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Abstract: The volatility of U.S. real GDP growth since 1984 has been markedly lower than that over the previous quarter-century. In this paper, we utilize frequency-domain and VAR methods to distinguish among several competing explanations for this phenomenon: 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. Our results support the "good-luck" hypothesis as the leading explanation for the decline in aggregate output volatility, although "good-practices" and "good-policy" are also contributing factors. Applying the same methods to consumer price inflation, we find that the post-1984 decline in inflation volatility can be attributed largely to improvements in monetary policy.

Keywords: GDP volatility, inflation stabilization, business cycles, frequency domain.
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1. Introduction

Three competing explanations have been given for the marked decline in volatility of U.S. real GDP growth since 1984: good policy, good practices, and good luck.[1] 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 during the Volcker-Greenspan era compared with 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 each explanation can be associated with a specific pattern for the shift: (1) improved monetary policy would be expected to shift the spectrum

[1] McConnell, Mosser, and Perez Quiros (1999) and McConnell and Perez Quiros (2000) initially documented the decline. Kim, Nelson, and Piger (2000) found similar results using Bayesian tests but observed the drop in volatility to be more broad-based than did the earlier work. Other studies include Simon (2000), Blanchard and Simon (2001), and Stock and Watson (2002).

[2] See Taylor (1999), Clarida, Gali, and Gertler (2000).

[3] See McConnell et al. (1999) and Kahn et al. (2000). Other changes in practices discussed in the literature are the elimination of interest rate ceilings under Regulation Q which, with the rise in a mortgage backed securities market, helped generate a steadier supply of funds for housing investment and stabilize residential investment. (See Ryding, 1990 and Throop, 1986). Also a weakening of trade barriers may have allowed a smoother flow of goods across countries.

[4] Simon (2000) finds strong support for the good luck hypothesis, using a three-variable structural VAR approach with a long-run Blanchard-Quah-style decomposition of shocks.

primarily at business-cycle frequencies; (2) improved inventory management and other relevant changes in business practices would tend to be manifested 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, allowing us 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, as well as a broad range of components, 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 GDP growth call into question the view that conventional good policy and good practices hypotheses are the *leading* explanations of the decline in output volatility, while lending considerable support to the good luck hypothesis. 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 ensured a unique rational expectations equilibrium, innovation variances could be reduced, as shifts in expectations 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 rule out the hypothesis that lower inflation volatility has been due to good luck alone, and support the view that monetary policy has been crucial in taming inflation volatility.

2. Documenting and Characterizing the Decline in Output Variance

Before discussing the causes of the shift in output volatility, we detail the decline itself. Figure 1 graphs the annualized quarterly growth rate of GDP. It is immediately apparent that the swings in GDP growth have been much more muted in the past 15 years than in the previous period. This is true even if the very volatile period of 1980-83, shaded in gray, is not considered. The magnitude of the decline, shown in the first row of table 1, 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 in the first period to 2.3 in the second period.[5]

This apparent change in the volatility of GDP growth has been confirmed in previous work, using statistical methods. In particular, McConnell and Perez Quiros (2000), test for structural change in the mean and variance of GDP growth using a variety of techniques.[6] They find little evidence for a break in mean growth, but statistically significant evidence of a variance break around 1984. Using an alternative Bayesian approach, Kim et al. (2001) also find a volatility break in real GDP growth at about the same time.

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[5]Stock and Watson (2002) report much lower standard deviation numbers, but use four-quarter growth rates that smooth out some of the period-to-period noise. The percentage decline in their volatility measure is roughly the same (about 40 percent, rather than 50 percent).

[6]The tests they use include a CUSUM and CUSUM of squares test and Nyblom's L test as described in Hansen (1992).

We verify and extend the previous results using a test that allows for multiple breakpoints. Specifically, we use the absolute value of the deviation of GDP growth from its mean as a measure the volatility of real GDP growth; we test for multiple breaks in the mean of this series using an algorithm proposed by Bai and Perron (1998). We also test for a break in volatility by modeling GDP growth as an AR(4) process and applying the Bai-Perron test to the absolute value of the residuals from this AR model. For the sample period 1953:2-2001:3, we cannot reject the hypothesis that there is a single break in real GDP at 1984:2.[7]

Given the existence of a break in GDP volatility, it is instructive to look more closely at the components of GDP–whose volatilities are also presented in table 1–to better characterize the break. The first two columns of the table show the standard deviation of the annualized quarterly growth rates of the major components of GDP over the periods 1960:1 to 1983:4 and 1984:1 to 2002:1. Volatility has declined notably across all major demand components (shown in the second panel), with the greatest fall being in investment and exports and imports. Consumption growth shows one of the smallest declines in variance but, given its large share in GDP, accounts for a good amount of the decline in the overall volatility. Figure 2 plots movements in the annualized growth rates of the demand components, providing a visual look at the changes in volatility.

The third panel of the table breaks down the volatility of GDP growth by its product components. Here, there is more heterogeneity across components. The decline in the variance

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[7]For real GDP, we conducted two other tests: We estimated an AR model of the absolute value of GDP growth, allowing for a break point in the mean of the series. We used recursive OLS to estimate the model for different break dates and selected the breakpoint that maximizes the F-statistic, determining its significance using bootstrapped critical values, as suggested by Diebold and Chen (1996). We also used a MLE model of GDP growth that directly estimates the variance and uses similarly constructed critical values. (We thank Norman Morin for these two tests. The exact break date differs only slightly depending on the lag length of the AR model).

of GDP growth is concentrated in goods and structures components, with little change in the volatility of services GDP across the two periods. The comparative stability of service volatility also comes across plainly in the left side of figure 3.

The last panel of table 1 shows the breakdown of real GDP growth into domestic final sales (which constitutes 99.5 percent of nominal GDP) and the contribution of the change in private inventories to GDP growth. Final sales are further split into durable final sales and nondurable final sales. Table 1 and the right panel of figure 3 suggest that there have been large declines in the volatility of both final sales growth and the inventory contribution to GDP growth over the two periods. The decline in volatility is also evident in the nondurable and durable component of final sales. Overall, table 1 and figures 2 and 3 illustrate the broad-based nature of the decline in GDP volatility, which is also highlighted in Stock and Watson (2002). These authors test for volatility breaks in over 150 U.S. macroeconomic and financial variables and find generally similar results to those for U.S. GDP.

Most of the previous studies that have allowed for only one break when testing for changes in volatilities. We extend this work by applying the Bai-Perron test that allows for multiple breaks to the variables listed in table 1, as well as to final sales of automobiles and two nominal variables–inflation and the federal funds rate. We use quarterly data over the period 1953:2-2001:3, choosing the starting observation to match that of McConnell and Perez Quiros. A subset of our results for break tests on the absolute values of the demeaned series are shown in table 2 (more detailed tables are in the table appendix). The results on GDP volatility have already been discussed. In general, the results for multiple break tests reported in table 2 confirm that a clear break in volatility occurs in many macroeconomic time series around the early- to mid-1980s; even when multiple breaks are allowed, they generally occur either very early in the sample (where their plausibility can be questioned based on end-point problems) or fall somewhere in the period 1981-1984.[8] In particular, like GDP, the variance of the growth of goods GDP and final sales, and the change in inventories all have breaks in 1983 or 1984. Finally, it should be noted that services volatility exhibits a single break in 1967:1.

The result for final sales is worthy of further attention, as researchers have reached different conclusions about the volatility of this variable. McConnell and Perez Quiros and Stock and Watson find no break in the volatility of this series, while Kim et al. (2001), using Bayesian methods, do find evidence of a break in the early 1980s and one in the early 1990s. McConnell and Perez Quiros's finding of no break in the volatility of final sales prompted them in further work, Kahn et al. (2000), to try to model the decline in the volatility of GDP growth as arising from changes in inventory management alone.

However, we believe that visually (see chart 2) the evidence for a break in the volatility of final sales is compelling. The Bai-Perron test for the volatility break in final sales also comes up with one break in final sales in 1983:3. Moreover, Stock and Watson in their work note that their point estimates indicate a reduction in the variance of final sales that is very similar to the reduction in volatility of GDP growth but the estimates are not very precisely determined. It is possible that the Bai-Perron test has more power and picks up the break in final sales volatility better; the 95 percent confidence intervals (shown in our appendix tables) do seem to be tighter than those for the same variables in Stock and Watson. Our results suggest that the question of a break in final sales volatility is, at least, debatable and, therefore, one should not at the outset

[8]These results hold regardless of whether the absolute values of the demeaned series themselves or the absolute value of the residuals from the AR(4) process is used. However, the results for durable final sales growth and inflation depend on the method used. Taking just the absolute values of the demeaned series, two structural breaks are detected in durable final sales growth, 1956:1 and 1991:1. In contrast, with the absolute values of the residuals from the AR model, one break is detected in 1991:4.

rule out more broad-based explanations of the decline in output variability.

Finally, we consider the volatility of consumer price inflation. As indicated in table 1, the standard deviation of inflation has declined by a factor of two since 1984. The Bai-Perron test results (shown in table 2) confirm that inflation volatility exhibits a structural break in the early 1980s. Two additional breaks (in 1973:1 and 1978:4) are also statistically significant, although we do not systematically consider those breaks in our subsequent analysis.

3. Frequency Domain

Now we analyze the properties of GDP growth in the frequency domain. We begin by splitting the sample into two periods and calculating the spectrum of GDP in each period. Since the variance of output growth is given by integrating its spectrum $g(\omega)$ over all frequencies $-\pi \leq \omega \leq \pi$, the post-1984 decline in variance should show up as a downward shift in the spectrum. Furthermore, we can obtain some insight into the nature of the volatility decline by determining whether this downward shift is spread evenly across all frequencies or is concentrated within a specific frequency range.

If the decline in variance is primarily due to improved monetary and fiscal policies that acted to smooth out business cycles, then we should find that the post-1984 decline in the 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. 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.

According to 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 has an infinite moving average representation, MA(∞). Thus, using this representation, the good luck hypothesis can be interpreted as a decline in innovation variance with no change in the MA coefficients. Since the spectrum of any MA(∞) process is proportional to the innovation variance, this hypothesis implies a parallel downward shift in the spectrum. (See Appendix for further details.)

We can proceed to test the good luck hypothesis by constructing the normalized spectrum $h(\omega) = g(\omega)/\sigma^2$, which indicates the fraction of the total variance σ^2 occurring at each frequency ω. Since both the numerator and denominator of this ratio are proportional to the innovation variance, the normalized spectrum is *invariant* to the innovation variance. Thus, under the good luck hypothesis, the normalized spectrum would exhibit no post-1984 shift at all.

