RECENT U.S. MACROECONOMIC STABILITY: GOOD POLICIES, GOOD PRACTICES, OR GOOD LUCK?
Shaghil Ahmed, Andrew Levin, and Beth Anne Wilson*

Abstract—The volatility of U.S. real GDP growth since 1984 has been markedly lower than over the previous quarter century. We utilize frequency-domain and VAR methods to distinguish among competing explanations for this reduction: improvements in monetary policy, better business practices, and a fortuitous reduction in exogenous disturbances. We find that reduced innovation variances account for much of the decline in aggregate output volatility, suggesting that good luck is the most likely explanation. Good practices and good policy appear to have played a more important role in explaining the post-1984 decline in the volatility of consumer price inflation.

I. Introduction

RECENT analysis has identified a marked decline in the volatility of U.S. GDP growth since the mid-1980s.\(^1\) The magnitude of the decline is striking; the standard deviation of GDP growth has halved from the 1960:1–1983:4 period to the 1984:1–2002:1 period, falling from 4.4 percentage points in the first period to 2.3 in the second period. Furthermore, the decline in output variability appears to be mirrored in all major demand-side and product-side components of GDP, as well as in the inflation rate and many other macroeconomic and financial variables.

Three competing explanations have been given for the post-1984 decline in U.S. output volatility: good policy, good practices, and good luck. According to the first view, better monetary policy has tamed the business cycle. This view is consistent with empirical studies that have documented systematic differences in monetary policy between the Volcker-Greenspan era and the previous period.\(^2\) An alternative explanation focuses on the effects of improved business practices—such as just-in-time inventory management—that have been facilitated by rapid advances in information technology.\(^3\) Finally, the decline in aggregate output volatility may simply reflect a sharp drop in the variance of exogenous disturbances hitting the U.S. economy.\(^4\)

In this paper, we utilize both frequency-domain and vector autoregression (VAR) methods to distinguish among the explanations. In the frequency domain, we use the spectrum of GDP growth to decompose its variance by frequency. Characterizing the post-1984 shift in the spectrum of GDP growth is useful because basic versions of each explanation can be associated with different patterns for the shift: (1) improved monetary policy would be expected to shift the spectrum primarily at business-cycle frequencies; (2) improved inventory management and other relevant changes in business practices would tend to be manifested more at relatively high frequencies; and (3) reduced innovation variance would generate a proportional decline in the spectrum at all frequencies. VAR analysis provides a complementary perspective, providing one way to determine in a multivariate setting whether the reduction in output volatility is primarily due to changes in the variances of the shocks impacting the economy or to changes in the structure of the economy.

We find that reduced innovation variance accounts for the bulk of the decline in output volatility. For aggregate GDP, we cannot reject the hypothesis that the post-1984 shift in the spectrum is proportional across all frequencies. Estimating VARs across the two periods provides some evidence of structural breaks in the coefficients, and more support than our frequency-domain results for the importance of changes in the structure of the economy; however, a majority of the decline in output variance still appears to be due to a reduction in innovation variance.

Our results for aggregate GDP growth are consistent with the good luck hypothesis as the leading explanation for the fall in output volatility. They are unsupportive of versions of the good policy and good practices explanations that work through changes in how the economy reacts to shocks (which would be manifested in changes in the contour of the spectrum), rather than exclusively through changes in the nature of the shocks themselves (which would imply parallel shifts in the level of the spectrum). However, it should be noted that the results are consistent with a rather different view of improved monetary policy, in which—as argued by Clarida et al. (2000)—aggressive policy works to reduce aggregate volatility by eliminating “sunspot” equilibria. More specifically, if improved monetary policy during the Volcker-Greenspan era has worked predominately through ensuring a unique rational expectations equilibrium, innovation variances could be reduced, as shifts in expectations

\(^*\) Board of Governors of the Federal Reserve System.

Received for publication July 2, 2002. Revision accepted for publication August 5, 2003.

We benefited from comments by Chris Sims and other participants in a session at the January 2001 AEA meetings, as well as suggestions from David Bowman, Darrel Cohen, Jon Faust, Norman Morin, David Skidmore, James Stock, Stacey Tevlin, Mark Watson, Karl Whelan, and two anonymous referees. Jon Jellema, Jonathan Huntley, Lisa Schroeer, and Kristina Lund provided excellent research assistance. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System.

1 This decline was initially identified by McConnell, Mosser, and Perez Quiros (1999), and has subsequently been analyzed by McConnell and Perez Quiros (2000), Kim, Nelson, and Figer (2000), Simon (2000), Blanchard and Simon (2001), Stock and Watson (2002), and Ahmed, Levin, and Wilson (2002), among others.


