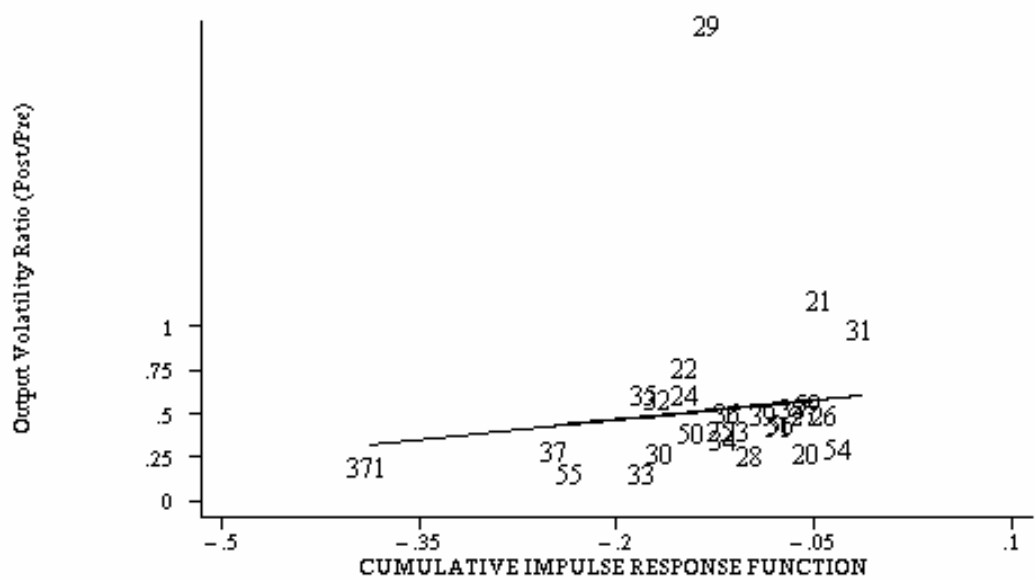
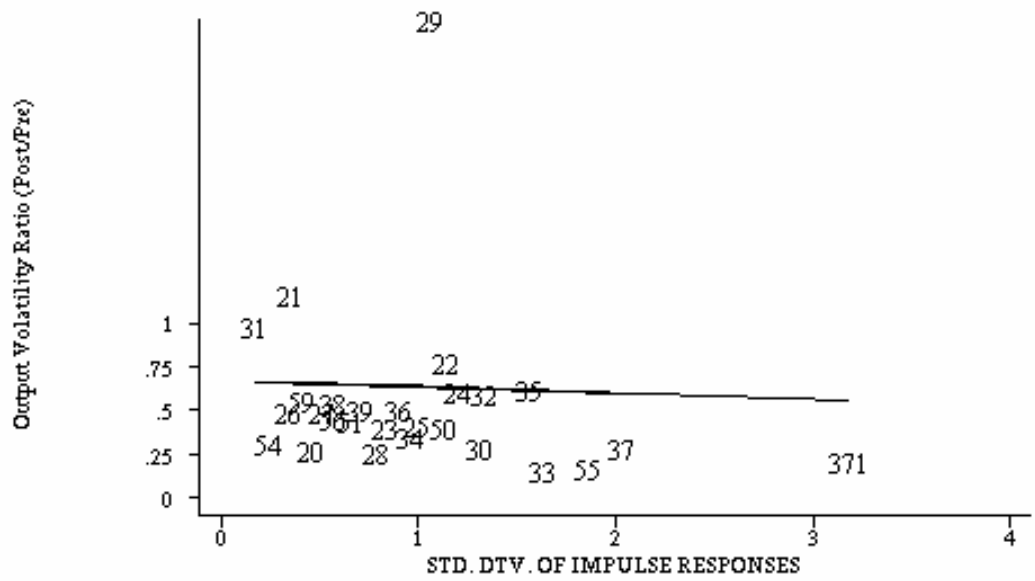
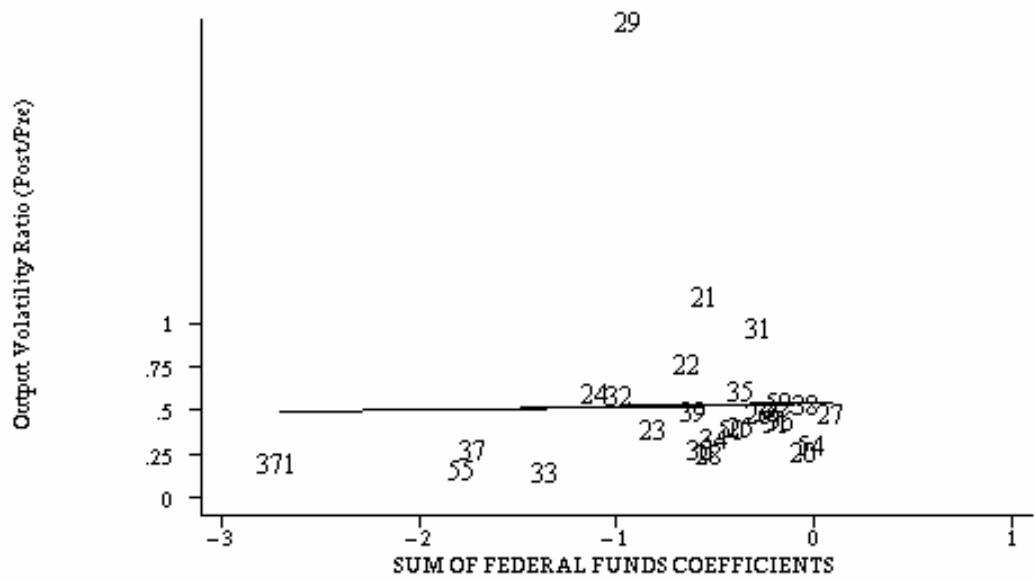