Our frequency-domain approach is illustrated in figure 4. For each of the two periods, the upper panel of figure 4 depicts an illustrative estimate of the spectrum of real GDP growth, while the lower panel depicts the normalized spectrum.[9] The horizontal axis expresses the frequency ω as a fraction of π, while varying degrees of shading indicate three different frequency ranges: low, business-cycle, and high. As in Baxter and King (1995), the business-cycle frequencies ($\pi/16$ to $\pi/3$) correspond to cycles of 6 to 32 quarters.[10] Note that the post-1984 decline in volatility of GDP growth is evident from the downward shift in the spectrum.

[9]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.

[10]We also computed a narrow range for the business cycle frequency of frequencies $\pi/8$ to $\pi/4$, corresponding to cycles of 8 to 16 quarters (as in Sargent, 1979); the results were largely similar.

Figure 4 provides some striking (though informal) evidence in favor of the good luck hypothesis. In particular, the normalized spectra for the two sample periods look remarkably similar at the high frequencies. In addition, while from the upper panel of the figure it looks like the drop in the volatility of GDP growth occurred primarily at the business cycle frequencies, the normalized spectrum for the two periods look much more alike, with the second period spectrum only slightly below that of the first period. At low frequencies, the spectrum appears 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 too seriously.

The *integrated* spectrum is invaluable in pursuing this approach more formally. For a particular frequency range, the integrated spectrum $G(\omega_1, \omega_2) = 2\int_{\omega_1}^{\omega_2} g(\omega)d\omega$ indicates the variance attributable to the frequency range $\omega_l \leq |\omega| \leq \omega_2$.[11] Thus, over the whole frequency range (i.e. with $\omega_l = 0$ and $\omega_2 = \pi$), the integrated spectrum gives the variance of the series. The integrated spectrum can be estimated as follows:

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

where $\hat{\Gamma}(j)$ represents the *j*th-order sample autocovariance. As shown in Priestley (1982), this estimator is consistent 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

[11]Note that the spectrum is symmetric around zero; that is, $g(-\omega) = g(\omega)$.

requires the use of a kernel and the selection of a particular bandwidth parameter), it should be noted that the integrated spectrum can be estimated consistently without performing any smoothing of the spectrum.

The integrated normalized spectrum $H(\omega_1, \omega_2) = G(\omega_1, \omega_2)/\sigma^2$ indicates the fraction of the variance attributable to the frequency range $\omega_1 \leq | \omega | \leq \omega_2$. Thus, with $\omega_1 = 0$ and $\omega_2 = \pi$, the integrated normalized spectrum has a value of unity. A consistent estimate of the integrated normalized spectrum can be obtained by taking the ratio of the estimated integrated spectrum to the sample variance of the series; details of its asymptotic distribution are given in the appendix.

Tables 3 and 4 present our frequency domain results. The first two columns of table 3 report the estimates of the integrated spectrum for each of the three frequency ranges for period I and period II, respectively. The third 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 this null hypothesis with the alternative hypothesis being that the period I spectrum is greater than the period II spectrum. The test is one-tailed since we are interested in assessing whether volatility has *declined* in the post-1984 period.

We report results for aggregate real GDP, selected components, and inflation; more detailed results are found in our appendix tables. 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. (The exception is inventories where chain-weighted data begin in 1967:1).

Note that the period 1980-1983 is omitted. There are several reasons for this. First, the Bai and Perron test does not indicate a structural break exactly at 1984 for each series; however typically the break falls in the 1979-1984 range. Second, it is generally believed that the monetary policy rule being followed was quite different in the 1979-84 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.[12]

Consider first the results for aggregate real GDP, presented in table 3. The low frequency, the business cycle frequency, and the high frequency rows sum to the sample variance of real GDP growth. Thus, the first two columns for the GDP growth variable show that the variance has fallen from about 16 to about 4½ 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 zero in each case for each period. The business cycle frequency variance is about 7 in the first period and about 1½ in the second period. Looking at the differences between the two periods, we can see from the third column that the variance at the business cycle and higher frequencies is significantly greater in the first period. (The above results for aggregate GDP carry over for the most part to the demand-side components of GDP, reported in the appendix in table A2.)

Turning to the product-side components, goods GDP growth also shows a decline in variance at the business cycle frequencies and high frequencies. For services, however, there appears to be no significant change in the variance at any of the frequency ranges–consistent

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[12] In some cases, e.g. nondurable and durable final sales, exports, and imports, a structural break outside of the 1979-1984 range was found. In such cases, we have also estimated the integrated and integrated normalized spectra for those series using that break date.

with our ocular examination of the data in figure 3. Table 3 also reports results for final sales and some of its components. Interestingly, final sales growth exhibits a statistically significant decline in variance at the business cycle frequencies, but not at high frequencies. The same holds for durable final sales, while inventories showed no sign of a significant decline.

The results from estimation of the integrated normalized spectrum are reported in table 4. In each panel, the rows in the first two columns correspond to the proportion of variance accounted for by the three frequency ranges. The third 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. The fourth column gives the marginal significance level associated with this test statistic. Note that in this case we use a two-tailed test because if the proportion of the variance explained by a particular frequency range falls, then the proportion explained by other frequency ranges has to rise.

The results in table 4 are easy to summarize: We cannot reject the null hypothesis that the integrated normalized spectrum is unchanged across the two periods for any of the three frequency ranges and for any of the components reported in the table, except durable final sales. In the case of durable final sales, a lower variance is found at the business cycle frequency in the second period. These results are quite remarkable, although it should be noted that the point estimates of the integrated normalized spectrum do indicate some decrease in volatility at the business cycle frequency, but the decline is not statistically significant. For the low frequencies, the differences across periods in the point estimates are even greater in a few cases but, where this is so, they are also much more imprecisely determined.

Our results show that we cannot statistically reject the hypothesis that the decline in output variability is evenly distributed across frequencies, rather than being concentrated at particular frequencies. This is consistent with the hypothesis that the fall in volatility can largely be accounted for by a decline in the variance of structural disturbances hitting the economy. For durable goods growth, however, the decline in volatility is concentrated at the business cycle frequency, suggesting that improved policy has played a relatively larger role in explaining the decline in its variance.

We take our evidence to be in agreement with the good luck hypothesis, although it does not completely rule out the other explanations. It is possible that practices and policy may have played a larger role, but our results imply that it could only be if their effects somehow show up as smaller shocks (at least at the quarterly frequency), rather than changes in the structure of the economy. Until plausible models in which this happens are explicitly constructed, it seems natural to give more credence to the good luck hypothesis, given our results.

Our results for inflation indicate that the post-1984 volatility decline can be attributed largely to improvements in policy and/or practices. Specifically, as seen in table 3, inflation volatility declines by an order of magnitude at low frequencies and by a factor of four at business cycle frequencies, while showing negligible change at high frequencies. Thus, as seen in table 4, the proportion of inflation variance accounted for by high frequencies rises from about 10 percent to more than 30 percent of the total variance. The null hypothesis of no post-1984 break in the integrated normalized spectrum is rejected at the 95 percent confidence level, thereby ruling out the idea that the decline in inflation volatility could be explained by good luck alone.

4. VAR Results

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–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 have been.

Simon (2000) also estimates a VAR to study the issue of the reduction in volatility.[13] Our work is in the same spirit, but can be distinguished from his in several respects. First, his model has somewhat different variables than our basic model. Second, we are interested in extending the basic VAR model to distinguish between final sales and inventories. We also compare results using monthly and quarterly data, since, as we will elaborate below, such issues pertain to distinguishing between the better business practices explanation from the other two explanations. Third, when retrieving structural VARs from the reduced-form, we use short-run identification schemes, traditionally found in the monetary policy VAR literature, rather than the long-run identification schemes that Simon uses.

Our basic VAR model is in the spirit of small-scale VAR models as Sims (1980) and Christiano, Eichenbaum, and Evans (1998). Specifically, our VAR consists of the following four variables: output growth, consumer price inflation, commodity price inflation, and the federal funds rate. The volatility of output growth and inflation are of direct interest, and the federal funds rate is included as the policy variable.

As noted above, two other VAR systems are also analyzed–one that estimates the basic model using monthly data and one that distinguishes between final sales and inventories. The monthly model 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

[13]Stock and Watson (2002) also contains VAR analysis and reports similar findings.

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 better inventory management hypothesis; it is possible that the result of better inventory management is fewer shocks to inventories, and that these shocks account for the bulk of the reduction in the innovation variance of real GDP growth.

Tables 5 and 6 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 1980-83. Data on real GDP, final sales, and inventories have already been described. As for the other variables, we use the aggregate consumer price index to compute CPI inflation; our commodity price index is the PPI index for crude materials, which quite closely tracks the index of sensitive materials that the CEE and other models have used in the past, but is more up to date; and the federal funds rate is used as our monetary policy variable.

Table 5 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. This suggests that the existence of a mean break in GDP growth is a less robust finding than it was a few years ago. 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 6. The reduction in the standard deviation of the growth of real GDP, final sales, and inventories has already been discussed, as has the dramatic reduction in the volatility of inflation. In addition, the standard deviation of the federal funds rate has fallen by about 25 percent. In contrast, the volatility of commodity price inflation has increased significantly in the post-84 period, suggesting that this variable is not the source of good luck in the second period.

Reduced-form VARs

We first estimate reduced-form VAR models separately over the two periods, 1960-1979 and 1984-present, and then conduct Goldfeld-Quandt tests of constancy of error variances and Chow tests of regression coefficient stability.

The results from tests of changes in the coefficients are shown in table 7. Note that, 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 clearer evidence of coefficient instability, with all equations, except the commodity price inflation equation, displaying structural breaks.

The reduced-form error variances and test results on their volatility breaks are shown in table 8. 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 evidence that the commodity price inflation innovations have higher volatility in the second period. The evidence on the error terms of the inflation equation is more 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 hypotheses–good policy, good practices, and good luck–appear to be viable candidates for explaining the drop in aggregate volatility.

Identified VARs

To examine which *fundamental* disturbances are behind the decrease in reduced-form innovation variances, and whether the structural breaks in the coefficients are primarily in the policy rules being followed or the structural output equation (perhaps emphasizing business practices), we need to move from reduced-form VARs to structural VARs. This, of course, comes at the expense of making identification assumptions. In identifying our system, we use a recursive causal ordering, with causality going from output to inflation to commodity price inflation to the federal funds rate–the ordering used by Christiano, Eichenbaum, and Evans.

