Output Fluctuations in the United States: What Has Changed Since the Early 1980s?

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Abstract

We document a structural decline in the volatility of real U.S. GDP growth in the first quarter of 1984. As a means of understanding the dramatic volatility reduction, we decompose output growth by major product type and provide evidence that the break emanates from a reduction in the volatility of durable goods production. We further show that the break in durables is roughly coincident with a break in the proportion of durables accounted for by inventories. We note that the break in output volatility affects the implementation of a wide range of simulation and econometric techniques and offer one important illustration of this in the context of a regime-switching model of output growth.

1 Introduction

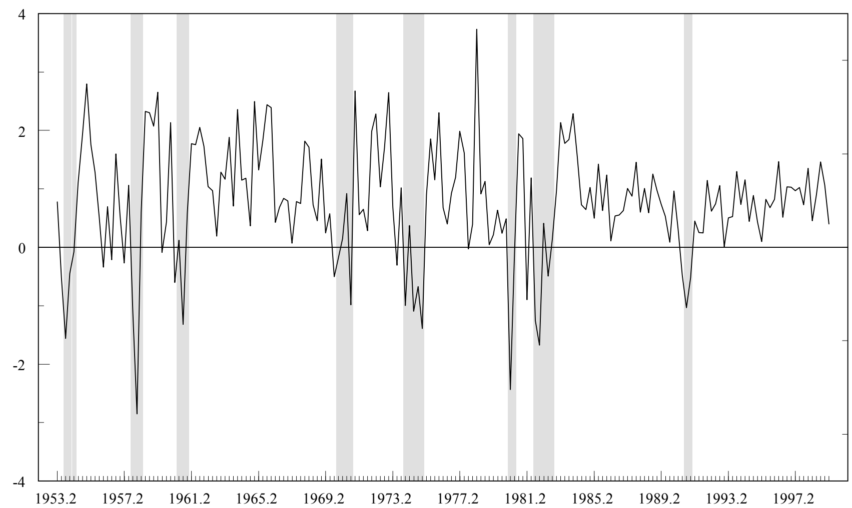
The business press is currently sprinkled with references to the 'death' or 'taming' of the business cycle in the United States. While such claims are at best premature, they are in part rooted in the apparent reduction in the volatility of U.S. output fluctuations over the period starting in the early 1980's. Figure 1 plots the growth of U.S. real GDP over the period 1953:2 to 1999:2; the variance of output fluctuations over the period ending in 1983 is more than four times as large as the variance for the period since 1984.

In this paper, we document a structural break in the volatility of U.S. GDP growth in the first quarter of 1984. As a means of understanding this dramatic reduction in volatility, we decompose output growth by major product type and provide evidence that the aggregate volatility break emanates from a reduction in the volatility of durable goods production. We show that the break in durables is roughly coincident with a break in the proportion of durables output accounted for by inventories.

The break in output volatility affects the implementation of a range of simulation and econometric techniques. For example, one common method for taking theory to the data is to compare the moments of data generated from calibrated models with the moments of actual data. The presence of a one-time reduction in output volatility in the early 1980's clearly affects the time horizon over which the second and higher moments of output growth should be computed.

On the empirical front, the volatility break implies that linear models for output growth over periods that span the break are misspecified. In addition, signal-to-noise ratios in state-space characterizations of business cycle fluctuations, such as dynamic factor or Markov-switching models, will be reduced when the variance is modeled as constant. We present one important example of this in the paper. Finally, the reduction in the variance of output fluctuations should alter the interpretation policymakers place on a particular realization of quarterly GDP growth; what may have been considered a moderate fluctuation in activity prior to the break may now be viewed as severe.

Figure 1: U.S. Real GDP Growth: 1953:2 to 1999:2



The paper proceeds as follows. In Section 2, we use a series of structural stability tests to characterize the nature and timing of the changes in the process for output in recent years. We also use a regime-switching framework to examine the implications of lower quarter-to-quarter output volatility for modeling business cycle fluctuations. In Section 3, we examine disaggregate output data in order to isolate the source of the volatility decline. Section 4 concludes.

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2 The Decline in U.S. Output Volatility

There is a large literature exploring the question of whether the magnitude and duration of economic fluctuations have changed across the pre- and post-WWII periods (examples include DeLong and Summers (1986), Romer (1986a, 1986b, 1989, 1994), Shapiro (1988), Diebold and Rudebusch (1992), Lebergott (1986) and Watson (1994)). While the evidence on this issue is mixed (resulting in no small part from the difficulties associated with the construction of comparable data series across the two periods), the general pursuit of documenting changes in the process governing output fluctuations is an important element of macroeconomic research. Such documentation is valuable for the reasons that it leads to a collection of stylized facts and may also provide insight into whether such changes are likely to be permanent or temporary.

In this section we characterize recent changes in the process for U.S. output growth. We focus on quarter-to-quarter fluctuations in the growth rate of GDP, rather than on changes in the business cycle per se. In addition, since we are interested in the rather dramatic reduction in output volatility in the most recent two decades relative to the previous three, we use only post-war data and thereby avoid the problems associated with pre-and post-war data comparability.

2.1 Structural Change

To complement the ocular evidence presented in Figure 1, we begin our empirical analysis with a simple nonparametric characterization of the changes in process for U.S. real GDP over the post-war period. Throughout the paper we use chain-weighted GDP data, as constructed by the Bureau of Economic Analysis (BEA), for the sample 1953:2 to 1999:2. Looking first for evidence of instability in the mean growth rate, we fit a constant and a linear trend to real GDP growth. This regression yields a negative, but statistically insignificant, coefficient on the trend term. The insignificance of the trend term is robust to the use of the first difference of GDP growth rather than the level, as well as to the inclusion of a lagged dependent variable.