3 See McConnell et al. (1999) and Kahn, McConnell, and Perez Quiros (2000). Potentially relevant changes in practices also include development of a mortgage-backed securities market (Rydberg, 1990; Throop, 1986) and reduction of trade barriers.

4 Simon (2000) finds strong support for this hypothesis using a VAR with long-run identifying restrictions.
unrelated to macroeconomic fundamentals—possibly at work in previous periods—would now be prevented from influencing the economy.

Finally, we apply the same methodologies to detect and analyze shifts in U.S. inflation volatility. Like GDP growth, inflation shows a sharp decline in variance in the post-1984 period. However, our results indicate that lower inflation volatility cannot entirely be accounted for by a reduction in innovation variances. Instead changes in the structure of the economy (the coefficients in a VAR framework) appear to play an important role, consistent with the view that monetary policy has been crucial in taming inflation volatility.

The remainder of this paper is organized as follows. Section II describes our frequency-domain analysis. Section III reports on our VAR analysis. Conclusions are given in section IV.

II. Frequency-Domain Analysis

A. Motivation

The variance of output growth can be expressed as the integral of the spectrum, \( g(\omega) \), across all frequencies \(-\pi \leq \omega \leq \pi\). Therefore, the post-1984 decline in variance should show up as a downward shift in the spectrum, on balance. Furthermore, some insight into the nature of the volatility decline can be obtained by determining whether this downward shift is spread evenly across all frequencies or is concentrated at a specific frequency range.

If improved monetary and fiscal policies act to dampen business cycle fluctuations, as is likely, then we should find that the post-1984 decline in spectrum occurred disproportionately at business cycle frequencies. Improved business practices (such as better inventory management techniques, more sophisticated financial markets, or expanding international trade flows) seem likely to smooth output on a quarter-by-quarter basis, for example, by better matching output to final sales. Thus, if the reduction in variance reflected better business practices, we would expect the decline in variance to occur primarily at relatively high frequencies. Moreover, if improvements in data construction are behind the fall in variance, this too should be evident at high frequencies. In any case, these two explanations (good policies and good practices) would likely work, partly at least, by changing the structure of the economy rather than exclusively through changes in the nature of the shocks hitting the economy.

By contrast, under the good luck hypothesis, the fall in output volatility is due exclusively to a reduction in the volatility of the shocks hitting the economy, with no change in the structure of the economy. Assuming that output growth is covariance-stationary, Wold’s theorem indicates that it can be represented as an infinite moving-average (MA) process. Thus, the good luck hypothesis can be interpreted as a decline in innovation variance with no change in the MA coefficients. Because the spectrum of any MA(\(\infty\)) process is proportional to the innovation variance, this hypothesis implies a parallel downward shift in the spectrum.

The hypothesis of a parallel shift in the spectrum can be analyzed more precisely by constructing the normalized spectrum, \( h(\omega) = g(\omega)/\sigma^2 \), which indicates the fraction of the total variance \( \sigma^2 \) occurring at each frequency \( \omega \). Because both the numerator and the denominator of this ratio are proportional to the innovation variance, the normalized spectrum is invariant to the magnitude of the innovation variance. Thus, under the good luck hypothesis, the normalized spectrum would exhibit no post-1984 shift at all, although, as we determined earlier, a particular version of the monetary policy explanation could also give this result. Note that, if the decrease in volatility were due to a combination of factors, say good luck and a conventional version of good practices, the parallel shift in the spectrum due to good luck would still likely be overlain by a disproportional decline in the spectrum at some specific frequency range.

Our frequency-domain approach is illustrated in figure 1. For each of the two periods, the upper panel depicts an illustrative estimate of the spectrum of real GDP growth, and the lower panel depicts the normalized spectrum. The horizontal axis expresses the frequency \( \omega \), labeled in terms of the length of the cycle; the horizontal lines delineate three different frequency ranges: low, business cycle, and high. As in Baxter and King (1999), the business cycle frequencies \((\pi/16 \text{ to } \pi/3)\) correspond to cycles of 6 to 32 quarters. The post-1984 decline in volatility of GDP growth is evident from the downward shift in the spectrum. Figure 1 provides some striking (though informal) evidence consistent with the good luck hypothesis. In particular, the normalized spectra of the two sample periods look remarkably similar at high frequencies. In addition, though the upper panel seems to indicate that the drop in output volatility occurred primarily at business cycle frequencies, the normalized spectra for the two periods appear much more similar, with the second period’s spectrum only slightly below that of the first period. At low frequencies, the spectrum seems higher in the second period, but, as will be seen later, the estimated spectrum at low frequencies is subject to greater sampling variation, and hence the cross-sample deviation apparent at these frequencies should not be taken very seriously.