Note from table 9 that the evidence for structural breaks in the coefficients of the output equations is somewhat weak, while that for breaks in the policy rule being followed depends on which model is used, with the five-variable and four-variable monthly models indicating policy breaks. In contrast, there is strong evidence for structural breaks in the inflation equation in all three models. Turning to the differences in the structural innovations, table 10 provides strong evidence of a reduction in volatility of the monetary policy shocks and the fundamental output shocks. On the other hand, the volatility of the commodity price shocks has increased in the second period, while the volatility of CPI inflation shocks has remained the same, according to the quarterly models, and decreased, according to the monthly model.[14]

Our structural VAR results–which, of course, are conditional on our identification assumptions–suggest that, to the extent that good luck has played a role in explaining the decline

[14]The generally low correlations among the reduced-form innovations suggested that changing the recursive causal ordering of the variables was unlikely to alter these results. Some robustness checks confirmed this, with a few alternative orderings giving the same conclusions. It should be noted, however, as discussed in Faust (1998), there are many other *non-recursive* identification schemes that can give very plausible impulse responses for the effects of monetary policy shocks. Faust's work shows that the results on the importance of monetary policy shocks in driving output fluctuations is not very robust when *all* possible "plausible" identifications are considered.

in aggregate output volatility, it has not come in the form of smaller or less frequent disturbances to aggregate prices or commodity prices. However, the question of whether the so-called good-luck is less erratic policy or good luck of a plainer variety still remains open. In addition, given structural breaks in the policy equation and the inflation equation, it seems quite plausible the dramatic reduction in inflation volatility may have a lot to do with changes in the way monetary policy was conducted over the two periods.

Counterfactuals using VARs

Finally, to quantify the relative contribution of changes in structure versus changes in shocks, and of the individual structural shocks themselves, we used our VAR models to compute unconditional variances of the variables that go into the system under various assumptions. A similar exercise has been conducted by Stock and Watson and they find an even larger role for shocks (closer to 90 percent), although their use of four-quarter changes likely masks some of the effects of the changes in structure, if the reactions occur within a four-quarter period.[15]

Table 11 presents our results using 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 6.

The first of our counterfactuals, shown in rows 3 and 4 of table 11, 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

[15]Furthermore, although they use the same variables in their VAR, the functional form is different. Most notably, they use changes in inflation, rather than inflation, in their VARs.

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 percent, 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.

Given the importance of the shocks in accounting for the reduction in output volatility, we use the Christiano-Eichenbaum-Evans identification scheme to examine which specific structural shock accounts for the decline in output volatility. Rows 5 through 12 in table 11 contain results from switching only one particular shock. When only the output shock variance is switched to that of the other period, the computed unconditional variance of output is very close to that obtained when all the shocks are switched (rows 5 and 6). In other words, the effect of the decline in output shock volatility on overall GDP volatility is almost as sizable as the effect of all the shocks put together. Consistent with this, even though monetary policy has been significantly less erratic in the second period, this accounts for hardly any of the decline output volatility (rows 11 and 12). 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 though non-trivial 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 11, roughly 85-90 percent 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 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.

The results from the monthly model, presented in table 12, yield virtually identical conclusions, with about 45-70 percent of the decline in volatility being explained by the shocks and roughly all of the decline in volatility of inflation being explained by changes in the structure. However, the results from the five-variable quarterly model presented in table 13 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.

5. Concluding Remarks

In this paper we have attempted to distinguish among the good policy, good practices, and good luck explanations of the reduction in U.S. output volatility over the last 15-20 years using frequency domain and VAR techniques. In the frequency domain, for aggregate output and for all of its broad demand-side and product-side components, except for durable final sales, we cannot reject the hypothesis that the decline in variance has been evenly distributed at the various frequencies; for durable final sales the decline in variance is concentrated at the business cycle frequencies. Although the latter result is consistent with better inventory management, overall, our frequency domain results lend considerable support to the good luck explanation.

Our VAR results indicate a moderately bigger role for changes in the structure of the economy, as opposed to changes in the probability distributions of the shocks, 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 (e.g. Simon, 2000). 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 10-15 years, good-luck is probably the leading explanation. 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 to good luck alone. 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 support the view that monetary policy has played a crucial role in stabilizing inflation over the past two decades.

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Table 1: Volatility of Growth of Selected Series

Standard Deviations of Annualized Quarterly Growth Rates

	Standard Deviation I:1960:1-1983:4	Standard Deviation II:1984:1-2002:1	Difference (II-I)	Share in Nominal GDP (pct.)
GDP	4.43	2.26	-2.16	100
Demand Components				
Consumption	3.41	2.04	-1.37	67.6
Investment	22.02	14.04	-7.97	17.5
Government	4.50	3.77	-.73	6.2
Exports	21.65	8.83	-12.82	10.8
Imports	20.04	8.78	-11.26	13.5
Product Components				
Goods	8.00	4.77	-3.23	37.6
Structures	11.80	6.77	-5.03	9.1
Services	1.76	1.41	-0.36	53.3
Other				
Final Sales	3.48	2.09	-1.27	99.5
Final Sales of Durables	10.02	8.47	-1.54	
Final Sales of Nondurables	4.45	3.08	-1.36	
Contrib. of Inventories to GDP Growth	2.72	1.76	- .97	0.5
Consumer Price Inflation	3.63	1.47	-2.16	

Table 2: Results from Volatility-Break Tests Allowing For Multiple Breaks

Variable*	No. of Breaks	Date(s)	90% Confidence Intervals
GDP	1	1984:2	1981:1-1987:1
Goods	1	1984:2	1981:3-1987:1
Services	3	1955:3 1958:1 1967:1	1954:1-1957:1 1953:1-1963:2 1953:1-1981:2
Final Sales	1	1983:3	1976:4-1990:2
Durable Final Sales	2	1956:1 1991:1	1953:1-1960:1 1980:2-2001:3**
Change Pvt Inventories	3	1969:2 1981:4 1984:3	1968:2-1970:2 1970:4-1992:4 1977:1-1992:1
CPI Inflation	3	1973:1 1978:4 1981:3	1970:2-1975:4 1978:1-1979:3 1981:1-1982:1

*Absolute values of demeaned growth rates.
**Outside sample range.

Table 3: Estimates of Integrated Spectrum

Variable & Frequency	Integrated Spectrum Period I	Period II	H_0: Period I = Period II H_1: Period I > Period II Test	p-Value
Real GDP Growth:				
Low	.97 (.73)	.79 (.71)	.18	.43
Business Cycle	7.58 (2.69)	1.85 (.83)	2.04	.02
High	8.36 (2.21)	2.47 (.75)	2.52	.01
Goods GDP Growth:				
Low	1.52 (1.20)	1.95 (1.73)	-.20	.58
Business Cycle	19.34 (7.12)	7.51 (3.39)	1.50	.07
High	33.76 (8.54)	13.32 (4.02)	2.17	.02
Services GDP Growth:				
Low	.74 (.61)	.45 (.37)	.40	.34
Business Cycle	.48 (.19)	.30 (.13)	.77	.22
High	1.56 (.42)	1.22 (.33)	.65	.26
Final Sales Growth:				
Low	.88 (.69)	.79 (.70)	.09	.47
Business Cycle	4.78 (1.77)	.97 (.45)	2.09	.02
High	4.98 (1.40)	2.59 (.73)	1.51	.07
Dur. Final Sales Growth:				
Low	3.17 (2.68)	5.99 (5.49)	-.46	.68
Business Cycle	32.88(12.49)	9.39 (4.43)	1.77	.04
High	51.63(14.64)	56.42(15.30)	-.23	.59
Inventories Growth:				
Low	.17 (.17)	1.51 (1.37)	-.97	.83
Business Cycle	6.14 (3.11)	7.47 (3.97)	-.27	.60
High	4.18 (1.43)	4.38 (1.25)	-.11	.54
Inflation:				
Low	7.44 (7.13)	.61 (.49)	.96	.17
Business Cycle	4.16 (2.40)	.95 (.38)	1.32	.09
High	1.10 (.32)	.71 (.21)	1.02	.15

NOTES:
1. Standard errors in parentheses.
2. Low freq. range = $0,\pi/16$; BCB = Bus. cycle broad freq. range = $\pi/16,\pi/3$; High freq. range = $\pi/3,\pi$.
3. Period 1 is from 1960:1 to 1979:4 and period 2 is from 1984:1-2000:1. For inventories growth, however, period 1 begins in 1967:2 and ends in 2001:4.
4. p-value is the marginal significance level of the test.

Table 4: Estimates of Integrated Normalized Spectrum

	Integrated Normalized Spectrum		H_0: Period I = Period II H_1: Period I ≠ Period II	
Variable & Frequency	Period I	Period II	Test	p-Value
Real GDP Growth:				
Low	.06 (.04)	.15 (.13)	-.71	.48
Business Cycle	.45 (.13)	.36 (.15)	.43	.66
High	.49 (.12)	.48 (.14)	.06	.95
Goods GDP Growth:				
Low	.03 (.02)	.09 (.07)	-.75	.45
Business Cycle	.35 (.12)	.33 (.14)	.14	.89
High	.62 (.13)	.58 (.15)	.17	.87
Services GDP Growth:				
Low	.27 (.19)	.23 (.17)	.14	.89
Business Cycle	.17 (.07)	.15 (.07)	.18	.85
High	.56 (.15)	.62 (.15)	-.25	.80
Final Sales Growth:				
Low	.08 (.06)	.18 (.15)	-.62	.54
Business Cycle	.45 (.14)	.22 (.10)	1.35	.18
High	.47 (.11)	.60 (.15)	-.67	.50
Dur. Final Sales Growth:				
Low	.04 (.03)	.08 (.07)	-.59	.56
Business Cycle	.37 (.12)	.13 (.06)	1.78	.08
High	.59 (.13)	.79 (.16)	-.94	.35
Inventories Growth:				
Low	.02 (.02)	.11 (.10)	-.96	.34
Business Cycle	.59 (.23)	.56 (.24)	.08	.94
High	.40 (.13)	.33 (.11)	.41	.68
Inflation:				
Low	.59 (.44)	.27 (.19)	.66	.51
Business Cycle	.33 (.21)	.42 (.15)	-.35	.72
High	.09 (.04)	.31 (.10)	-2.13	.03

NOTES:
1. Standard errors in parentheses.
2. Low freq. range = $0,\pi/16$; BCB = Bus. cycle broad freq. range = $\pi/16,\pi/3$; High freq. range = $\pi/3,\pi$.
3. Period 1 is from 1960:1 to 1979:4 and period 2 is from 1984:1-2000:1. For inventories growth, however, period 1 begins in 1967:2 and ends in 2001:4.
4. p-value is the marginal significance level of the test.