Figure 2: Distributions of Interest Sensivity Measures



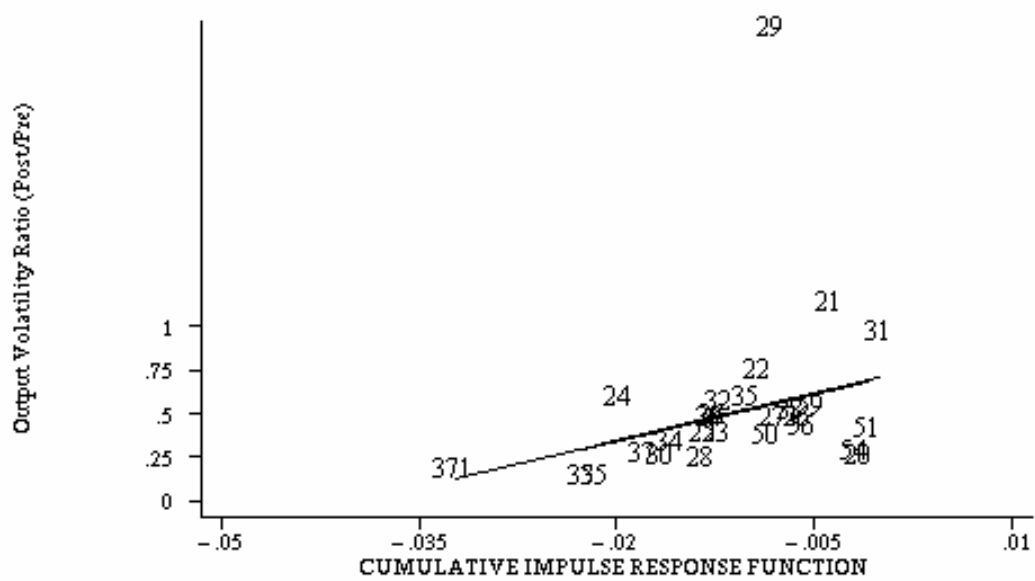
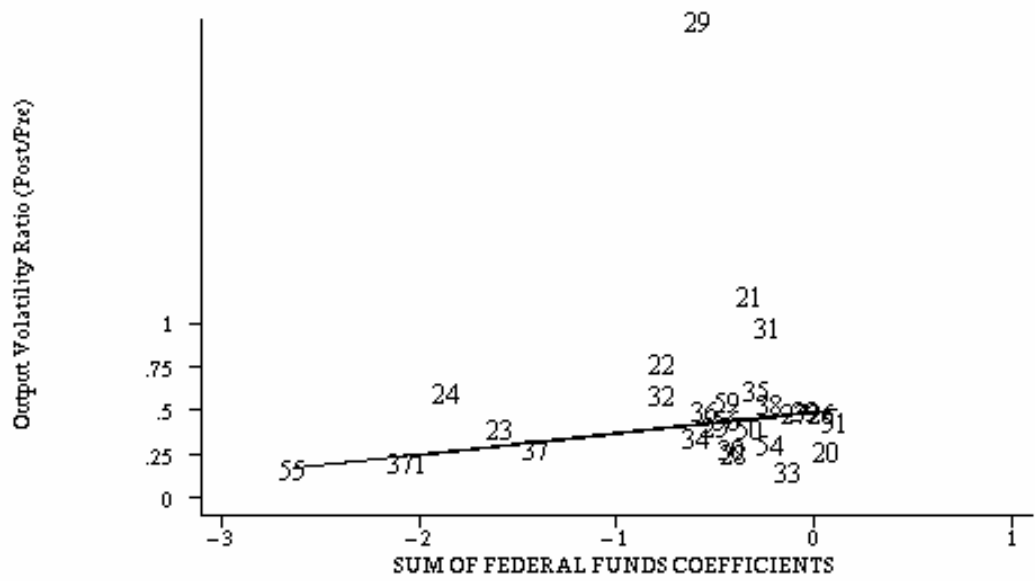
Note: Based on VARs from 1959:Q1 through 1983:Q4, Fed Funds 5th.<sup>18</sup>