Whatever instability the trend term fails to detect in the mean rate of output growth, it uncovers easily in the variance. For example, regressing the square of GDP growth on a constant and a trend yields a coefficient on the trend that is negative and significant at the one percent level. The sign and significance of the trend term is robust to the substitution of the absolute value of GDP growth for the square and to the inclusion of lagged values of the dependent variable. Finally the trend term is negative and highly significant when included in the variance term of an ARCH or GARCH specification for the residual from an AR(1) specification for GDP growth.

As an alternative exercise, we remove the mean of GDP growth and perform a CUSUM and CUSUM of squares test on the residuals. The CUSUM test (Brown, Durbin, and Evans, 1975) is based on the cumulative sum of the one-step ahead forecast error resulting from a recursive estimation. Instability in the parameters of the mean is indicated if the cumulative sum goes outside the area between the two critical lines. The CUSUM of squares test is based on the cumulative sum of the squared one-step ahead forecast error resulting from a recursive estimation. Movement outside the critical lines is suggestive of variance instability. Figure 2 plots these two test statistics. The CUSUM test, shown in the left panel, does not reveal instability in the mean, while the CUSUM of squares test, shown in the right panel, detects instability in the variance beginning in the early 1980s.

Imposing a bit more structure on the problem, we follow Hess and Iwata (1997) and model GDP growth as an AR(1).[1] To detect parameter instability in this model we use Nyblom's L test as described in Hansen (1992a). Large values of the test statistic imply a rejection of the null hypothesis of stability. Using the asymptotic critical values for a 5 percent test from Hansen, we see in Table 1 that we cannot reject the stability of both the constant term and autoregressive coefficient over our sample, but we can reject stability of the variance.[2] Finally, we reject the hypothesis

[1] Hess and Iwata show that a ARIMA(1,1,0) model is at least as good as many widely used nonlinear models at replicating the duration and amplitude of fluctuations in the log of real GDP. In addition we use standard lag selection to criteria to test for the best model for our sample and find that we cannot reject an AR(1) specification in favor of one with longer lags.

[2] Hansen (1992a) points out that if both the autoregressive and error variance have shifted, the

Figure 2: U.S. Real GDP: 1953:2 to 1999:2

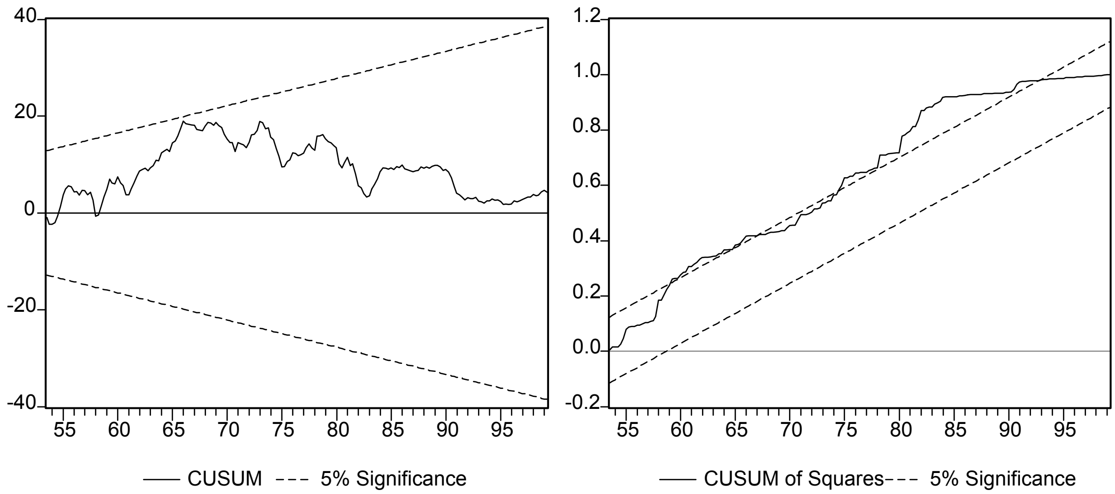


Table 1: Nyblom's L Test for Stability of U.S. Real GDP Growth - 1953:2 to 1999:2

Specification: $\Delta y_t = \mu + \phi \Delta y_{t-1} + \epsilon_t$				
	Estimate		L_c	CV(5 percent)
μ	0.50	(0.10)	0.09	0.48
ϕ	0.34	(0.08)	0.10	0.48
σ^2	0.89	(0.12)	0.82	0.48
Joint L_c			1.06	1.02

Note: Nyblom's L test as described in Hansen (1992). Δy is real GDP growth. p-values in parentheses to the right of estimates. L_c is the test statistic for a breakpoint in each of the coefficients listed in the first column. CV(5 percent) is the five percent critical value for the null hypothesis of no break.

of the joint stability of the parameters at the 2.5 percent level.