Table 5: Mean of Model Variables

Means of Annualized Quarterly Growth Rates

	Mean		Difference
	I:60:1-79:4	II:84:1-02:1	(II-I)
GDP	3.74	3.20	-.54
CPI Inflation	4.76	3.10	-1.66
Commodity Price Inflation	5.41	-.17	-5.58
Federal Funds Rate (level)	5.64	6.06	.42
Final Sales	3.75	3.23	-.52
Inventories*	4.10	2.98	-1.12

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

Table 6: Volatility of Model Variables

Standard Deviations of Annualized Quarterly Growth Rates

	Standard Deviation		Difference
	I:60:1-79:4	II:84:1-02:1	(II-I)
GDP	3.98	2.21	-1.77
CPI Inflation	3.38	1.47	-1.91
Commodity Price Inflation	13.39	19.12	5.73
Federal Funds Rate (level)	2.63	2.04	-.59
Final Sales	3.14	2.04	-1.10
Inventories*	3.20	3.61	.41

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

Table 7: Coefficient Stability Tests of Reduced-Form VAR

Variable	F-Stat	p-Value
	4-Variable Quarterly Model	
ΔGDP	1.31	.20
ΔCPI	2.51	.00
ΔCommodity Prices	1	.46
Federal Funds Rate	1	.46
	4-Variable Monthly Model	
ΔIP	1.21	.17
ΔCPI	2.12	.00
ΔCommodity Prices	1.82	.00
Federal Funds Rate	1.45	.03
	5-Variable Quarterly Model	
ΔFinal Sales	1.52	.09
ΔInventories	1.72	.04
ΔCPI	2.55	.00
ΔCommodity Prices	0.71	.81
Federal Funds Rate	7.72	.00

Table 8: Innovations from Reduced-Form VAR

	Standard Deviation			Stability Test	
Variable	Period I	Period II	% Change	F-Stat	p-Value
	4-Variable Quarterly Model				
ΔGDP	3.2	1.76	-45	3.16	.00
ΔCPI	1.00	.89	-11	1.2	.32
ΔComm. Prices	11.11	16.03	44	2.17*	.92
FFR	.58	0.4	-31	2.02	.00
	4-Variable Monthly Model				
ΔIP	8.52	5.33	-37	2.48	.00
ΔCPI	1.97	1.65	-16	1.38	.02
ΔComm. Prices	21.90	31.70	45	2.16*	.00
FFR	.32	.20	-38	2.48	.00
	5-Variable Quarterly Model				
ΔFinal sales	2.22	1.51	-32	2.72	.00
ΔInventories	1.79	2.03	13	1.04*	.48
ΔCPI	.74	.89	20	1.15*	.35
ΔComm. Prices	11.25	16.13	43	1.64*	.09
FFR	.68	.38	-44	3.93	.00

* indicates that the null hypothesis is that the volatility is *higher* in the second period.

Table 9: Coefficient Stability Tests of the Structural VAR

Variable	F-Stat	p-Value
	4-Variable Quarterly Model	
ΔGDP	1.31	.20
ΔCPI	2.36	.00
ΔCommodity Prices	1.39	.14
Federal Funds Rate	1.14	.32
	4-Variable Monthly Model	
ΔIP	1.21	.17
ΔCPI	2.09	.00
ΔCommodity Prices	1.67	.00
Federal Funds Rate	1.39	.05
	5-Variable Quarterly Model	
ΔFinal Sales	1.52	.09
ΔInventories	1.63	.06
ΔCPI	2.32	.00
ΔCommodity Prices	1.06	.40
Federal Funds Rate	6.07	.00

Table 10: Innovations from the Structural VAR

	Standard Deviation			Stability Test	
Variable	Period I	Period II	% Change	F-Stat	p-Value
	4-Variable Quarterly Model				
ΔY	3.2	1.76	-45	3.16	.00
ΔCPI	1.00	.89	-11	1.20	.25
ΔComm. Prices	10.16	13.01	28	1.72*	.02
FFR	.54	.36	-33	2.16	.00
	4-Variable Monthly Model				
ΔIP	8.52	5.33	-37	2.48	.00
ΔCPI	1.97	1.64	-17	1.41	.01
ΔComm. Prices	20.56	29.49	43	2.12*	.00
FFR	.32	.19	-41	2.65	.00
	5-Variable Quarterly Model				
ΔFinal sales	2.22	1.51	-32	2.72	.00
ΔInventories	1.78	2.01	13	1.00*	.51
ΔCPI	.70	.88	26	1.22*	.30
ΔComm. Prices	10.22	12.75	25	1.18*	.35
FFR	.65	.32	-51	5.39	.00

* indicates that the null hypothesis is that the volatility is *higher* in the second period.

Table 11: Explaining Stability
(Unconditional Standard Deviations using the Structural VAR)

		Quarterly Four-Variable Structural VAR			
Coefficients	Shocks	ΔY	π	ΔPc	FFR
Period I	Period I	4.22	4.26	13.39	3.18
Period II	Period II	2.13	1.28	18.76	1.8
Period I	Period II	3.08	3.77	14.90	2.79
Period II	Period I	3.61	1.58	19.33	2.97
Period I	Period II - ΔGDP	3.09	3.76	12.65	2.79
Period II	Period I - ΔGDP	3.57	1.44	20.41	2.74
Period I	Period II - ΔCPI	4.18	4.06	13.2	30.60
Period II	Period I - ΔCPI	2.15	1.38	19.42	1.82
Period I	Period II - ΔPc	4.39	4.51	15.90	3.38
Period II	Period I - ΔPc	2.10	1.25	16.39	1.79
Period I	Period II - FFR	4.09	4.23	13.14	3.08
Period II	Period I - FFR	2.18	1.36	19.16	2.14

Table 12: Explaining Stability
(Unconditional Standard Deviations using the Structural VAR)

		Monthly Four-Variable Structural VAR			
Coefficients	Shocks	ΔIP	π	ΔPc	FFR
Period I	Period I	11.49	4.53	26.4	3.07
Period II	Period II	6.40	2.20	39.11	1.83
Period I	Period II	9.33	4.81	33.17	3.34
Period II	Period I	10.04	2.82	38.11	2.85
Period I	Period II - ΔIP	8.98	4.35	26.06	2.91
Period II	Period I - ΔIP	9.55	2.41	41.86	2.55
Period I	Period II - ΔCPI	11.33	4.21	25.64	2.96
Period II	Period I - ΔCPI	6.46	2.51	40.76	1.85
Period I	Period II - ΔPc	12.35	5.33	34.63	3.71
Period II	Period I - ΔPc	6.34	2.15	31.59	1.80
Period I	Period II - FFR	11.03	4.43	25.59	2.89
Period II	Period I - FFR	7.09	2.40	40.37	2.24

Table 13: Explaining Stability
(Unconditional Standard Deviations using the Structural VAR)

		Quarterly Five-Variable Structural VAR				
Coefficients	Shocks	ΔFS	ΔIVT	π	ΔPc	FFR
Period I	Period I	3.73	3.74	3.30	16.32	2.89
Period II	Period II	2.02	3.57	1.27	18.94	1.81
Period I	Period II	2.99	3.50	2.85	17.06	2.28
Period II	Period I	2.72	4.02	1.30	17.20	2.74
Period I	Period II -ΔFS	3.04	3.40	2.86	15.25	2.44
Period II	Period I - ΔFS	2.72	4.10	1.34	17.40	2.27
Period I	Period II -ΔIVT	3.75	3.87	3.32	16.42	2.89
Period II	Period I - ΔIVT	2.00	3.42	1.26	18.89	1.79
Period I	Period II - ΔCPI	3.81	3.82	3.47	16.74	2.94
Period II	Period I - ΔCPI	1.97	3.51	1.10	17.82	1.78
Period I	Period II - ΔPc	3.83	3.92	3.40	18.46	2.98
Period II	Period I - ΔPc	2.00	3.43	1.24	16.74	1.79
Period I	Period II - FFR	3.48	3.44	3.00	15.29	2.58
Period II	Period I - FFR	2.10	3.81	1.40	20.01	2.43