Figure 3: Output Volatility Ratios vs. Interest Sensitivity Measures  
Levels VAR, Federal Funds Fifth



Footnote: Oil price sensitivity measure in regression is of same type as Interest sensitivity.

Figure 4: Output Volatility Ratios vs. Interest Sensitivity Measures  
 Differences VAR, Federal Funds Fifth



Footnote: Oil price sensitivity measure in regression is of same type as Interest sensitivity.

### Table 1: Interest Sensitivities

Industry SIC #	Output Volatility Ratio	Scaled IRF Std. Dev.				Cumulative IRF				Sum of Coeffs.		Avg Rank Std Dev.	Avg Rank Cum IRF	Avg Rank Sum Coeff	Avg Int. Sens.	Avg Oil Price Sens.	
		Levels FF 5th	Levels FF 1st	Diffs FF 5th	Diffs FF 1st	Levels FF 5th	Levels FF 1st	Diffs FF 5th	Diffs FF 1st	Levels FF 5th	Diffs FF 5th						
	<b>Nondurables Mfrs. .27</b>																
20	Food	.20	.46	.47	.19	.40	-.056	-.074	-.002	-.004	-.05	.07	25	23	26.5	<b>26</b>	24
21	Tobacco	1.08	.36	.18	.66	.74	-.045	-.021	-.004	-.001	-.55	-.32	20	25.5	13.5	<b>18</b>	26
22	Textiles	.69	1.14	1.13	.88	.86	-.148	-.169	-.009	-.007	-.64	-.77	10.5	11.5	7	<b>9</b>	18
23	Apparel	.33	.83	.91	1.28	1.67	-.108	-.122	-.012	-.005	-.81	-1.59	12	17	5	<b>12</b>	11
26	Paper	.42	.35	.47	.39	.30	-.042	-.070	-.006	-.005	-.27	.05	26	22	22	<b>25</b>	15
27	Printing	.42	.51	.66	.47	.38	-.058	-.087	-.008	-.006	.09	-.09	18	19	26.5	<b>21</b>	6
28	Chemicals	.19	.79	.72	.74	.80	-.099	-.095	-.014	-.008	-.52	-.40	17	13	13.5	<b>15</b>	9
29	Petroleum	2.66	1.07	.88	1.72	1.50	-.130	-.127	-.008	-.007	-.93	-.58	8	15	8	<b>11</b>	13
30	Rubber	.20	1.32	1.38	.95	.95	-.166	-.196	-.017	-.010	-.57	-.41	6	5	10	<b>7</b>	10
31	Leather	.91	.17	.23	.55	.86	-.015	.004	.000	.006	-.28	-.23	21	27	21	<b>24</b>	20
	<b>Durables Mfrs. .23</b>																
24	Lumber	.53	1.20	1.14	1.64	1.77	-.148	-.162	-.020	-.022	-1.11	-1.86	5	4	3.5	<b>4</b>	14
25	Furniture	.33	.99	1.02	.89	.98	-.120	-.134	-.013	-.010	-.37	-.50	10.5	8.5	12	<b>10</b>	17
32	Stone,Clay,Glass	.51	1.34	1.29	.87	.95	-.169	-.184	-.012	-.008	-.98	-.76	7	7	6	<b>5</b>	7
33	PrimaryMetals	.08	1.63	1.77	1.65	2.10	-.180	-.193	-.023	-.007	-1.36	-.13	4	6	11	<b>6</b>	1