B. Testing Methodology

The integrated spectrum provides a useful tool for implementing formal tests of these hypotheses. For a given

---

5 This estimate was computed in RATS 5.0 using the tent-shaped spectral window with width equal to the square root of the sample size.
6 The results were largely similar on using a narrower range for the business cycle frequency, namely, \(\pi/8 \text{ to } \pi/4\), corresponding to cycles of 8 to 16 quarters (as in Sargent, 1979).

---

This page contains the text of the RECENT U.S. MACROECONOMIC STABILITY page from the journal issue.
frequency range, \( G(\omega_1, \omega_2) = 2 \int_{\omega_1}^{\omega_2} g(\omega) \, d\omega \) indicates the variance attributable to the frequency range \( \omega_1 \leq |\omega| \leq \omega_2 \).

As noted above, the total variance of the series is obtained by integrating the spectrum over all frequencies (that is, letting \( \omega_1 = 0 \) and \( \omega_2 = \pi \)). The integrated spectrum can be estimated as follows:

\[
\hat{G}(\omega_1, \omega_2) = \frac{\omega_2 - \omega_1}{\pi} \hat{\Gamma}(0) + \frac{2}{\pi} \sum_{j=1}^{T-1} \hat{\Gamma}(j) \frac{\sin \omega_2 j - \sin \omega_1 j}{j},
\]

where \( \hat{\Gamma}(j) \) represents the \( j \)-th order sample autocovariance.

As shown in Priestley (1982), this estimator is consistent

\[\text{FIGURE 1.—GDP Growth}\]

\[\text{THE REVIEW OF ECONOMICS AND STATISTICS}\]
and has an asymptotic normal distribution. (Details are provided in the appendix.) In contrast to consistent estimation of the spectrum at a particular frequency, which requires the use of a kernel and the selection of a particular bandwidth parameter, the integrated spectrum can be estimated consistently without performing any smoothing of the spectrum.

The integrated normalized spectrum \( H(\omega_1, \omega_2) = G(\omega_1, \omega_2) / \sigma^2 \) gives the fraction of the variance attributable to the frequency range \( \omega_1 \leq \omega \leq \omega_2 \). By construction, integrating the normalized spectrum over all frequencies (that is, setting \( \omega_1 = 0 \) and \( \omega_2 = \pi \)) yields a value of unity. A consistent estimate of the integrated normalized spectrum can be obtained by taking the ratio of the estimated integrated spectrum, given by equation (1), to the sample variance of the series; details of its asymptotic distribution are provided in section 1 of the appendix.

As reported in section 2 of the appendix, we have performed Monte Carlo simulations to evaluate the empirical properties of these tests, and find reasonable size and power, except for the low frequency range. Thus, in the section that follows, we concentrate mainly on the results for the business cycle and high frequency ranges.

C. Results

We report results for aggregate real GDP, selected components of GDP, and inflation.\(^8\) Chain-weighted NIPA data are used in the computation of all the GDP statistics. In each case it is assumed that a structural break occurs around the start of 1984, corresponding to the period where we and others find the structural break in GDP volatility. In general, the first sample period is 1960:1 to 1979:4, and the second sample period is 1984:1 to 2002:1.\(^9\) (The exception is inventories, where chain-weighted data begin in 1967:1). The period 1980–1983 is omitted for several reasons. First, the various break tests used in the literature do not indicate a structural break exactly at 1984 for each series; however, the break typically falls in the 1979–1984 range.\(^10\) Second, it is generally believed that the monetary policy rule being followed was quite different in the 1979–1984 period from the other two periods. Finally, omitting some observations from the middle should lend more power to our tests for detecting differences across the subsamples.

The test results are reported in tables 1 and 2. The second and third columns of table 1 report the estimates of the integrated spectrum for each of the three frequency ranges for period I and period II, respectively. The fourth column gives the test statistic of the null hypothesis that the spectrum is equal in period I and period II, and the last column reports the marginal significance level (the \( p \)-value) for a one-tailed test of the null hypothesis. The alternative hypothesis is that the period I spectrum is greater than the period II spectrum, which would be consistent with a decline in volatility in the post-1984 period.

Consider first the results in table 1 for aggregate real GDP. The low-frequency, the business-cycle-frequency, and the high-frequency rows sum to the sample variance of real GDP growth. Thus, the results for GDP growth imply that its variance has fallen from approximately 17 to approximately 5 from the first to the second period. Also, the variance is concentrated at the business cycle and high frequencies, where it is significantly different from 0 in each case for each period. Looking at the differences between the two periods, we can see from the final two columns that the variance at the business cycle and higher frequencies is significantly greater in the first period.