FIGURE 1

Real GDP Growth

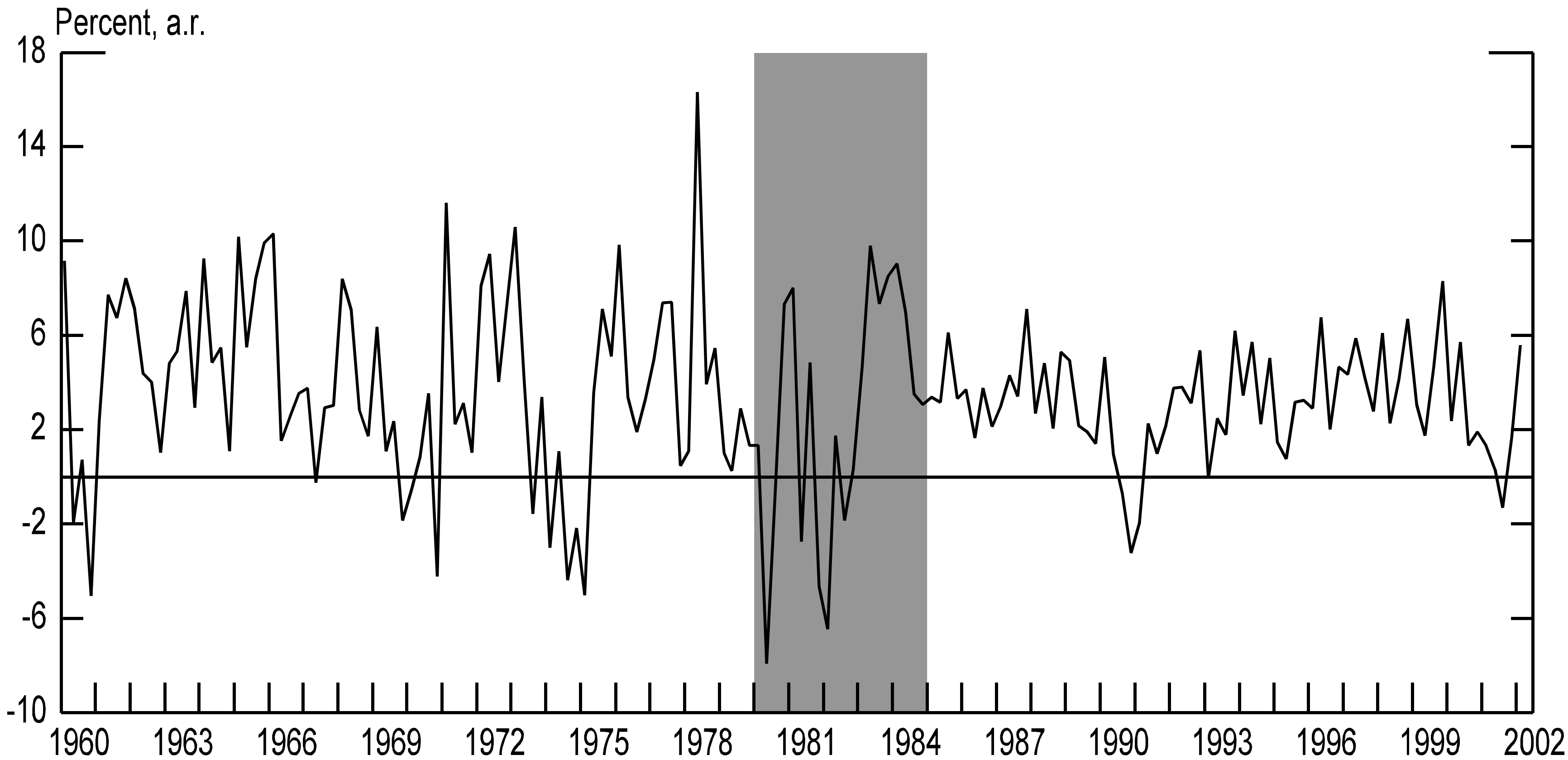


FIGURE 2

Components of Real GDP Growth

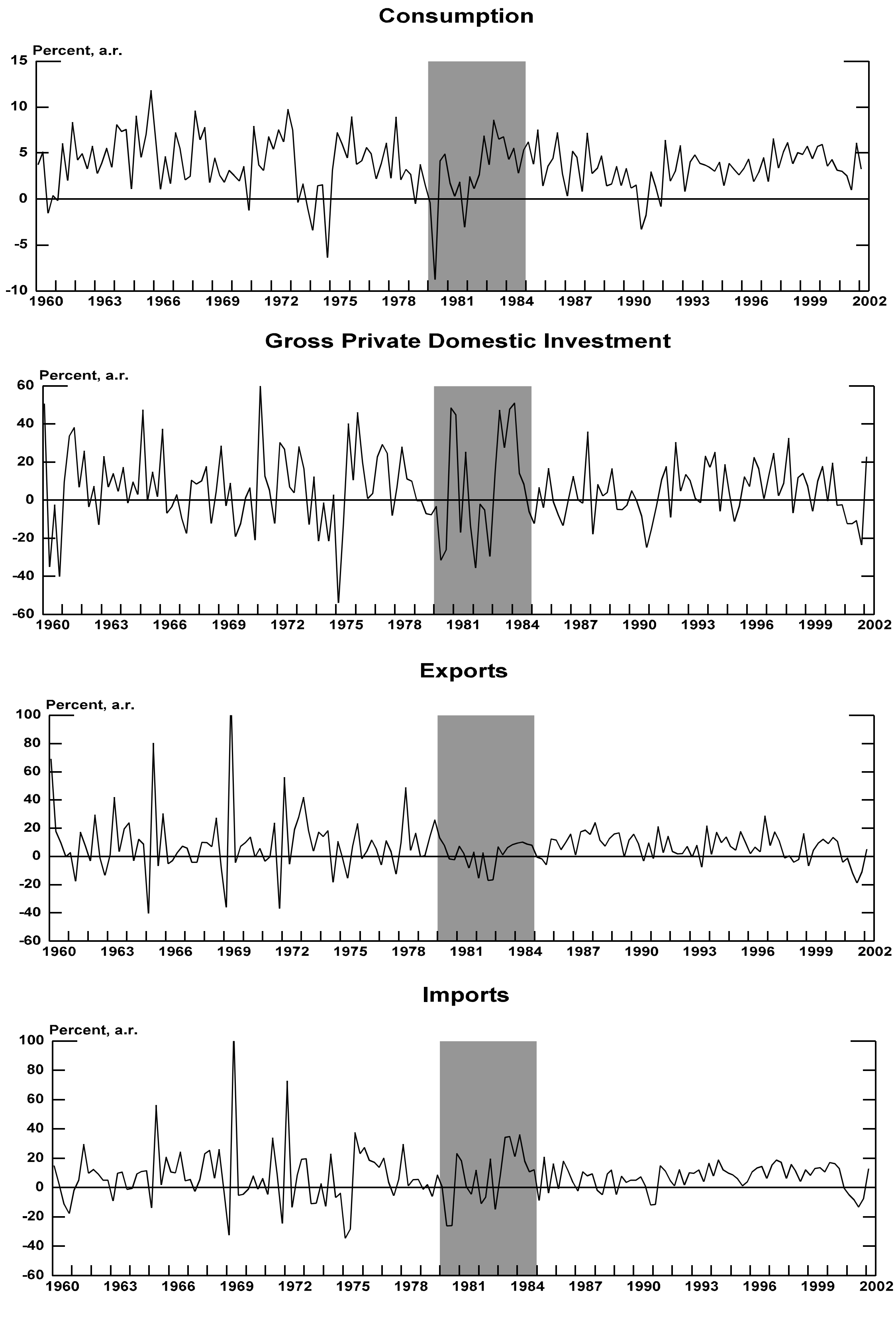
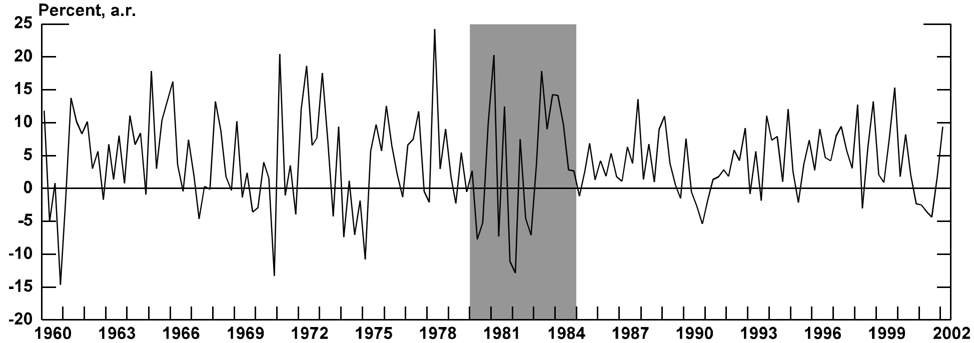