34	FabricatedMetals	.28	.96	1.09	1.09	1.29	-.119	-.137	-.016	-.009	-.50	-.60	9	8.5	9	<b>8</b>	5
35	IndustrialMach.	.54	1.56	1.32	.58	.63	-.179	-.156	-.010	-.003	-.37	-.29	13	14	19	<b>16</b>	23
36	ElectronicMach.	.43	.91	.97	.86	.87	-.115	-.128	-.013	-.009	-.24	-.55	14	11.5	15	<b>13</b>	8
37	Transportation	.21	2.03	1.93	2.30	1.93	-.247	-.264	-.018	-.012	-1.73	-1.40	2	3	3.5	<b>3</b>	4
371	MotorVehicles	.13	3.18	3.02	4.02	3.26	-.389	-.430	-.032	-.025	-2.72	-2.06	1	1	1.5	<b>1</b>	3
38	Instruments	.46	.58	.52	.42	.33	-.066	-.061	-.007	-.005	-.04	-.21	22.5	21	23	<b>22</b>	19
39	Misc.Mfg.	.43	.71	1.01	.83	.66	-.087	-.154	-.013	-.012	-.61	-.03	15	10	17	<b>14</b>	2
50	WholesaleDurables	.32	1.14	1.00	.46	.64	-.142	-.134	-.009	-.004	-.41	-.32	16	16	16	<b>17</b>	16
51	WholesaleNondurabl	.36	.67	.58	.43	.35	-.076	-.079	-.001	.000	-.19	.11	19	24	25	<b>23</b>	21
54	RetailFoodStores	.23	.25	.25	.20	.22	-.032	-.039	-.002	-.003	-.02	-.21	27	25.5	24	<b>27</b>	25
55	RetailAutomotive	.10	1.86	1.91	2.19	1.82	-.234	-.283	-.022	-.020	-1.79	-2.64	3	2	1.5	<b>2</b>	12
56	RetailApparelStores	.37	.57	.58	.35	.36	-.074	-.090	-.006	-.008	-.16	-.44	24	18	19	<b>19</b>	22
59	Misc.Retail	.48	.41	.58	.38	.39	-.053	-.088	-.005	-.007	-.17	-.44	22.5	20	19	<b>20</b>	27

Note: Interest Sensitivities based on early period sample period, 1959 Q1 through 1983 Q4

\*Rank 1 is most sensitive on average

**Table 2: Interest Sensitivity Measure Rank Correlations**

		Sum of Coefficients		Scaled Std. Deviations of IRF				Cumulative IRF Responses			
		Levels	Diffs	Levels FF 5th	Levels FF 1st	Diffs FF 5th	Diffs FF 1st	Levels FF 5th	Levels FF 1st	Diffs FF 5th	Diffs FF 1st
<b>Sum of Coefficients</b>	Levels	1.00	.66	.78	.75	.89	.88	.78	.78	.75	.58
	Diffs		1.00	.61	.58	.72	.73	.62	.62	.60	.62
<b>Scaled Std. Deviations of IRF</b>	Levels FF 5th			1.00	.96	.80	.76	.9994	.95	.83	.61
	Levels FF 1st				1.00	.79	.75	.96	.98	.88	.70
	Diffs FF 5th					1.00	.95	.79	.78	.84	.66
	Diffs FF 1st						1.00	.76	.75	.80	.64
<b>Cumulative IRF Responses</b>	Levels FF 5th							1.00	.95	.83	.61
	Levels FF 1st								1.00	.87	.75
	Diffs FF 5th									1.00	.83
	Diffs FF 1st										1.00