2.2 The Timing of the Break

In this section we estimate the timing of the structural change in the process for GDP growth and assess its statistical significance. Continuing to model GDP growth as an AR(1), we test for a structural break in the residual variance from the following specification for GDP growth:

$$\Delta y_t = \mu + \phi \Delta y_{t-1} + \epsilon_t \tag{1}$$

If ϵ_t follows a normal distribution, $\sqrt{\frac{\pi}{2}}|\hat{\epsilon}_t|$ is an unbiased estimator of the standard deviation of ϵ_t. Therefore, we look for a break in an equation of the form:

$$\sqrt{\frac{\pi}{2}}|\hat{\epsilon}_t| = \alpha + \mu_t \tag{2}$$

where α is the estimator of the standard deviation.[3]

We estimate a break point by jointly estimating the following system using GMM:

$$\Delta y_t = \mu + \phi \Delta y_{t-1} + \epsilon_t \tag{3}$$

$$\sqrt{\frac{\pi}{2}}|\hat{\epsilon}_t| = \alpha_1 D_{1t} + \alpha_2 D_{2t} + \mu_t \tag{4}$$

where

$$D_{1t} = \begin{cases} 0 & \text{if } t \leq T \\ 1 & \text{if } t > T \end{cases}$$

power of the L test to detect the shift in the autoregressive parameter is low and thus this test does not allow us to rule out instability in the autoregressive parameter with any degree of certainty. This issue also arises with the tests for structural change used in the next section. At that point we apply a correction suggested in Hansen (1999).

[3]Our choice of specification here follows the convention of the finance literature and appeals to the fact that the absolute value specification is more robust to departures from conditional normality (as pointed out in Davidian and Carroll (1987)) than the estimator of the variance, $\hat{\epsilon}_t^2$.

$$D_{2t} = \begin{cases} 1 & \text{if } t \leq T \\ 0 & \text{if } t > T \end{cases}$$

and T is the estimated break point, and α_1 and α_2 are the corresponding estimators of the standard deviation. The instruments for each period t are a constant, Δy_{t-1} , D_{1t}, and D_{2t}.

The appearance of the parameter T under the alternative hypothesis but not under the null implies that the LM, LR and Wald tests of equality of the coefficients α_1 and α_2 do not have standard asymptotic properties. Andrews (1993) and Andrews and Ploberger (1994) develop tests for cases such as this, when a nuisance parameter is present under the alternative but not under the null. They consider the function, $F_n(T)$, where n is the number of observations, defined as the Wald or LM statistic of the hypothesis that $\alpha_1 = \alpha_2$, for each possible value of T. We assume that T lies in a range T_1, T_2, where $T_1 = .15 * n$ and $T_2 = .85 * n$. Andrews (1993) shows the asymptotic properties of the statistic:

$$\sup_{T_1 \leq T \leq T_2} F_n = \sup F_n(T) \tag{5}$$

and reports the asymptotic critical values. In this test, the T that maximizes $F_n(T)$ will be the estimated date of the break point. Andrews and Ploberger (1994) propose two additional test statistics:

$$\exp F_n = \ln(1/(T_2 - T_1 + 1)) * \sum_{T=T_1}^{T_2} \exp(1/2 * F_n(T)) \tag{6}$$

and

$$\text{ave } F_n = (1/(T_2 \_ T_1 + 1)) * \sum_{T=T_1}^{T_2} F_n(T). \tag{7}$$

The p-values associated with these statistics are computed using the approximation suggested by Hansen (1997).

Table 2: Structural Break Tests: U.S. Real GDP Growth - 1953:2 to 1999:2

Panel A				
Specification: $\Delta y_t = \mu + \phi \Delta y_{t-1} + \epsilon_t$, $\epsilon_t \sim N(0, \sigma_t^2)$ **where** $\sigma_t^2 = \sigma_1^2$ **if** $t \leq T$, **and** $\sigma_t^2 = \sigma_2^2$ **if** $t > T$				
Null	**Sup**	**Exp**	**Ave**	
$\sigma_1^2 = \sigma_2^2$	17.80	6.54	6.71	
	(0.00)	(0.00)	(0.00)	
Estimated break date: **1984:1**				
Panel B				
Specification: $\Delta y_t = \mu + \phi \Delta y_{t-1} + \epsilon_t$, $\epsilon_t \sim N(0, \sigma_t^2)$ **where** $(\mu_t = \mu_1, \phi_t = \phi_1)$ **if** $t \leq T$, **and** $(\mu_t = \mu_2, \phi_t = \phi_2)$ **if** $t > T$				
Null	**Sup**	**Exp**	**Ave**	**Chow**
$\mu_1 = \mu_2$, $\phi_1 = \phi_2$	6.34	0.77	1.11	0.23
	(0.55)	(0.75)	(0.78)	(0.89)
Estimated break date: **none**				
$\mu_1 = \mu_2$	1.48	0.24	0.45	0.13
	(0.99)	(0.82)	(0.76)	(0.71)
Estimated break date:**none**				
$\phi_1 = \phi_2$	2.53	0.34	0.59	0.00
	(0.85)	(0.67)	(0.62)	(0.99)
Estimated break date: **none**				

Note: Panel A presents the results of structural break tests of the type discussed in Andrews (1992) and Andrews and Ploberger (1994) for the null hypothesis of no break in the variance parameter. 'Sup', 'Exp' and 'Ave' refer to the supremum, exponential and average test statistics described in Equations 5, 6, and 7, respectively. p-values appear in parentheses below test statistics. Panel B presents the results from same tests for the null hypothesis of no break in all and each of the parameters for the mean. This panel also presents the results of a Chow test that imposes the 1984:1 estimated break for all and each of the mean parameters.

The results of the tests for structural change in the residual variance of the process for the growth rate of GDP are reported in the top panel of Table 2. Each of the three test statistics indicate a strong rejection of the null hypothesis that $\sigma_1 = \sigma_2$, and the estimated break date occurs in the first quarter of 1984.

We next consider the possibility that the observed break in the residual variance is actually the result of a break in the parameters characterizing the mean of the output process. We therefore estimate:

$$\Delta y_t = \mu_1 D_1 + \mu_2 D_2 + \phi_1 \Delta y_{t-1} D_1 + \phi_2 \Delta y_{t-1} D_2 + \epsilon_t \tag{8}$$

where D_1 and D_2 are as defined above, first testing jointly for a break in the constant and the AR coefficient, and then for a break in each separately.