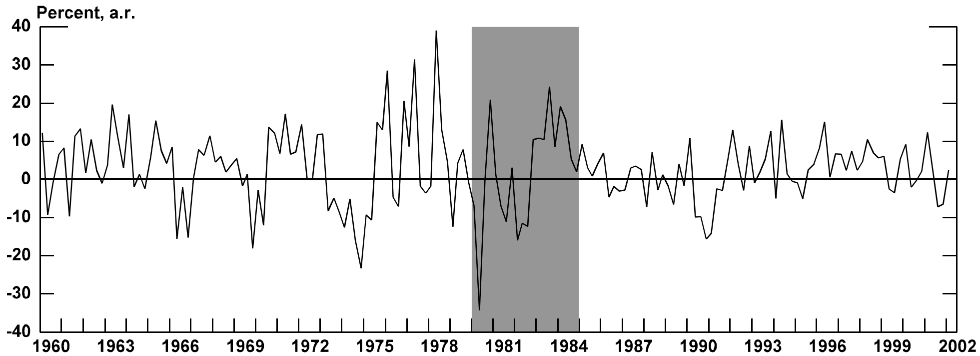
FIGURE 3

Components of Real GDP Growth

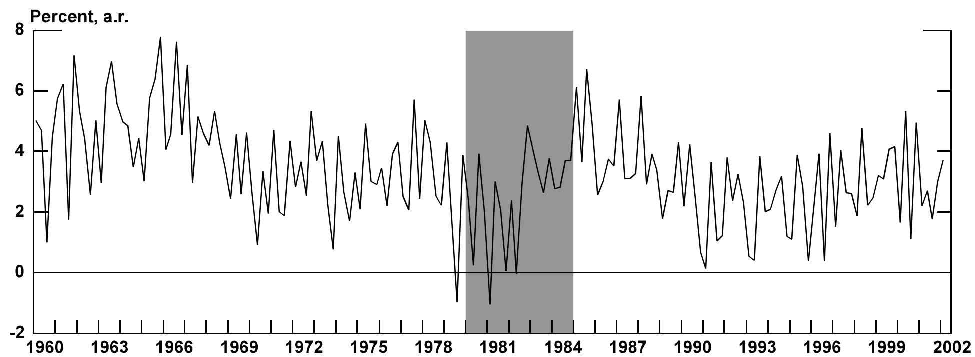
Goods



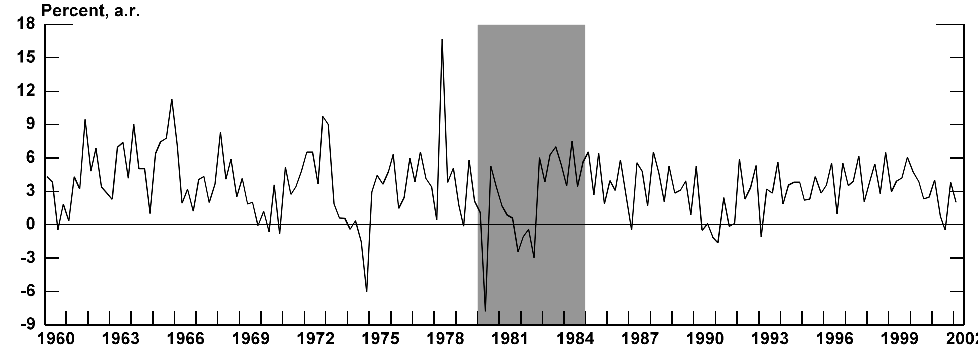
Structures



Services



Final Domestic Sales



Contributions of Inventories to Percent Change in GDP

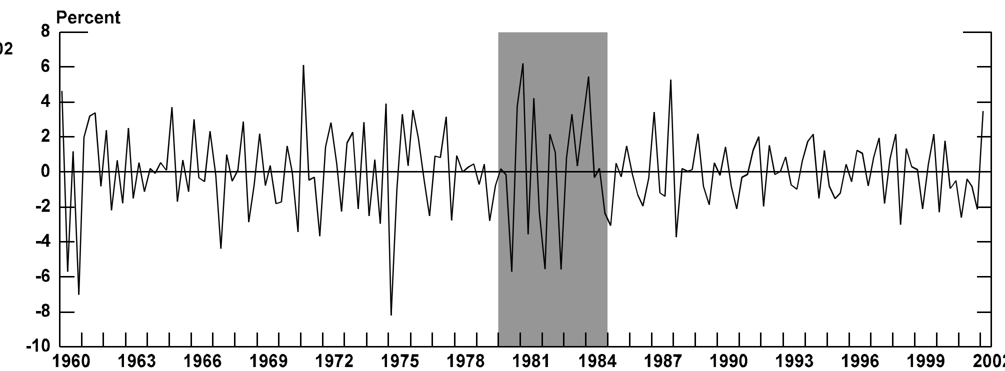
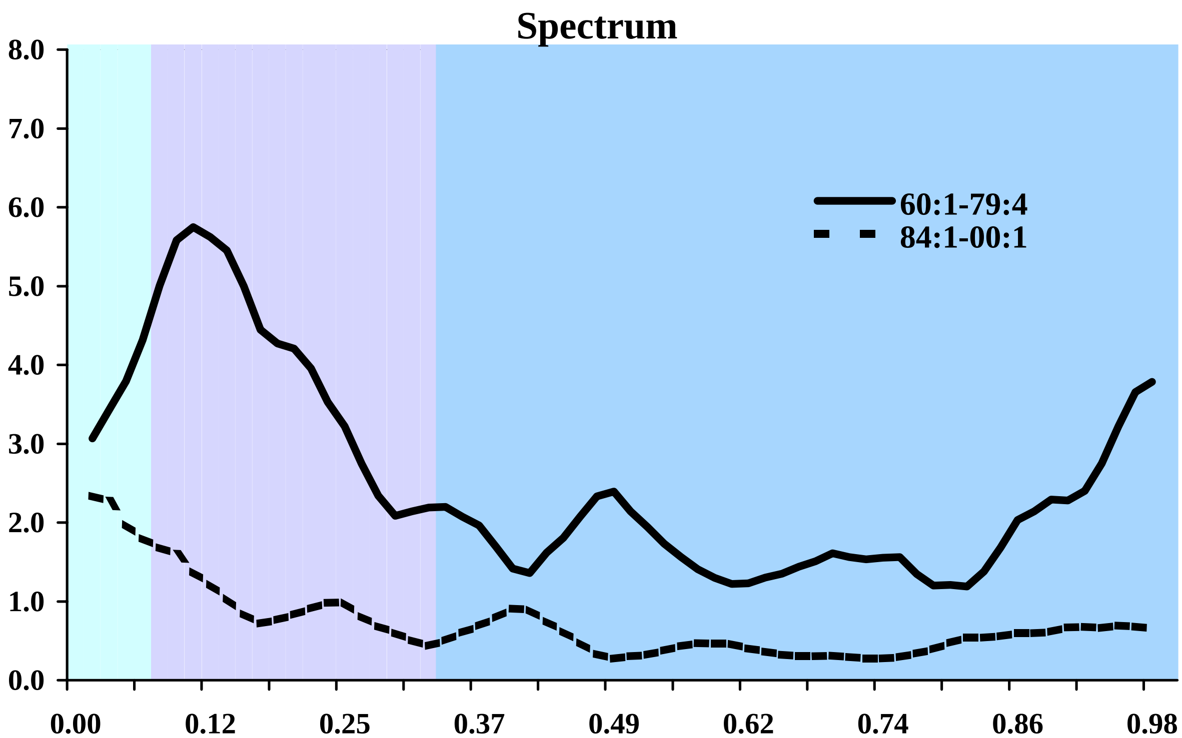
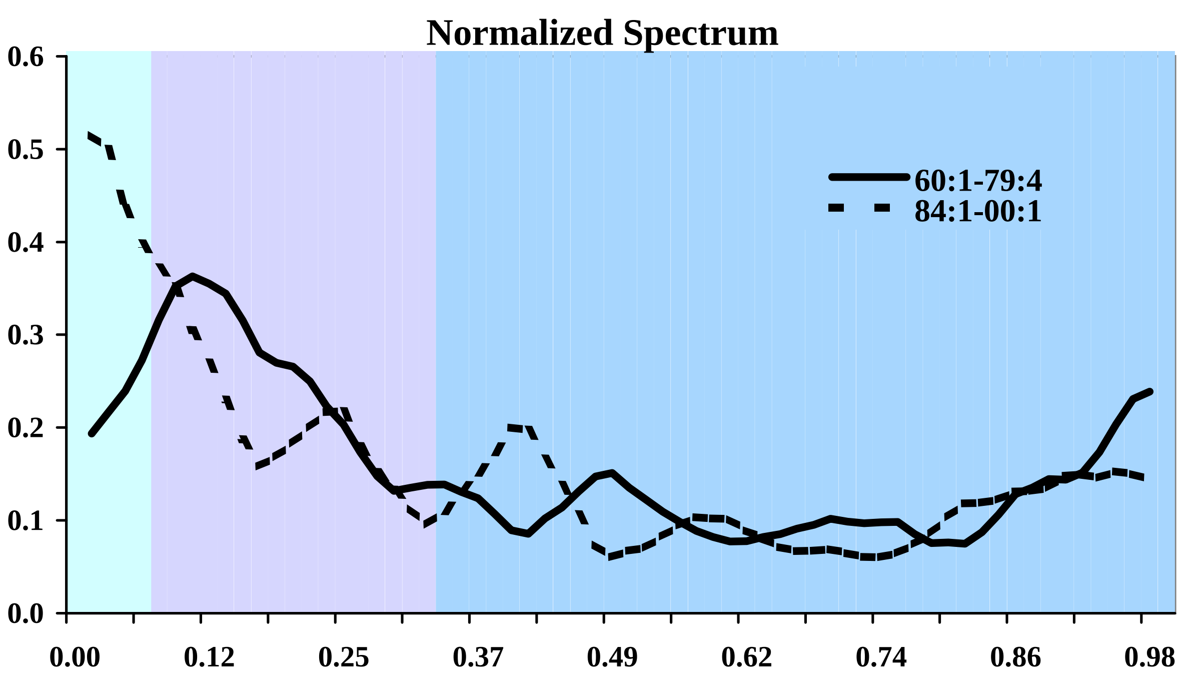


Figure 4

GDP Growth





Appendix

I. Why the good-luck hypothesis implies a parallel downward shift in the spectrum:

The spectrum of a series, X_t, is the Fourier transform of its covariogram and is given by:

$$g(\omega) = \sum_{j=-\infty}^{\infty} \Gamma(j) e^{-i\omega j}, \qquad -\pi < \omega < \pi \tag{A1}$$

where $\Gamma(j)$ represents the *j*th lag population autocovariance and ω is the angular frequency.

Under the assumption of covariance stationarity process, recall from Wold's theorem that the series, X_t, has the MA(∞) representation:

$$X_t = \theta(L)\varepsilon_t = \sum_{j=0}^{\infty} \theta_j L^j \tag{A2}$$

where ϵ_t is i.i.d. with mean 0 and variance σ_ε^2. The representation (A2) implies that the spectral density (A1) can also be written as:

$$g(\omega) = \frac{1}{2\pi} \theta(e^{i\omega}) \sigma_\varepsilon^2 \theta(e^{-i\omega}) \tag{A3}$$

Noting that:

$$\sigma_X^2 = \sigma_\varepsilon^2 \sum_{j=0}^{\infty} \theta_j^2 \tag{A4}$$

the normalized spectrum can be written as:

$$h(\omega) \equiv \frac{g(\omega)}{\sigma_X^2} = \frac{\theta(e^{i\omega})\theta(e^{-i\omega})}{2\pi \sum_{j=0}^{\infty} \theta_j^2} \tag{A5}$$

which is independent of σ_ε^2. Hence, if only the innovation variance has gone down, and the MA parameters have not changed, the normalized spectrum should be the same in the two subsamples.

II. Consistency and asymptotic normality of the integrated spectrum:

The integrated spectrum is defined as:

$$G(\omega_1, \omega_2) \equiv 2 \int_{\omega_1}^{\omega_2} g(\omega) d\omega \tag{A6}$$

The sample periodogram for a sample of size T is:

$$\hat{I}(\omega) \equiv \sum_{j=1-T}^{T-1} \hat{\Gamma}(j)e^{i\omega j} = \sum_{j=1-T}^{T-1} \hat{\Gamma}(j)\cos(\omega j) \quad \text{(A7)}$$

where the $\hat{\Gamma}(j)$'s represent sample autocovariances given by:

$$\hat{\Gamma}(j) = \frac{1}{T}\sum_{t=1}^{T-j}(X_t - \overline{X})(X_{t-j} - \overline{X}) \quad \text{(A8)}$$

An estimate of the integrated spectrum (A6) is obtained by taking (A1), plugging (A7) on the right hand side, and integrating over frequencies $\omega_1 \leq \omega \leq \omega_2$. Using the formula for the integral of a cosine function and simplifying, yields equation (1) in the text.

To develop further results, it will be useful to set up the following notation:

$$\Phi = 8\pi\int_{\omega_1}^{\omega_2} g^2(\omega)d\omega \quad \text{(A9)}$$

$$e = \left(\frac{E(\varepsilon_t^4)}{\sigma_\varepsilon^4} - 3\right) \quad \text{(A10)}$$

Note that e in (A10) refers to excess kurtosis (relative to the Gaussian distribution). It will also be useful to define sample counterparts of Φ and e, given by:

$$\hat{\Phi} = 8\pi\int_{\omega_1}^{\omega_2} \hat{I}^2(\omega)d\omega \quad \text{(A11)}$$

$$\hat{e} = \left(\frac{1/T\sum_{t=1}^{T}\hat{\varepsilon}_t^4}{[1/T\sum_{t=1}^{T}\hat{\varepsilon}_t^2]^2} - 3\right) \quad \text{(A12)}$$

where the $\hat{\varepsilon}$'s, the estimated innovations, are the residuals from an AR(p) model of X, with p chosen based on AIC.