**Table 3 - Monetary Policy Sensitivity Regressions  
(All Industries)**

VAR Model Specification		Slope Coefficient on Interest Sensitivity				Slope Coefficient on Oil Sensitivity		
Data	Order	Interest Sensitivity Measure	Expect Sign	Estimate	T-Stat	Estimate	T-Stat	Oil Price Sensitivity Measure
Levels	FF 5th	Std. dev.	-	-.04	-.20	-.16	-1.04	Std. dev.
Levels	FF 1st	Std. dev.	-	-.12	-.61	-.11	-.68	Std. dev.
Diffs	FF 5th	Std. dev.	-	.14	.75	-.28	-1.06	Std. dev.
Diffs	FF 1st	Std. dev.	-	.14	.64	-.27	-.98	Std. dev.
Levels	FF 5th	Cum. IRF	+	.74	.53	1.55	.65	Cum. IRF
Levels	FF 1st	Cum. IRF	+	1.17	.90	.96	.40	Cum. IRF
Diffs	FF 5th	Cum. IRF	+	17.87	.80	2.11	.12	Cum. IRF
Diffs	FF 1st	Cum. IRF	+	8.53	.46	9.96	.81	Cum. IRF
Levels		Sum Coeff.	+	.02	.12	3.70	.83	Sum Coeff.
Diffs		Sum Coeff.	+	.12	.81	-1.23	-.74	Sum Coeff.
Levels	FF 5th	Std. dev.	-	-.09	-.52	1.53	.64	Cum. IRF
Levels	FF 1st	Std. dev.	-	-.18	-.95	.73	.29	Cum. IRF
Diffs	FF 5th	Std. dev.	-	.16	1.06	22.15	1.74	Cum. IRF
Diffs	FF 1st	Std. dev.	-	.16	.90	20.77	1.64	Cum. IRF
Levels	FF 5th	Cum. IRF	+	1.04	.84	3.30	.78	Sum Coeff.
Levels	FF 1st	Cum. IRF	+	1.29	1.16	2.75	.65	Sum Coeff.
Diffs	FF 5th	Cum. IRF	+	37.76	2.57	-3.57	-2.00	Sum Coeff.
Diffs	FF 1st	Cum. IRF	+	28.43	1.71	-2.32	-1.32	Sum Coeff.
Levels		Sum Coeff.	+	-.09	-.50	-.22	-1.46	Std. dev.
Diffs		Sum Coeff.	+	.05	.29	-.10	-.52	Std. dev.
Levels	FF 5th	Std. dev.	-	-.13	-.83	3.24	.76	Sum Coeff.
Levels	FF 1st	Std. dev.	-	-.19	-1.18	2.42	.56	Sum Coeff.
Diffs	FF 5th	Std. dev.	-	-.08	-.51	-1.44	-.71	Sum Coeff.
Diffs	FF 1st	Std. dev.	-	-.10	-.57	-1.45	-.74	Sum Coeff.
Levels	FF 5th	Cum. IRF	+	.35	.25	-.16	-1.06	Std. dev.
Levels	FF 1st	Cum. IRF	+	.84	.63	-.12	-.81	Std. dev.
Diffs	FF 5th	Cum. IRF	+	45.94	1.87	.40	1.22	Std. dev.
Diffs	FF 1st	Cum. IRF	+	17.08	.89	-.01	-.03	Std. dev.
Levels		Sum Coeff.	+	-.06	-.30	2.63	1.01	Cum. IRF
Diffs		Sum Coeff.	+	.03	.23	12.70	1.23	Cum. IRF

Note: Regression is: Output Volatility Ratio = a+b(Interest Sensitivity)+c(Oil Price Sensitivity)