Table 1 also presents results for selected components of GDP growth that we view are especially relevant for the good policy and good practices hypotheses. For example, it seems reasonable that consumption and investment and, perhaps, final sales on the supply side would be most
sensitive to changes in policy that affected business cycles. In addition, practices that improved inventory management would likely affect the volatility of inventory growth and goods GDP (as opposed to structures or services). As seen in the table, consumption and investment growth show significant declines in variance at the business cycle frequencies and high frequencies. Final sales growth also exhibits a decline in variance at the business cycle and higher frequencies, the former being statistically significant and the latter being borderline; and the variance of goods GDP has fallen considerably in both higher frequency regions. There has been no significant decline in the variance of inventories growth, however, suggesting that changes in inventory techniques are not dampening swings in inventory growth.

To investigate more formally how the shape of the spectrum has shifted, we next consider estimates of the integrated normalized spectrum, which are reported in table 2. In each panel, the rows in the first two columns of results correspond to the proportion of variance accounted for by the three frequency ranges. The penultimate column reports the test statistic for the null hypothesis that the integrated normalized spectrum is the same across the two time periods—that is, the proportion of the variance accounted for by the particular frequency range considered has not changed. Note from the final column that in this case we use a two-tailed test; this is because a decline in the normalized spectrum at one range of frequencies must be associated with an increase at other frequencies.

For real GDP growth, we cannot reject the null hypothesis that the integrated normalized spectrum is unchanged across the two periods for any of the three frequency ranges. Thus, the decline in output variability appears to be evenly distributed across frequencies, rather than concentrated at particular frequencies. This is consistent with the good luck hypothesis, which implies that the fall in volatility can largely be accounted for by a decline in the variance of structural disturbances hitting the economy. However, the results do not definitively rule out other explanations. For example, good policy and good practices could have played an important role if they affected the economy solely via a reduction in innovation variance (at least at the quarterly frequency), rather than through changes in the structure of the economy. Turning to the results for the components of GDP in table 2, for the most part these reinforce the above conclusions. Growth of consumption and investment shows no shift in the normalized spectrum, so business cycle fluctuations in these variables have not been smoothed more than fluctuations at other frequencies. The decline in the variance of final sales growth, however, does appear to be concentrated at the business cycle frequencies, which is consistent with policy having some effect through smoothing of the business cycle. Among the product-side components of GDP, we would expect changes in inventory and trade practices to have the greatest impact on goods GDP growth. Although there are various channels through which these changes in practices impact output, they typically involve changes in the structure of the economy. (see, for example, Kahn et al., 2000). Although changes to the structure can manifest themselves as reductions in any part, or parts, of the spectrum, they are inconsistent with parallel shifts in the spectrum. Thus, it is difficult to reconcile standard models of changes in practices with the evidence of no shift in the normalized spectrum for goods GDP, shown in the table.

In contrast to our GDP results, our results for inflation are inconsistent with good luck being the primary explanation. As seen in table 2, the proportion of inflation variance accounted for by high frequencies rises from approximately 10% to more than 30%. The null hypothesis of no post-1984 break in the integrated normalized spectrum is rejected at the 99% confidence level, thereby ruling out the hypothesis that the decline in inflation volatility can be explained by a decline in innovation variance alone. Natural interpretations of changes in the structure of the economy being a source of the decline in inflation volatility are the good policy and good practices hypotheses.

### III. VAR Analysis

In this section, we extend our analysis to the time domain using a multivariate framework. A VAR provides one simple way to study how important changes in propagation and
dynamic interactions between variables—plausibly due to improvements in business practices and monetary policy—have been in reducing volatility and how important reductions in the volatility of the shocks themselves (or good luck) have been.

Our basic VAR model is similar to small-scale VAR models such as those of Sims (1980) and Christiano, Eichenbaum, and Evans (1998). Specifically, our basic VAR consists of the following four variables: output growth, consumer price inflation, commodity price inflation, and the federal funds rate, variants of which are also used in the complementary works of Simon (2000) and Stock and Watson (2002).

Expanding on our basic model, we also analyze two other VAR systems—one that extends the basic model to monthly data and one that distinguishes between final sales and inventories. The first extension is intended to examine the possibility that structural changes at the monthly frequency may be attributed to shocks at the quarterly frequency, thus understating the role of business practices and policy in the quarterly model. This can happen, for example, if the adjustment of inventories and/or the reaction of monetary policy to shocks occurs within the quarter. The motivation for the five-variable model is to more directly test the hypothesis of better inventory management; it is possible that the result of better inventory management is fewer shocks to inventories, and then it would be relevant whether these shocks account for the bulk of the reduction in the innovation variance of real GDP growth.