<u>*Proposition:*</u> See Priestley (1982).

$$\lim_{T\to\infty} E[\hat{G}(\omega_1,\omega_2) = G(\omega_1,\omega_2) \quad \text{(A13)}$$

$$\sqrt{T}[\hat{G}(\omega_1,\omega_2) - G(\omega_1,\omega_2) \to N(0,\Omega_G) \quad \text{(A14)}$$

where

$$\Omega_G = \Phi + eG^2(\omega_1,\omega_2) \quad \text{(A15)}$$

Thus we can use $\hat{G}(\omega_1, \omega_2)$, given in equation (1) of the text, as a consistent estimate of the integrated spectrum and do standard hypothesis testing, once we derive an expression for the sample variance of G, $\hat{\Omega}_G$. Using (A15) and the expressions given in (A11), (A12), and (A7), and some tedious algebra, this can be shown to be:

$$\hat{\Omega}_G = \frac{1}{T}[\hat{\Phi} + \hat{e}\hat{G}^2(\omega_1, \omega_2)]$$

$$= \frac{1}{T\pi} \times \left\{ \begin{array}{l} 2(\omega_2 - \omega_1)\hat{\Gamma}(0)^2 + 8\hat{\Gamma}(0)\sum_{j=1}^{T-1} \hat{\Gamma}(j) \dfrac{[\sin(\omega_2 j) - \sin(\omega_1 j)]}{j} \\ + 4\sum_{j=1}^{T-1} \hat{\Gamma}(j)^2 \left[(\omega_2 - \omega_1) + \dfrac{1}{2} \dfrac{\sin(2\omega_2 j) - \sin(2\omega_1 j)}{j} \right] \\ + 8\sum_{j=1}^{T-1} \sum_{k=j+1}^{T-1} \hat{\Gamma}(j)\hat{\Gamma}(k) \left[\begin{array}{l} \dfrac{\sin(\omega_2(j+k)) - \sin(\omega_1(j+k))}{j+k} \\ + \dfrac{\sin(\omega_2(k-j)) - \sin(\omega_1(k-j))}{k-j} \end{array} \right] \end{array} \right\} + \frac{1}{\mathrm{T}} \mathrm{e}\hat{\mathrm{G}}^2(\omega_1, \omega_2) \quad \text{(A16)}$$

Given that $\hat{\Phi} \to \Phi$ and $\hat{e} \to e$, $\hat{\Omega}_G \to \Omega_G$.

III. Consistency and asymptotic normality of the integrated normalized spectrum:

The estimated integrated normalized spectrum is obtained by taking the integrated spectrum and dividing it by the sample variance of X:

$$\hat{H}(\omega_1, \omega_2) = \hat{G}(\omega_1, \omega_2) / \hat{\Gamma}(0) \equiv \hat{G}(\omega_1, \omega_2) / s_X^2 \quad \text{(A17)}$$

Taking (A17), noting that $\hat{G}_T(\omega_1, \omega_2) \equiv \int_{\omega_1}^{\omega_2} \hat{I}_T(\omega) d\omega$ and $s_X^2 = \int_{-\pi}^{\pi} \hat{I}_T(\omega) d\omega$, and using (A15), it can be shown that the joint distribution of the estimated integrated spectrum and of the sample variance of X has the following properties:

$$\begin{pmatrix} \hat{G}(\omega_1, \omega_2) \\ s_X^2 \end{pmatrix} \sim \left[\begin{pmatrix} G(\omega_1, \omega_2) \\ \sigma_X^2 \end{pmatrix}, \frac{1}{T} \begin{pmatrix} \Phi + eG^2(\omega_1, \omega_2) & \Phi + eG^2(\omega_1, \omega_2)\sigma_X^2 \\ \Phi + eG^2(\omega_1, \omega_2)\sigma_X^2 & \Phi + e\sigma_X^2 \end{pmatrix} \right] \quad \text{(A18)}$$

Using (A18), the delta-method can be used to get the asymptotic distribution of the variance of the ratio of the estimated integrated spectrum to the sample variance, which is our estimate of the integrated normalized spectrum.

In particular, if a vector random variables has a multivariate normal distribution $\hat{Z} \to N(\mu, \Sigma)$, and $\left.\frac{\partial g}{\partial Z}\right|_{Z=\mu}$ exists, then

$$g(\hat{Z}) \sim N\left[g(Z), \left(\left.\frac{\partial g}{\partial Z'}\right|_{Z=\mu} \Sigma \left.\frac{\partial g}{\partial Z}\right|_{Z=\mu} \right) \right] \tag{A19}$$

Using this approach and setting $g(\hat{Z}) = g(\hat{G}(\omega_1, \omega_1), s_X^2) = \hat{G}(\omega_1, \omega_1) / s_X^2$, we can then establish from (A18) and (A19) that (A17) represents a consistent estimate of the integrated normalized spectrum and that its variance is given by:

$$\operatorname{var} \hat{H}(\omega_1, \omega_2) = \begin{pmatrix} 1/s_X^2 & -\hat{G}(\omega_1, \omega_2)/s_X^2 \end{pmatrix} \begin{bmatrix} \hat{\Phi} + \hat{e}\hat{G}^2(\omega_1, \omega_2) & \hat{\Phi} + \hat{e}\hat{G}^2(\omega_1, \omega_2) s_X^2 \\ \hat{\Phi} + \hat{e}\hat{G}^2(\omega_1, \omega_2) s_X^2 & \hat{\Phi} + \hat{e} s_X^2 \end{bmatrix} \begin{pmatrix} 1/s_X^2 \\ -\hat{G}(\omega_1, \omega_2)/s_X^2 \end{pmatrix} \tag{A20}$$

Appendix Tables

Table A1a: Results from Multiple Break Tests on Absolute Value of Demeaned Changes

Variable	No. of Breaks	Date(s)	95% Conf. Intervals	90% Conf. Intervals
GDP	1	1984:2	1980:2-1988:2	1981:1-1987:1
Consumption	1	1993:1	1988:2-1997:4	1989:4-1996:2
Investment	2	1980:1 1984:1	1978:1-1982:2 1983:1-1985:1	1978:4-1981:2 1983:2-1984:4
Government	1	1967:1	1966:3-1970:3	1964:3-1969:3
Exports	1	1973:1	1965:3-1980:3	1967:4-1978:2
Imports	1	1984:2	1973:4-1994:4	1977:1-1991:3
Goods	1	1984:2	1978:4-1989:4	1981:3-1987:1
Structures	2	1973:3 1984:2	1970:4-1976:2 1982:4-1985:4	1971:3-1975:3 1983:2-1985:2
Services	3	1955:3 1958:1 1967:1	1953:2-1957:4 1953:1-1965:3 1953:1-1987:2	1954:1-1957:1 1953:1-1963:2 1953:1-1981:2
Final Sales	1	1983:3	1974:1-1993:1	1976:4-1990:2
Goods Final Sales	3	1975:2 1977:4 1980:2	1973:2-1977:2 1977:1-1978:3 1978:1-1982:3	1973:4-1976:4 1977:2-1978:2 1978:4-1981:4
Durable Final Sales	2	1956:1 1991:1	1953:1-1961:3 1975:4-2001:3*	1953:1-1960:1 1980:2-2001:3*
Auto Final Sales	3	1961:1 1964:3 1988:1	1954:3-1967:3 1958:3-1970:3 1975:4-2000:2	1956:3-1965:3 1960:2-1968:4 1979:3-1996:3
Nondurable FS	1	1986:1	1979:1-1993:1	1981:1-1991:1
Change Pvt Inventories	3	1969:2 1981:4 1984:3	1967:4-1970:4 1967:1*-1997:3 1974:1-1995:1	1968:2-1970:2 1970:4-1992:4 1977:1-1992:1
Contrib. of Invent.	1	1988:1	1976:4-1999:2	1980:1-1996:1
CPI Inflation	3	1973:1 1978:4 1981:3	1969:1-1977:1 1977:3-1980:1 1980:4-1982:2	1970:2-1975:4 1978:1-1979:3 1981:1-1982:1
Commodity Price Inflation	2	1972:3 1974:2	1972:1-1973:1 1973:2-1975:2	1971:4-1973:2 1973:4-1976:2
Federal Funds Rate	1	1955:2 1978:3 1984:4	1954:4-1955:4 1953:1-2001:3* 1953:1-2001:3*	1954:4-1955:4 1953:1-2001:3 1953:1-2001:3

* Outside of data range.

Table A1b: Results from Multiple Break Tests on AR Residuals

Variable	No. of Breaks	Date(s)	95% Confidence Intervals	90% Confidence Intervals
GDP	1	1984:1	1979:2-1988:4	1980:4-1987:2
Consumption	1	1992:1	1987:4-1996:2	1988:1-1995:1
Investment	3	1957:3 1961:3 1984:1	1974:4-1981:4 1979:2-1980:4 1982:4-1985:2	1975:4-1980:4 1979:3-1980:3 1983:2-1984:4
Government	1	1960:3	1957:2-1963:4	1958:2-1962:4
Exports	1	1973:2	1965:4-1980:4	1968:1-1978:3
Imports	1	1984:2	1974:2-1994:2	1977:2-1991:2
Goods	1	1984:1	1977:1-1991:1	1979:1-1989:1
Structures	2	1974:2 1983:3	1971:4-1976:4 1982:1-1985:1	1972:3-1976:1 1982:3-1984:3
Services	1	1956:4	1956:2-1957:2	1956:2-1957:2
Final Sales	1	1982:4	1971:1-1994:3	1974:3-1991:1
Goods Final Sales	3	1975:2 1977:4 1980:3	1971:4-1978:4 1976:4-1978:4 1977:3-1983:3	1972:4-1977:4 1977:1-1978:3 1978:2-1982:4
Durable Final Sales	1	1991:4	1978:1-2001:3*	1982:2-2001:2
Auto Final Sales	1	1988:1	1973:3-2001:3*	1977:4-1988:2
Nondurable FS	1	1986:1	1979:3-1992:3	1981:1-1990:3
Change Pvt Inventories	3	1973:3 1975:2 1996:3	1971:3-1975:3 1974:1-1978:3 1984:3-2001:3*	1972:1-1975:1 1974:3-1978:1 1988:2-2001:3*
Contrib. of Inventories	1	1988:1	1979:4-1996:2	1982:2-1993:4
CPI Inflation	1	1991:2	1984:2-1998:2	1986:2-1996:2
Commodity Price Inflation	2	1972:4 1975:2	1972:2-1973:2 1974:2-1976:2	1972:2-1973:2 1974:3-1976:1
Federal Funds Rate	3	1956:2 1979:2 1982:2	1955:3-1957:1 1954:1-2001:3* 1960:2-2001:3*	1955:4-1956:4 1959:2-1999:2 1967:1-1997:3

* Outside of data range.