These results are reported in the bottom panel of Table 2. In all cases we cannot reject the null of no break and therefore conclude that the variance break is not attributable to a change in the constant and AR component of the model.[4] Even when we conduct Chow tests and impose the estimated break date of 1984:1, we still cannot reject the null of no break. The p-values and test statistics for the Chow test are reported in the last column of Table 2.

Finally, one might hypothesize that the break in 1984:1 simply reflects a return to stability after the highly volatile 1970s. To investigate this possibility, we test for additional breaks in the subsamples 1953:2 to 1983:4 and 1984:1 to 1999:2, conditional on having found the first break in 1984:1. Though we do not report the results here,

[4]The p-values presented in Table 2 are based on asymptotic critical values. In order to calculate the small sample properties of our tests we use a bootstrap technique proposed in Hansen (1999), who points out that the use of standard bootstrap techniques is inappropriate in the presence of structural change in the regressors. The p-values obtained using this correction are nearly identical to those presented here. We also examine the small sample properties of our variance break tests using the stationary bootstrap proposed by Politis and Romano (1994). This bootstrap methodology is applicable under the null hypothesis of no break in the variance, given that we reject a break in the mean using Hansen (1999). For 1000 iterations, we obtain a p-value of 0.004 for the supreme, 0.002 for the exponential and 0.004 for the average. Thus we can still strongly reject the hypothesis of no break in the variance.

we find that we cannot reject the hypothesis of no break in either subsample.[5]

2.3 Implications for Business Cycle Modeling

Hamilton (1989) uses a regime switching framework to show that by allowing the mean rate of GDP growth to switch between two states, one can capture the periodic shifts between positive and negative real GDP growth in the U.S. He further shows that such shifts accord well with the NBER business cycle peaks and troughs. A number of researchers have since found this to be a useful approach to characterizing business cycles, including Lam (1990), Boldin (1994), Durland and McCurdy (1994), Filardo (1994), Kim (1994), and Diebold and Rudebusch (1996).

A typical formulation of this model for GDP growth is one in which the mean of an autoregressive specification is allowed to vary across states of the economy (usually two) and the residual variance is assumed constant. In this section, we augment this standard formulation in two ways. First, we allow the mean and the variance to follow independent switching processes. Second, we allow the two-state process for the mean, which we consider the business cycle component of the model, to vary according to the state of the variance.

In particular, we estimate the following augmented Markov model for GDP growth:

$$\Delta y_t = \mu_{S_t,V_t} + \phi(\Delta y_{t-1} - \mu_{S_{t-1},V_{t-1}}) + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma_{V_t}) \tag{9}$$

where S_t and V_t are latent variables for the states of the mean and variance, respectively, of output growth, each of which can independently assume a value of 1 or 2.[6] This specification yields two possible states for the variance, with σ_1 being the vari-

[5] In independent research Koop and Potter (2000) use a Bayesian methodology to search over a number of alternative models of output data for the U.S. and U.K. Their results suggest that for U.S. real GDP growth a model with a structural break in the variance in the early- to mid-1980's is the preferred model.

[6] Our use of just one autoregressive lag differs from Hamilton's AR(4) specification. For both Hamilton's original constant variance specification and our more general model, however, an AR(1) specification fit best over our sample.

ance in the high variance state and σ_2 the variance in the low variance state, along with four possible states for the mean of output growth:

$$\begin{aligned}
&\mu_{11} \text{ for } S_t = 1, V_t = 1 \\
&\mu_{21} \text{ for } S_t = 2, V_t = 1 \\
&\mu_{12} \text{ for } S_t = 1, V_t = 2 \\
&\mu_{22} \text{ for } S_t = 2, V_t = 2
\end{aligned}$$

where μ_{11}, for example, indicates the mean rate of growth in the high mean, high variance state and μ_{21} is growth in the low mean, high variance state.

The results of this estimation are reported in Table 3. The columns in the top panel of the table indicate the state of the variance parameter. Note that the residual variance drops from 0.87 per quarter in the high variance state to 0.14 in the low variance state.

To aid in the interpretation of the coefficients reported in the table, the top panel of Figure 3 plots the smoothed probabilities of the low variance state ($V = 2$). Consistent with the structural break results presented in the previous section, we find a sharp increase in the probability of the low variance state during the years 1983-1984. Note also that the pattern of smoothed probabilities reflects a one-time switch to the low variance state in the early 1980's, rather than a switch *out of* the low variance state in the 1970's and a switch back into that state in the early 1980's. The pattern observed here reinforces our earlier finding that the break in 1984:1 is not simply due to a return to stability after the highly volatile 1970's.

One powerful feature of the regime-switching model used by Hamilton is its ability to generate smoothed probabilities that correspond closely to the NBER business cycle peaks and troughs. However, Hamilton estimated his model using data through 1984, the year in which we date the decline in volatility. Does the addition of the lower volatility years affect the ability of the widely used switching mean, constant variance specification to identify periods of recession and expansion?