Tables 3 and 4 report some basic statistics on the six variables used in the two quarterly VARs. Note that, as with our frequency-domain analysis, we drop the period from 1980 to 1983. Data on real GDP, final sales, and inventories have already been described. We use the aggregate consumer price index to compute CPI inflation; our commodity price index is the PPI index for crude materials; and the federal funds rate is our monetary policy variable.

Table 3 shows that the mean growth rate of real GDP differs little between the pre-1980 and post-1984 periods, consistent with the formal testing in this regard in McConnell and Perez Quiros (2000). The mean of the federal funds rate is also about the same in the two periods. In contrast, there has been a significant decline in the mean of the inflation rate and a dramatic decline in the mean of commodity price inflation in the second period.

Our primary interest here is in differences in volatility of these variables, which are shown in table 4. The reduction in the standard deviation of the growth of real GDP and final sales has already been noted, as has the dramatic reduction in the volatility of inflation. Moreover, the standard deviation of the federal funds rate has fallen by approximately 25%. In contrast, the volatility of commodity price inflation has increased significantly in the post-1984 period, making it questionable whether this variable could be the source of good luck in the second period.11

### A. Reduced-Form VARs

We first estimate reduced-form VAR models separately over the two periods, 1960–1979 and 1984–early 2002, and then conduct Goldfeld-Quandt tests of constancy of error variances and Chow tests of regression coefficient stability. The results from tests of coefficient stability are shown in table 5. In the four-variable quarterly model, only the inflation equation appears to display coefficient instability across the two periods. The monthly model and the five-variable quarterly model provide more evidence of coefficient instability with most equations.

The standard deviations of the reduced-form errors and test results on their volatility breaks are shown in table 6. There is clear evidence from all three models that the reduced-form error variances for the output growth equation (the final sales equation in the case of the five-variable model) and the federal funds rate equation display much less volatility in the second period. There is also some weaker support for commodity price inflation innovations having higher volatility in the second period. The evidence on the error term of the inflation equation is mixed, showing stable volatility for the quarterly models, but reduced volatility in the second period for the monthly model.

The reduced-form results serve to show that there have been substantial changes in both the structure of the economy and in the volatility of the shocks, and hence all three

### Table 3.—Mean of Model Variables: Means of Annualized Quarterly Growth Rates

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean I: 60:1–79:4</th>
<th>Mean II: 84:1–02:1</th>
<th>Difference (II – I)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP</td>
<td>3.74</td>
<td>3.20</td>
<td>–0.54</td>
</tr>
<tr>
<td>CPI inflation</td>
<td>4.76</td>
<td>3.10</td>
<td>–1.66</td>
</tr>
<tr>
<td>Commodity price inflation</td>
<td>5.41</td>
<td>–0.17</td>
<td>–5.58</td>
</tr>
<tr>
<td>Federal funds rate (level)</td>
<td>5.64</td>
<td>6.06</td>
<td>0.42</td>
</tr>
<tr>
<td>Final sales</td>
<td>3.75</td>
<td>3.23</td>
<td>–0.52</td>
</tr>
<tr>
<td>Inventories</td>
<td>4.10</td>
<td>2.98</td>
<td>–1.12</td>
</tr>
</tbody>
</table>

*Inventory data are from 1968:1 to 2001:4.

### Table 4.—Volatility of Model Variables: Standard Deviations of Annualized Quarterly Growth Rates

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP</td>
<td>3.98</td>
<td>2.21</td>
<td>–1.77</td>
</tr>
<tr>
<td>CPI inflation</td>
<td>3.38</td>
<td>1.47</td>
<td>–1.91</td>
</tr>
<tr>
<td>Commodity price inflation</td>
<td>13.39</td>
<td>19.12</td>
<td>5.73</td>
</tr>
<tr>
<td>Federal funds rate (level)</td>
<td>2.63</td>
<td>2.04</td>
<td>–0.59</td>
</tr>
<tr>
<td>Final sales</td>
<td>3.14</td>
<td>2.04</td>
<td>–1.10</td>
</tr>
<tr>
<td>Inventories</td>
<td>3.20</td>
<td>3.61</td>
<td>0.41</td>
</tr>
</tbody>
</table>

*Inventory data are from 1968:1 to 2001:4.
exercise has independently been conducted by Stock and Watson. The top panel of table 7 presents our results for the basic four-variable quarterly VAR. The first two rows show the unconditional variances from using each period’s own shocks and coefficients. These are fairly similar to the actual sample standard deviations shown in table 4.