**Table 4 - Monetary Policy Sensitivity Regressions**  
(Only Industries with Declining Variance)

VAR Model Specification		Slope Coefficient on Interest Sensitivity				Slope Coefficient on Oil Sensitivity		
Data	Order	Interest Sensitivity Measure	Expect Sign	Estimate	T-Stat	Estimate	T-Stat	Oil Price Sensitivity Measure
Levels	FF 5th	Std. dev.	-	-.11	-1.66	-.02	-.33	Std. dev.
Levels	FF 1st	Std. dev.	-	-.14	-1.83	.00	-.05	Std. dev.
Diffs	FF 5th	Std. dev.	-	-.03	-.45	-.12	-1.24	Std. dev.
Diffs	FF 1st	Std. dev.	-	-.02	-.21	-.14	-1.37	Std. dev.
Levels	FF 5th	Cum. IRF	+	.77	1.54	.85	1.02	Cum. IRF
Levels	FF 1st	Cum. IRF	+	.82	1.75	.66	.77	Cum. IRF
Diffs	FF 5th	Cum. IRF	+	4.94	.65	7.17	1.21	Cum. IRF
Diffs	FF 1st	Cum. IRF	+	5.60	.90	8.07	1.93	Cum. IRF
Levels		Sum Coeff.	+	.10	1.73	1.67	1.04	Sum Coeff.
Diffs		Sum Coeff.	+	.03	.57	1.27	1.95	Sum Coeff.
Levels	FF 5th	Std. dev.	-	-.09	-1.52	.83	.98	Cum. IRF
Levels	FF 1st	Std. dev.	-	-.11	-1.57	.63	.70	Cum. IRF
Diffs	FF 5th	Std. dev.	-	-.02	-.40	9.05	1.97	Cum. IRF
Diffs	FF 1st	Std. dev.	-	-.02	-.28	9.46	2.08	Cum. IRF
Levels	FF 5th	Cum. IRF	+	.93	2.16	2.15	1.44	Sum Coeff.
Levels	FF 1st	Cum. IRF	+	.92	2.34	1.91	1.29	Sum Coeff.
Diffs	FF 5th	Cum. IRF	+	9.62	1.60	.57	.74	Sum Coeff.
Diffs	FF 1st	Cum. IRF	+	8.52	1.39	.89	1.28	Sum Coeff.
Levels		Sum Coeff.	+	.10	1.50	-.02	-.35	Std. dev.
Diffs		Sum Coeff.	+	.01	.14	-.15	-2.09	Std. dev.
Levels	FF 5th	Std. dev.	-	-.11	-2.13	2.10	1.40	Sum Coeff.
Levels	FF 1st	Std. dev.	-	-.12	-2.14	1.76	1.15	Sum Coeff.
Diffs	FF 5th	Std. dev.	-	-.05	-1.00	.94	1.24	Sum Coeff.
Diffs	FF 1st	Std. dev.	-	-.05	-.92	1.01	1.37	Sum Coeff.
Levels	FF 5th	Cum. IRF	+	.89	1.68	-.02	-.41	Std. dev.
Levels	FF 1st	Cum. IRF	+	.95	1.97	-.01	-.23	Std. dev.
Diffs	FF 5th	Cum. IRF	+	10.33	1.10	-.03	-.27	Std. dev.
Diffs	FF 1st	Cum. IRF	+	7.22	1.09	-.10	-1.31	Std. dev.
Levels		Sum Coeff.	+	.08	1.20	.76	.80	Cum. IRF
Diffs		Sum Coeff.		.03	.53	9.74	2.72	Cum. IRF

Note: Regression is: Output Volatility Ratio = a+b(Interest Sensitivity)+c(Oil Price Sensitivity)