Table 3: Markov-Switching Model: U.S. Real GDP Growth, 1953:2 - 1999:2

	V=1		**V=2**	
$\boldsymbol{\mu_{1v}}$	1.07	(0.15)	0.76	(0.06)
$\boldsymbol{\mu_{2v}}$	-0.68	(0.48)	-0.54	(0.31)
$\boldsymbol{\sigma^2_v}$	0.87	(0.14)	0.14	(0.03)
$\boldsymbol{\phi}$	0.12 (0.10)			
$\mathbf{p^{\mu}_{11}}$	0.95 (0.02)			
$\mathbf{p^{\mu}_{22}}$	0.65 (0.16)			
$\mathbf{p^{\sigma^2}_{11}}$	0.99 (0.00)			
$\mathbf{p^{\sigma^2}_{22}}$	0.99 (0.01)			
$H_o : \mu_{11} = \mu_{12}, \mu_{21} = \mu_{22}$	p-value=0.23			

Note: The parameter estimates reported in the table refer to the following model for GDP growth: $\Delta y_t = \mu_{S_t,V_t} + \phi(\Delta y_{t-1} - \mu_{S_{t-1},V_{t-1}}) + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma_{V_t})$. The parameter V indicates the variance state, with V =1 corresponding to the high variance state and V =2 to the low variance state, so that μ_{11} indicates the mean in the high mean, high variance state. p^k_{ij} indicates the probability of switching from state i to state j for the parameter k. The bottom panel reports the p-value for test of the restriction that the mean growth rate in recessions is equal across high and low variance states, and that the mean growth rate during expansions is equal across high and low variance states.

To answer this question we estimate the following model:

$$\Delta y_t = \mu_{S_t} + \phi(\Delta y_{t-1} - \mu_{S_{t-1}}) + \epsilon_t, \quad \epsilon_t \sim N(0,\sigma) \tag{9'}$$

which is simply a restricted version of Equation 9, with all terms defined as in that equation. We refer to Equation 9' as the 'Hamilton' model because, following Hamilton (1989), the variance is modeled as constant. We plot the smoothed probability of the low mean state from our augmented model in the middle panel of Figure 3, and the analogous probability for the Hamilton model in the bottom panel.

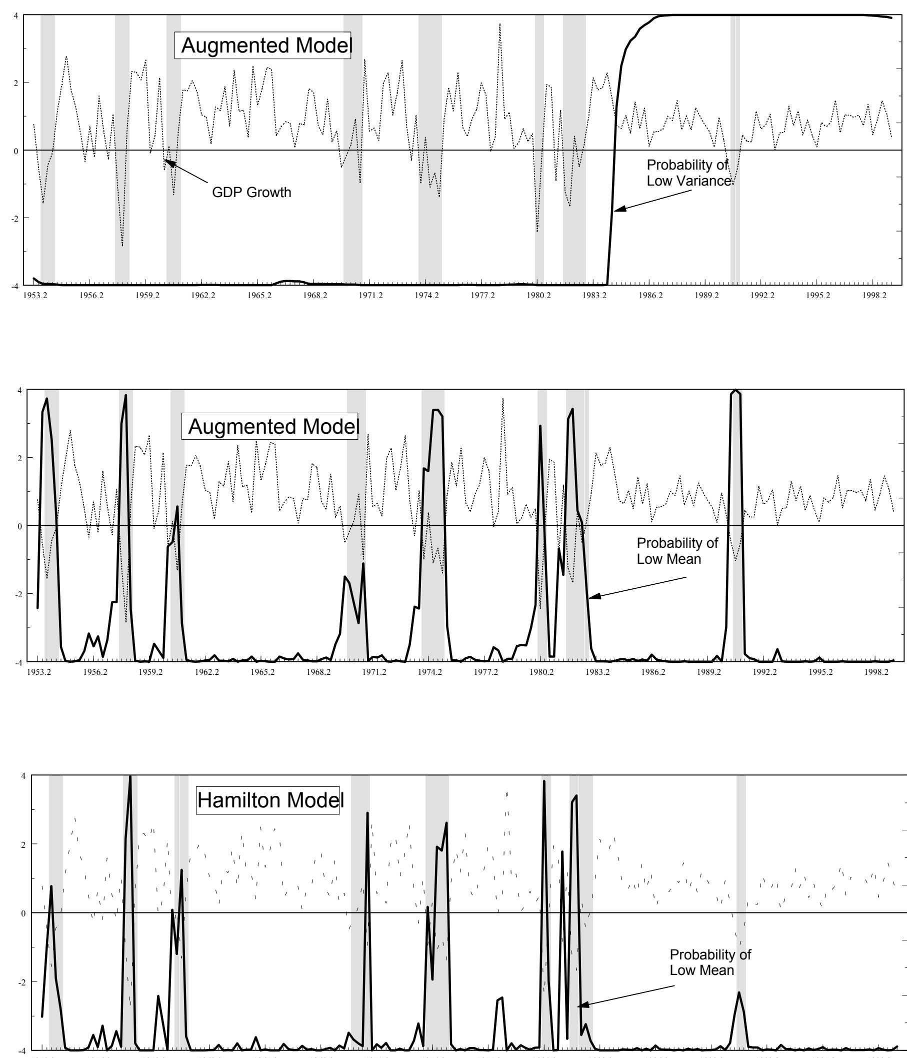
The most striking difference between these two plots is in the behavior of the smoothed probabilities during the recessionary period of the early 1990's. While the Hamilton model virtually misses this recession, the augmented model easily captures it. This exercise illustrates the importance of accounting for the volatility break in this type of state-space characterization of business cycle fluctuations: When the model is not augmented to allow for the dramatic change in the variance, the signal from the 1990-91 recession is simply too weak to register this period as a recession.[7]

Turning back to our point estimates, we see that the average rates of output growth in both expansions and recessions are lower in absolute value for the years since the early 1980s. Can one conclude from this that the business cycle has been muted, or 'tamed' in recent years, as suggested, for example, in Kim and Nelson (1999)?