Our counterfactual, reported in rows 3 and 4, examines what happens to the unconditional volatility when we substitute the other period’s shocks into the model for each period. When the period I model is subjected to period II’s shocks, we get a substantial reduction in output volatility—the standard deviation falls from 4.22 to 3.08—but not all the way to the actual period I model’s standard deviation of 2.13. Similarly, when the period II model is subjected to the period I shocks, output volatility increases to 3.61, but not all the way to the actual unconditional standard deviation over the first period (4.22). Thus, the shocks account for most of the decline in volatility (50% to 75%, depending on which of the two movements described above is considered) from the first to the second period, but by no means all of it. Stock and Watson find an even larger role for shocks (closer to 90%).

Taken together, the above VAR results also lend considerable support to the good luck hypothesis for explaining the decline in overall output volatility, with weaker hypotheses—good policy, good practices, and good luck—appear to be viable candidates for explaining the drop in aggregate volatility.

### B. Counterfactuals Using VARs

In order to quantify the relative contribution of changes in structure versus changes in shocks, we used our VAR models to compute unconditional variances of the variables that go into the system under various assumptions. A similar exercise has independently been conducted by Stock and Watson. The top panel of table 7 presents our results for the basic four-variable quarterly VAR. The first two rows show the unconditional variances from using each period’s own shocks and coefficients. These are fairly similar to the actual sample standard deviations shown in table 4.

Our counterfactual, reported in rows 3 and 4, examines what happens to the unconditional volatility when we substitute the other period’s shocks into the model for each period. When the period I model is subjected to period II’s shocks, we get a substantial reduction in output volatility—the standard deviation falls from 4.22 to 3.08—but not all the way to the actual period I model’s standard deviation of 2.13. Similarly, when the period II model is subjected to the period I shocks, output volatility increases to 3.61, but not all the way to the actual unconditional standard deviation over the first period (4.22). Thus, the shocks account for most of the decline in volatility (50% to 75%, depending on which of the two movements described above is considered) from the first to the second period, but by no means all of it. Stock and Watson find an even larger role for shocks (closer to 90%).

Taken together, the above VAR results also lend considerable support to the good luck hypothesis for explaining the decline in overall output volatility, with weaker hypotheses—good policy, good practices, and good luck—appear to be viable candidates for explaining the drop in aggregate volatility.
though nontrivial evidence of a role for changes in the structure of the economy.

The results for inflation are very different than those for output. As shown in column 2 of table 7, roughly 85% to 90% of the decline in inflation volatility can be explained by changes in the coefficients. This result is consistent with the hypothesis that better monetary policy has induced changes in the economy that have led to lower volatility of inflation in the second period, although the structural changes in the economy that are driving the reduction in inflation volatility could, in principle, have been the result of other factors as well. But the important point is that the decline in inflation volatility cannot be accounted for much by a decline in the volatility of the shocks alone.

The results from the monthly model, presented in the middle panel of table 7, yield virtually identical conclusions. However, the results from the five-variable quarterly model presented in the bottom set of rows are somewhat different: The contribution of shocks to explaining the decline in the volatility of final sales growth is now roughly half, at the maximum. Thus the results from the five-variable model do not come out as strongly in favor of the good luck hypothesis, suggesting that perhaps the four-variable models obscure somewhat the manner in which better business inventory management works through the economy.

IV. Concluding Remarks

In this paper we have attempted to distinguish among the good luck (changes in shocks) and good policy and good practices (changes in structure) explanations of the reduction in U.S. output volatility over the last 15 to 20 years, using frequency-domain and VAR techniques. In the frequency domain, for aggregate output, as well as for consumption and investment, we cannot reject the hypothesis that the decline in variance has been evenly distributed at the various frequencies. These results are consistent with the good luck hypothesis. However, for final sales there is some evidence that the decline in variance is concentrated at the business cycle frequencies; looked at from that side, good luck may not be everything, and policy and practices may also have played some role.

Our VAR results indicate a moderately bigger role, relative to our frequency domain results, for changes in the structure of the economy in explaining the decline in aggregate output volatility. However, it is still generally the case that the shocks account for most of the decline in output volatility, a result also found by others (for example, by Simon and by Stock and Watson). The results are robust to the use of monthly data, but we find somewhat weaker support for the good luck hypothesis when we distinguish between innovations to inventories and innovations to final sales using the five-variable quarterly model.

Overall, we conclude that, although better practices and better monetary policies have played some role in explaining the decline of U.S. output volatility in the past 15 years or so, the evidence is largely consistent with the idea that it may just have been good luck. This suggests that, as far as output variability is concerned, it might be premature to conclude that the reduction in volatility is a permanent feature of the U.S. economy.