## Appendix: Oil Sensitivities

Industry SIC #		Output Volatility Ratio	Scaled IRF Std. Dev.				Cumulative IRF				Sum of Coeffs.		Avg Rank Std	Avg Rank Cum	Avg Rank Sum	Avg Oil Sens.
			Levels	Levels	Diffs	Diffs	Levels	Levels	Diffs	Diffs	Levels	Diffs				
			FF 5th	FF 1st	FF 5th	FF 1st	FF 5th	FF 1st	FF 5th	FF 1st	Levels	Diffs				
	<b>Nondurables Mfrs.</b>	<b>.27</b>														
20	Food	.20	.18	.18	.26	.26	.006	.006	-.001	-.001	.000	-.009	25.5	24	21	24
21	Tobacco	1.08	.23	.23	.42	.42	.004	.004	-.001	-.001	.011	.015	23	25	25.5	26
22	Textiles	.69	.31	.31	.62	.62	.003	.003	-.005	-.005	-.012	-.022	22	18	16	18
23	Apparel	.33	.70	.70	1.42	1.42	-.024	-.024	-.008	-.008	-.045	-.062	12	14	8	11
26	Paper	.42	.51	.51	.65	.65	-.017	-.017	-.009	-.009	-.017	-.021	18	15.5	14.5	15
27	Printing	.42	1.44	1.44	1.17	1.17	-.067	-.067	-.016	-.016	-.039	-.109	8	7.5	3	6
28	Chemicals	.19	1.14	1.14	1.11	1.11	-.042	-.042	-.017	-.017	-.038	-.050	10.5	9.5	10	9
29	Petroleum	2.66	.49	.49	1.23	1.23	-.020	-.020	-.011	-.011	-.013	-.158	16	13	7	13
30	Rubber	.20	.88	.88	1.47	1.47	-.038	-.038	-.023	-.023	-.007	-.103	10.5	7.5	13	10
31	Leather	.91	.61	.61	.44	.44	-.019	-.019	.003	.003	-.004	.021	20.5	19.5	21	20
	<b>Durables Mfrs.</b>	<b>.23</b>														
24	Lumber	.53	.98	.98	1.00	1.00	-.043	-.043	-.009	-.009	-.025	-.024	13.5	12	11	14
25	Furniture	.33	.61	.61	.79	.79	-.016	-.016	-.005	-.005	-.010	.022	17	17	19	17
32	Stone, Clay, Glass	.51	2.17	2.17	1.14	1.14	-.095	-.095	-.017	-.017	-.013	-.091	6	6	12	7
33	Primary Metals	.08	3.51	3.51	1.92	1.92	-.160	-.160	-.029	-.029	-.087	-.095	1.5	1.5	3	1
34	Fabricated Metals	.28	1.10	1.10	1.50	1.50	-.050	-.050	-.024	-.024	-.021	-.113	6	4	6	5
35	Industrial Mach.	.54	1.09	1.09	.64	.64	.045	.045	-.002	-.002	.033	.057	15	26.5	27	23
36	Electronic Mach.	.43	.98	.98	1.63	1.63	-.041	-.041	-.019	-.019	-.020	-.103	6	9.5	9	8
37	Transportation	.21	1.60	1.60	1.53	1.53	-.069	-.069	-.021	-.021	-.023	-.148	4	5	3	4
371	Motor Vehicles	.13	2.34	2.34	2.32	2.32	-.100	-.100	-.034	-.034	-.017	-.151	1.5	1.5	5	3
38	Instruments	.46	1.14	1.14	.57	.57	.053	.053	-.005	-.005	.004	-.011	13.5	22.5	21	19
39	Misc. Mfg.	.43	1.98	1.98	1.61	1.61	-.089	-.089	-.021	-.021	-.045	-.132	3	3	1	2
50	Wholesale Durables	.32	.41	.41	.92	.92	-.010	-.010	-.013	-.013	-.001	-.049	19	15.5	17	16
51	Wholesale Nondurables	.36	.17	.17	.41	.41	.003	.003	-.003	-.003	-.001	-.014	25.5	19.5	18	21
54	Retail Food Stores	.23	.08	.08	.22	.22	-.003	-.003	.002	.002	-.001	.027	27	22.5	24	25
55	Retail Automotive	.10	1.05	1.05	1.42	1.42	-.043	-.043	-.013	-.013	-.004	-.067	9	11	14.5	12
56	Retail Apparel Stores	.37	.80	.80	.41	.41	.030	.030	-.005	-.005	.008	-.006	20.5	21	23	22
59	Misc. Retail	.48	.49	.49	.17	.17	.023	.023	-.001	-.001	.012	.011	24	26.5	25.5	27

Note: Interest Sensitivities based on early period sample period, 1959 Q1 through 1983 Q4 \*Rank 1 is most sensitit \*Rank 1 is most sensitive on averag