One way to test this hypothesis is to impose the restriction that μ_{11}=μ_{12} and μ_{21}=μ_{22}. To the extent that the mean rates of output growth rates during recessions and expansions are a cyclical characteristic of output growth, a rejection of this restriction would suggest some fundamental change in the business cycle. As shown in the bottom panel of Table 3, however, we cannot reject this restriction. Though not reported in the table, we also test each element of the above restriction separately. In

[7]See Estrella and Mishkin (1998), Kim and Murray (1998) and Hamilton and Perez Quiros (1996) for examples from the literature in which state space models that do not account for the volatility decline fail to identify the recession of the early 1990s.

Figure 3: Markov-Switching Model of U.S. Real GDP Growth: 1953:2 to 1999:2



each case we cannot reject the null hypothesis. Thus, while we find strong support for the hypothesis that quarter-to-quarter fluctuations in GDP growth have been muted, we do not find statistical support for the notion that expansions are now less robust and recessions less severe.[8] At the very least, it would seem that it is too soon to tell.

The implications of the volatility break extend well beyond those for state-space models. The decline should be accounted for in empirical macroeconomic techniques ranging from model calibration to the estimation of structural vector autoregression models over periods spanning the break. It also implies that policymakers and economic analysts should update their posterior distribution of quarter-to-quarter GDP growth to reflect the fact that extreme movements in output are much less likely to occur today than they were twenty or thirty years ago. For example, during the period 1953:2 to 1983:4, approximately 30% of quarterly GDP growth rates were in excess of 1.5%, while for the period beginning in 1984:1, only 3.2% of observations were as large as 1.5% (in fact, if we used 1984:3 rather than 1984:1, no quarterly growth rates would exceed 1.5%). On the other end of the distribution, realizations of output growth below 0% accounted for 22% of the total in the early period, but for only 4.8% for the period since 1984.

[8] Up to this point we have not discussed the case in which the variance is constant but the means in the later period are allowed to be different from those of the early period. The obvious difficulty here is defining the 'later' and 'earlier' periods if they are not defined by the switching variance. To correctly address this issue one needs a test in the spirit of Hansen (1992b) and Hansen (1994). Given the computational intensity of such a test we instead undertake the following exercise. We add a dummy variable to the augmented model that is defined to be zero before 1984:1 and one thereafter. We then impose two sets of restrictions. The first is identical to the one described above, in which the μ and ϕ parameters are set equal across variance states. We again find that we cannot reject this restriction (p-value=0.48). Next, we relax that restriction and impose one in which σ_1=σ_2. We are easily able to reject this restriction (p-value=0.00). We are therefore reasonably confident that we have two different variances over our sample, rather than two different means.

3 Sources of the Decline in Output Volatility

3.1 A Look at the Disaggregate Data

We analyze the sources of decreased volatility by decomposing GDP growth into expenditures on goods, services and structures. For each of these product types, we fit AR models to both the growth contribution and the growth rate. We then test for breaks in the residual variance and AR coefficients. Throughout our analysis, we compute growth contributions as the product of the share of nominal GDP accounted for by a particular component in period t-1 and the real growth rate of that component in period t.[9] We examine contributions because a break in the growth contribution of an individual component signals a potentially causal role for that component in the aggregate volatility decline. Further, we examine rates because a break in the growth rate of a particular component indicates whether the break in the growth contribution is emanating from increased stability *within* that sector, or whether there has instead been a change in the share of output accounted for by that sector.

The results of these product-type break tests are reported in Panel A of Table 4. Results for the growth contributions are given in the second through fifth columns, while the results for the growth rates are presented in the last four columns.[10] We identify a break in the growth contribution of goods in 1984:1, and in the growth contribution of structures in 1990:4. Looking now within sectors, we find that the growth rates of both the goods and services sectors stabilized during our sample. The volatility decline in goods, however, is dated 1984:1, and thus lines up with the

[9]The BEA uses a more complicated method to compute the quarterly growth contributions. We used annual data, however, to compare our method with the BEA's. The correlation between the BEA's growth contributions and those computed using the lagged nominal weights is greater than 0.99.

[10]With the exception of the second entry in Panel C of this table, all results refer to break tests on the residual variance from an optimally chosen AR specification for the variable listed in the first column. Results of the tests for breaks in the AR coefficients are omitted because we do not reject stability in any of the cases. We also tested for breaks in the covariances between each of these product types and find significant breaks only when there is also a significant break in the variance of one of the two components. Thus we are not able to extract any independent information from the analysis of the covariances.

aggregate volatility reduction, while the timing of the increased stability in services, 1967:1, does not.

Since we find a break in both the growth rate and growth contribution of the goods sector in 1984, we look further into this sector, putting aside for the moment the early 1990's break in the growth contribution of structures. Decomposing goods growth into contributions from growth in durables and nondurables, we again test for breaks in the residual variance and AR coefficients of the growth contributions and growth rates. Panel B of Table 4 reports that both the growth rate and contribution of durables break in the first quarter of 1985. The growth contribution of nondurables breaks in 1990:4, the same date as the structures contribution, but there is no evidence of increased stability within the nondurables sector itself.

This investigation reveals that the volatility of durable goods, total goods and aggregate GDP all declined in the early to mid 1980's, a fact that suggests that the reduction in aggregate volatility emanated from changes within the durable goods sector. We also find, however, breaks in the growth contributions of structures and nondurable goods in the early 1990's. In order to gauge the importance of these two findings for the behavior of aggregate volatility, we undertake two simple experiments.