Applying the same methods to consumer price inflation, we strongly reject the hypothesis of a proportional decline in the spectrum at all frequencies, thereby ruling out the idea that lower inflation volatility has been due solely to smaller shocks hitting the economy. Our VAR results for inflation reinforce this result; that is, changes in the structure of the economy account for the bulk of the post-1984 reduction in inflation volatility. These results are consistent with the view that monetary policy has changed the structure of the economy in such a way as to stabilize inflation over the past two decades.

REFERENCES


APPENDIX

1. Consistency and Asymptotic Normality of the Integrated Spectrum

The integrated spectrum is defined as $G(\omega_1, \omega_2) = \int_0^T g(\omega) \, d\omega$. The sample periodogram for a sample of size $T$ is

$$\hat{I}(\omega) = \sum_{j=1}^{T-1} \hat{\Gamma}(j) e^{i\omega j} = \sum_{j=1}^{T-1} \hat{\Gamma}(j) \cos \omega j$$  \hspace{1cm} (A-1)

where the $\hat{\Gamma}(j)$'s are sample autocovariances. An estimate of the integrated spectrum is obtained by integrating equation (A-1) over frequencies $\omega_1 \leq \omega \leq \omega_2$, which yields equation (1) in the main text.

Define $\Phi = 8\pi \int_0^\infty \hat{P}(\omega) \, d\omega$. Because $E(\hat{P}(\omega)) = 2\pi^2 \omega$ (cf. Priestley, 1982, p. 477), a consistent estimate of $\Phi$ is $\hat{\Phi} = 4\pi \int_0^\infty \hat{P}(\omega) \, d\omega$. The estimate $\hat{G}(\omega_1, \omega_2)$, given by equation (1) in the text, has an asymptotic $N(G(\omega_1, \omega_2), \Omega_G)$ distribution, where $\Omega_G = \Phi + \epsilon G^2(\omega_1, \omega_2)$ and $\epsilon$ is the excess kurtosis (relative to the Gaussian distribution) of the innovations to the underlying process (cf. Priestley, 1982, chapter 6). Thus, $\hat{G}(\omega_1, \omega_2)$ is a consistent estimate of the integrated spectrum, and we can do standard Gaussian inference, once we obtain a consistent estimate of $\Omega_G$. Let $\hat{G}$ be the usual consistent estimate of excess kurtosis based on estimated residuals [here obtained as error terms from an AR(p) model, with $p$ chosen based on AIC]. Given that $\hat{\Phi} \rightarrow \Phi$ and $\hat{\epsilon} \rightarrow \epsilon$, a consistent estimate of $\Omega_G$ can be obtained as $\hat{\Omega}_G = \left[ \hat{\Phi} + \epsilon \hat{G}^2(\omega_1, \omega_2) \right]/T$, where it can be shown that

$$\hat{\Phi} = \frac{1}{\pi} \left[ (\omega_1 - \omega_0)\hat{\Gamma}(0)^2 + 4\hat{\Gamma}(0) \sum_{j=1}^{T-1} \hat{\Gamma}(j) \sin \omega_0 j - \sin \omega_j j \right] + 4 \sum_{j=1}^{T-1} \hat{\Gamma}(j) \hat{\Gamma}(k) \left[ \sin \omega_0 (j + k) - \sin \omega_k (j + k) \right] + \frac{\sin \omega_0 (k - j) - \sin \omega_k (k - j)}{k - j} + 2 \sum_{j=1}^{T-1} \hat{\Gamma}(j) \left[ (\omega_1 - \omega_0) + \frac{\sin 2\omega_0 j - \sin 2\omega_j j}{4j} \right].$$

Note that the estimated integrated normalized spectrum $\hat{\mathcal{H}}(\omega_1, \omega_2)$ is obtained by taking the integrated spectrum and dividing it by the sample variance of the series: $\hat{G}(\omega_1, \omega_2)/s^2_G$. The estimate $\hat{G}(\omega_1, \omega_2) = \int_0^T \hat{P}(\omega) \, d\omega$ and $s^2 = \int_0^T \hat{\Gamma}(\omega) \, d\omega$, and using the expression for $\Omega_G$ above, it can be shown that the joint distribution of the estimated integrated spectrum and the sample variance has the following properties:

$$\left( \hat{G}(\omega_1, \omega_2) \right) \rightarrow N \left( G(\omega_1, \omega_2), \frac{\Phi + \epsilon G^2(\omega_1, \omega_2)}{\sigma^2_G} \right).$$

$$\frac{1}{T} \left[ \hat{\Phi} + \epsilon \hat{G}^2(\omega_1, \omega_2) \right] \rightarrow N \left( \Phi + \epsilon G^2(\omega_1, \omega_2), \frac{\Phi + \epsilon G^2(\omega_1, \omega_2)}{\sigma^2_G} \right).$$