Table A2: Estimates of Integrated Spectrum

Variable & Frequency	Integrated Spectrum: Period I		Integrated Spectrum: Period II		H_0: Period I = Period II; H_1: Period I > Period II: Test	p-Value
Real GDP Growth:						
Low	.97	(.73)	.79	(.71)	.18	.43
Business Cycle	7.58	(2.69)	1.85	(.83)	2.04	.02
High	8.36	(2.21)	2.47	(.75)	2.52	.01
Consumption Growth:						
Low	.71	(.51)	.85	(.74)	-.16	.57
Business Cycle	4.12	(1.69)	.94	(.43)	1.82	.03
High	5.25	(1.47)	2.35	(.71)	1.80	.04
Investment Growth:						
Low	3.58	(3.11)	17.70	(16.45)	-.84	.80
Business Cycle	152.73	(58.10)	64.97	(28.18)	1.40	.08
High	247.02	(70.41)	114.35	(30.36)	1.73	.04
Export Growth:						
Low	4.77	(4.32)	11.37	(9.19)	-.65	.74
Business Cycle	86.32	(36.08)	30.22	(12.77)	1.47	.07
High	438.24	(118.88)	36.35	(11.17)	3.37	.00
Import Growth:						
Low	9.43	(7.26)	10.92	(10.65)	-.12	.55
Business Cycle	84.04	(33.38)	27.81	(12.01)	1.59	.06
High	316.82	(92.16)	38.30	(9.96)	3.00	.00

NOTES:

1. Standard errors in parentheses.
2. Low freq. range = $0,\pi/16$; BCB = Bus. cycle broad freq. range = $\pi/16,\pi/3$; High freq. range = $\pi/3,\pi$.
3. Period 1 is from 1960:1 to 1979:4 and period 2 is from 1984:1-2000:1. For inventories growth, however, period 1 begins in 1967:2 and ends in 2001:4.
4. p-value is the marginal significance level of the test.

Table A2 (continued): Estimates of Integrated Spectrum

Variable & Frequency	Integrated Spectrum		H_0: Period I = Period II H_1: Period I > Period II	
	Period I	Period II	Test	p-Value
Goods GDP Growth:				
Low	1.52 (1.20)	1.95 (1.73)	-.20	.58
Business Cycle	19.34 (7.12)	7.51 (3.39)	1.50	.07
High	33.76 (8.54)	13.32 (4.02)	2.17	.02
Structures GDP Growth:				
Low	5.43 (4.79)	7.87 (6.83)	-.29	.62
Business Cycle	50.67 (19.26)	16.49 (7.38)	1.66	.05
High	66.12 (17.76)	21.47 (5.11)	2.42	.01
Services GDP Growth:				
Low	.74 (.61)	.45 (.37)	.40	.34
Business Cycle	.48 (.19)	.30 (.13)	.77	.22
High	1.56 (.42)	1.22 (.33)	.65	.26

Table A2 (continued): Estimates of Integrated Spectrum

Variable & Frequency	Integrated Spectrum				H_0: Period I = Period II H_1: Period I > Period II	
	Period I		Period II		Test	p-Value
<u>Final Sales Growth:</u>						
Low	.88	(.69)	.79	(.70)	.09	.47
Business Cycle	4.78	(1.77)	.97	(.45)	2.09	.02
High	4.98	(1.40)	2.59	(.73)	1.51	.07
<u>Dur. Final Sales Growth:</u>						
Low	3.17	(2.68)	5.99	(5.49)	-.46	.68
Business Cycle	32.88	(12.49)	9.39	(4.43)	1.77	.04
High	51.63	(14.64)	56.42	(15.30)	-.23	.59
<u>Nondur. Final Sales Gr.</u>						
Low	.84	(.75)	.27	(.23)	.73	.23
Business Cycle	5.38	(2.06)	2.04	(.87)	1.50	.07
High	13.09	(3.70)	7.20	(2.31)	1.35	.09
<u>Auto Final Sales Gr.</u>						
Low	21.27	(17.50)	6.53	(5.43)	.80	.21
Business Cycle	533.28	(218.89)	76.48	(33.42)	2.06	.02
High	1521.78	(523.27)	604.62	(157.66)	1.68	.05
<u>Inventories Growth:</u>						
Low	.17	(.17)	1.51	(1.37)	- .97	.83
Business Cycle	6.14	(3.11)	7.47	(3.97)	-.27	.60
High	4.18	(1.43)	4.38	(1.25)	-.11	.54

Table A2 (continued): Estimates of Integrated Spectrum

Variable & Frequency	Integrated Spectrum Period I	Period II	H_0: Period I = Period II H_1: Period I > Period II Test	p-Value
Inflation:				
Low	7.44 (7.13)	.61 (.49)	.96	.17
Business Cycle	4.16 (2.40)	.95 (.38)	1.32	.09
High	1.10 (.32)	.71 (.21)	1.02	.15
Federal Funds Rate:				
Low	3.03 (2.74)	2.07 (1.69)	.30	.38
Business Cycle	3.35 (2.00)	1.88 (1.01)	.66	.26
High	.45 (.14)	.17 (.06)	1.81	.04
Comm. Price Inflation:				
Low	32.53 (26.29)	6.68 (6.43)	.96	.17
Business Cycle	91.02 (35.04)	158.02 (65.08)	-.91	.82
High	94.52 (24.09)	162.70 (3.98)	-1.15	.88

Table A3: Estimates of Integrated Normalized Spectrum

Variable & Frequency	Integrated Normalized Spectrum		H_0: Period I = Period II H_1: Period I ≠ Period II	
	Period I	Period II	Test	p-Value
Real GDP Growth:				
Low	.06 (.04)	.15 (.13)	-.71	.48
Business Cycle	.45 (.13)	.36 (.15)	.43	.66
High	.49 (.12)	.48 (.14)	.06	.95
Consumption Growth:				
Low	.07 (.05)	.21 (.16)	-.80	.42
Business Cycle	.41 (.14)	.23 (.10)	1.03	.30
High	.52 (.13)	.57 (.15)	-.23	.82
Investment Growth:				
Low	.01 (.01)	.09 (.08)	- 1.00	.32
Business Cycle	.38 (.12)	.33 (.13)	.28	.78
High	.61 (.14)	.58 (.14)	.16	.87
Export Growth:				
Low	.01 (.01)	.15 (.11)	-1.22	.22
Business Cycle	.16 (.07)	.39 (.15)	-1.41	.16
High	.83 (.15)	.47 (.13)	1.78	.07
Import Growth:				
Low	.02 (.02)	.14 (.13)	- .90	.37
Business Cycle	.20 (.08)	.36 (.14)	-.99	.32
High	.77 (.15)	.50 (.13)	1.39	.16

NOTES:
1. Standard errors in parentheses.
2. Low freq. range = $0,\pi/16$; BCB = Bus. cycle broad freq. range = $\pi/16,\pi/3$; High freq. range = $\pi/3,\pi$.
3. Period 1 is from 1960:1 to 1979:4 and period 2 is from 1984:1-2000:1. For inventories growth, however, period 1 begins in 1967:2.
4. p-value is the marginal significance level of the test.

Table A3 (continued): Estimates of Integrated Normalized Spectrum

Variable & Frequency	Integrated Normalized Spectrum		H_0: Period I = Period II H_1: Period I ≠ Period II	
	Period I	Period II	Test	p-Value
Goods GDP Growth:				
Low	.03 (.02)	.09 (.07)	-.75	.45
Business Cycle	.35 (.12)	.33 (.14)	.14	.89
High	.62 (.13)	.58 (.15)	.17	.87
Structures GDP Growth:				
Low	.04 (.04)	.17 (.14)	-.88	.38
Business Cycle	.41 (.13)	.36 (.14)	.28	.78
High	.54 (.13)	.47 (.12)	.42	.67
Services GDP Growth:				
Low	.27 (.19)	.23 (.17)	.14	.89
Business Cycle	.17 (.07)	.15 (.07)	.18	.85
High	.56 (.15)	.62 (.15)	-.25	.80

Table A3 (continued): Estimates of Integrated Normalized Spectrum

Variable & Frequency	Integrated Normalized Spectrum		H_0: Period I = Period II H_1: Period I ≠ Period II	
	Period I	Period II	Test	p-Value
Final Sales Growth:				
Low	.08 (.06)	.18 (.15)	-.62	.54
Business Cycle	.45 (.14)	.22 (.10)	1.35	.18
High	.47 (.11)	.60 (.15)	-.67	.50
Dur. Final Sales Growth:				
Low	.04 (.03)	.08 (.07)	-.59	.56
Business Cycle	.37 (.12)	.13 (.06)	1.78	.08
High	.59 (.13)	.79 (.16)	-.94	.35
Nondur. Final Sales Gr.				
Low	.04 (.04)	.03 (.02)	.33	.74
Business Cycle	.28 (.10)	.21 (.09)	.48	.63
High	.68 (.15)	.75 (.18)	-.33	.74
Auto Final Sales Gr.				
Low	.01 (.01)	.01 (.01)	.07	.95
Business Cycle	.26 (.09)	.11 (.05)	1.44	.15
High	.73 (.16)	.88 (.16)	-.65	.52
Inventories Growth:				
Low	.02 (.02)	.11 (.10)	-.96	.34
Business Cycle	.59 (.23)	.56 (.24)	.08	.94
High	.40 (.13)	.33 (.11)	.41	.68

Table A3 (continued): Estimates of Integrated Normalized Spectrum

Variable & Frequency	Integrated Normalized Spectrum		H_0: Period I = Period II H_1: Period I ≠ Period II	
	Period I	Period II	Test	p-Value
Inflation:				
Low	.59 (.44)	.27 (.19)	.66	.51
Business Cycle	.33 (.21)	.42 (.15)	-.35	.72
High	.09 (.04)	.31 (.10)	-2.13	.03
Federal Funds Rate:				
Low	.44 (.34)	.50 (.33)	-.13	.90
Business Cycle	.49 (.27)	.46 (.23)	.10	.92
High	.07 (.03)	.04 (.02)	.70	.48
Comm. Price Inflation:				
Low				
Business Cycle	.15 (.11)	.02 (.02)	1.12	.26
High	.42 (.14)	.48 (.17)	-.30	.76
	.43 (.10)	.50 (.15)	-.36	.72