First, to assess the role of the decline in durables volatility in explaining the aggregate reduction, we generate a new series for durable goods in which the variance throughout our entire sample is assumed to be that of the pre-1985 period. We then use this new series to generate an aggregate output series (labeled GDPexp1), and test this series for the presence of a structural break. The result, reported in Panel D of Table 4, indicates that the output series generated under the counterfactual assumption of constant volatility in the durable goods sector does not experience a volatility break during our sample. Thus, the magnitude of the decline in durables volatility alone is sufficient to account for the break in the volatility of aggregate output.[11]

[11] This experiment is not strictly correct in that we should allow the weights to change each period as the growth rate of durables changes. Our omission of this portion of the exercise disadvantages our hypothesis that the reduction in the volatility of durables alone can account for the reduction

The second experiment evaluates the importance of the breaks in the growth contribution of durables and structures. First, it is useful to note that a break in the growth contribution of a particular component, in the absence of a corresponding break in its growth rate, indicates a change in the nominal share of that sector. Indeed, the nominal share of each of these sectors has changed over the course of our sample. Using 1990:4 to split the sample (the date of the breaks in the growth contributions of structures and nondurables), we find that nondurables accounted for, on average, 27 percent of output pre-1990:4 and only 21 percent post-1990:4. Likewise, structures declined from approximately 11 percent of output in the early period to 9 percent in the later period. Both of these declines, along with a slight decline in the share of durables output, have translated into an increase in the share of nominal output accounted for by the more stable service sector from 44 percent to 54 percent.

Our interest is in assessing the extent to which these changes in the nominal shares of each sector have affected aggregate output volatility. To do this, we hold each sector's share constant at its sample wide average, thereby not allowing the shares of structures and nondurables to decline in the way that they actually did. Under this assumption we generate a new output series (GDPexp2) and test this series for a break. Panel D of Table 4 reports that this series does experience a reduction in volatility in the second quarter of 1984. From this we conclude that changes in the composition of output, and the corresponding breaks in the growth contributions of structures and nondurables, are not sufficient to explain the reduction in aggregate volatility in the early 1980's.

Since our analysis points to a causal role for changes within the durable goods sector in stabilizing the aggregate economy, we consider the following decomposition

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in the volatility of GDP.

Table 4: Structural Break Tests: Disaggregate U.S. real GDP Growth - 1953:2 to 1999:2

	Growth Contributions				Growth Rates			
Component	**Date**	**Exp**	**Ave**	**Sup**	**Date**	**Exp**	**Ave**	**Sup**
Panel A								
Goods	1984.1	0.00	0.00	0.00	1984:1	0.01	0.00	0.01
Services	none	0.40	0.13	0.08	1967:1	0.09	0.02	0.00
Structures	1990:4	0.03	0.01	0.04	none	0.41	0.25	0.26
Panel B								
Durables	1985:1	0.01	0.00	0.00	1985:1	0.00	0.00	0.00
Nondurables	1990:4	0.07	0.04	0.07	none	0.54	0.36	0.34
Panel C								
GDPexp1					none	0.73	0.37	0.29
GDPexp2					1984:2	0.01	0.00	0.00
Panel D								
Durable Final Sales					none	0.55	0.62	0.72
Absolute Value of $(\Delta I/Dur)$					1984:4	0.00	0.00	0.00
Panel E								
GDB					1984:1	0.00	0.00	0.00
FSD					none	0.45	0.33	0.30

Note: With the exception of the second entry in Panel D, all results refer to break tests on the residual variance from an optimally chosen AR specification for either the growth contribution or growth rate of the variable listed in the first column. Results for growth contributions are reported in the second through fifth columns, while growth rate results are reported in the last four columns. Results of the tests for breaks in the AR coefficients are omitted because we do not reject stability in any of the cases. 'Sup', 'Exp' and 'Ave' refer to the supremum, exponential and average test statistics described in Equations 5, 6, and 7, respectively. Reported numbers are p-values of indicated test statistic. Estimated break dates are reported only when at least one test indicates significance at the 5 percent level. In Panel C, GDPexp1 is simulated output under the assumption of no reduction in the volatility of the durable goods sector after 1984:1. GDPexp2 is generated under the assumption of constant nominal shares of the components of GDP growth. In Panel E, GDB is gross domestic purchases and FSD is final shares to domestic purchasers.

of the growth rate of durable goods production:[12]

$$\Delta dur_t = \Delta sal_t (\frac{sal}{dur})_{t-1} + \Delta ii_t (\frac{ii}{dur})_{t-1} \tag{10'}$$

where Δsal is the growth rate of real sales of durable goods and Δii is the growth rate of real inventory investment. We test for breaks in Δsal and $\frac{ii}{dur}$, but do not analyze Δii_t since in addition to the obvious computational difficulties associated with its construction, it lacks a clear economic interpretation.

The structural break test results are reported in Panel D of Table 4. The first line in Panel D shows that there is no evidence of a change in the volatility of sales growth over our sample period. That we find no reduction in the volatility of durables sales, but strong evidence of a break in durables production, is unsurprising when we view plots of these two series. Figure 4 shows that for the period prior to the early 1980's, production is considerably more variable than sales, while for the period since, the variability of production dampens to a level apparently comparable to that of sales.