To get the asymptotic distribution of $\hat{\mathcal{H}}(\omega_1, \omega_2)$, note that if a vector of random variables has a multivariate normal distribution $Z \rightarrow N(\mu, \Sigma)$, and $\delta g(\partial Z|_{\omega=\mu})$ exists, then

$$g(Z) \rightarrow \mathcal{N} \left( g(Z), \left( \frac{\delta g}{\partial Z} \right) \left( \frac{\delta g}{\partial Z} \right)^T \right).$$

Using this approach, setting $g(\hat{Z}) = g(\hat{G}(\omega_1, \omega_2), \hat{s}_2) = \hat{G}(\omega_1, \omega_2)/\hat{s}_2^2$, and using sample counterparts of the elements of the covariance matrix given in equation (A-2) gives us a consistent estimate of the sample variance of $\hat{\mathcal{H}}(\omega_1, \omega_2)$.


We conducted Monte Carlo simulations to examine the properties of the test statistics used in tables 1 and 2. For brevity, we report results of our simulations for the integrated normalized spectrum test statistic only (results for the nonnormalized integrated spectrum are available on request). Data on $X$ are generated according to

$$X_t = \rho X_{t-1} + \epsilon_t,$$

where the $\epsilon_t$’s are random drawings from a $N(0, 1)$ distribution. For various pairs of $\rho$’s we generate two samples of data, with 80 observations and 73 observations, respectively, to match the lengths of the samples available to us in our empirical estimates. Based on the simulated data, we compute empirical rejection probabilities (using the critical values of the normal distribution) for the null hypothesis that the integrated normalized spectrum is the same across the two samples for each of our three frequency ranges. The results are presented in table A1.

The size can be judged by looking at the diagonal elements. In the case of business cycle and high frequencies, the size is very good for $\rho = 0$ or 0.5, as we should expect 5% rejections, and that is about what we are getting. However, the size appears to be poor for low frequencies for values of $\rho$ close to 0. Size weakens, even for business cycle frequencies and high frequencies, as we get to high levels of $\rho$. But in our empirical results we are getting mostly nonrejections of the null with $p$-values that are generally very high, so that the conclusions would hold even if the critical values implied by the simulations were used.

The power can be judged by looking at the off-diagonal elements. If the power is good, then, as the autoregressive coefficients diverge across the two samples, we should reject the null hypothesis nearly all the time, for at least some of the frequencies. The off-diagonal figures indicate that this is the case, and thus it appears that the power properties of our test statistics are fairly good.

\begin{table}[h]
\centering
\begin{tabular}{cccc}
\hline
& & A. Low Frequencies & \\
& & (95\% Nominal Confidence Level) & \\
\hline
First Sample & Second Sample $\rho$ & \\
\hline
0.00 & 0.01 & 0.07 & 0.76 & 0.86 \\
0.50 & 0.10 & 0.04 & 0.52 & 0.68 \\
0.90 & 0.81 & 0.58 & \textbf{0.14} & 0.17 \\
0.95 & 0.90 & 0.74 & 0.17 & \textbf{0.14} \\
\hline
\end{tabular}
\caption{Table A1.—Empirical Rejection Probabilities$^*$
(95\% Nominal Confidence Level)}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{cccc}
\hline
& & & \\
\hline
First Sample & & Second Sample $\rho$ & \\
\hline
0.00 & 0.05 & 0.49 & 0.18 & 0.12 \\
0.50 & 0.49 & \textbf{0.06} & 0.15 & 0.26 \\
0.90 & 0.17 & 0.16 & \textbf{0.11} & 0.13 \\
0.95 & 0.11 & 0.29 & 0.13 & \textbf{0.11} \\
\hline
\end{tabular}
\caption{Table A1.—Empirical Rejection Probabilities$^*$
(95\% Nominal Confidence Level)}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{cccc}
\hline
& & & \\
\hline
First Sample & & Second Sample $\rho$ & \\
\hline
0.00 & 0.06 & 0.80 & 1.00 & 1.00 \\
0.50 & 0.80 & \textbf{0.06} & 0.83 & 0.91 \\
0.90 & 1.00 & 0.83 & \textbf{0.03} & 0.04 \\
0.95 & 1.00 & 0.91 & 0.04 & \textbf{0.03} \\
\hline
\end{tabular}
\caption{Table A1.—Empirical Rejection Probabilities$^*$
(95\% Nominal Confidence Level)}
\end{table}

$^*$Rejection probabilities for the null hypothesis that the normalized spectral density is identical in both subsamples.