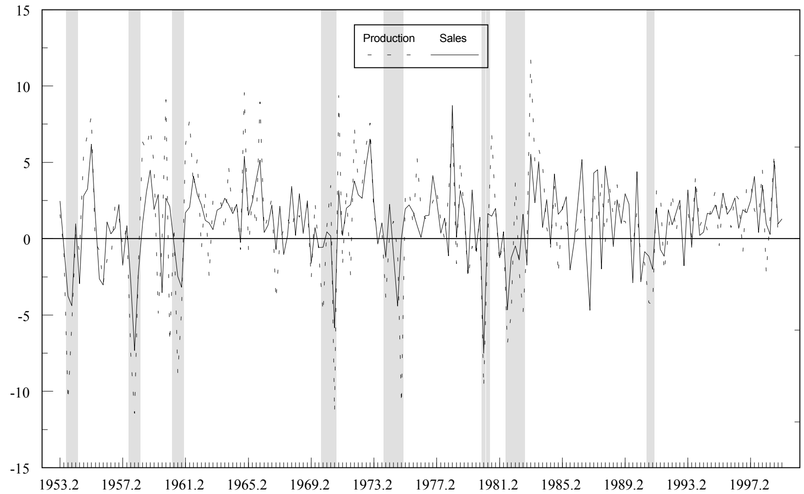
In contrast to the constant volatility of sales growth over our sample, the second line of Panel C reports strong evidence of a break in $|\frac{\Delta inv}{dur}|$ in the third quarter of 1984, a date that corresponds closely to that found for aggregate output. Note that we test the absolute value of $\frac{ii}{dur}$ because we are interested in determining whether inventory movements, either positive or negative, have become a smaller fraction of durables production. Our results indicate that this is precisely what has happened–for the period since the early 1980's, the average share of this extremely volatile component of durables output is approximately half its previous value.

3.2 Discussion

Our decomposition of U.S. real GDP growth sheds light on the economic sources of the volatility decline. For example, while one might be tempted to attribute the

[12]Though our interest is in the variance of durables growth rather than its level, we simplify the analysis by testing for breaks in the terms of Equation 10' since the terms of the expression for the variance are only more complicated functions of the former.

Figure 4: Production and Sales of Durable Goods - 1953:2 to 1999:2



increased stability to a shift towards services and away from goods production, our analysis indicates that such compositional shifts have been of little importance for stabilizing real GDP growth. Further, since the aggregate volatility drop stems from a reduction in volatility *within* the durable goods sector itself, its source is clearly not a shift in the composition of output across broad sectors of the economy.[13] Further, since the aggregate volatility drop stems from a reduction in volatility *within* the goods sector itself, its source is clearly not a shift in the composition of output across broad sectors of the economy.

Looking in another direction, there is a growing literature documenting changes in the conduct of U.S. monetary policy before and after 1979 and discussing the extent to which such changes are likely to have rendered policy a more stabilizing influence in the later period (see for example, Clarida, Galí and Gertler (1998)). While the timing of this explanation lines up closely enough with the volatility decline documented in this paper, any argument for an important role for policy would have to explain why

[13]Filardo (1997) points out that while employment shares in manufacturing have fallen dramatically, productivity increases in that sector have offset the effects of declining employment on output.

we observe a decline only in durables volatility, with no corresponding decline in the volatility of any other sector of the economy. Further, even if one can argue that the interest sensitive durable goods sector might be the most responsive to policy, it is difficult to imagine a model in which policy has effects on the production of durable goods, but leaves the process for sales unaffected. Though an important role for policy cannot be ruled out by our decomposition, neither is it easy to construct a policy related story consistent with the facts presented here.

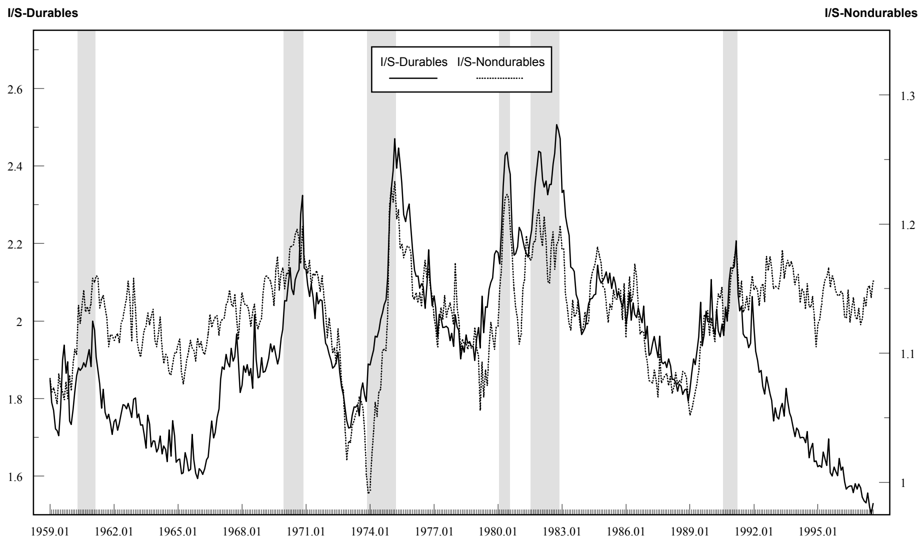
One might also hypothesize that trade patterns shifted in such a way that the U.S. began importing, rather than producing, goods from relatively volatile sectors. To examine this hypothesis, we conducted structural break tests on gross domestic purchases of goods and services (denoted GDB), which is essentially gross domestic production with imports added back in and exports subtracted out. The first row of panel D in Table 4 shows that the volatility decline is also a feature of domestic purchases, suggesting that changes in trade patterns are not an important factor in the volatility decline.

None of the above scenarios explains why we observe a dramatic decline in durables production volatility, but no decline in sales volatility. Nor do they explain why a sharp reduction in the share of durables output accounted for by inventories occurred around the same time as the aggregate volatility decline. These stylized facts suggest an important role for durables inventories in explaining the aggregate volatility decline.

One hypothesis is that changes in inventory management, such as the use of 'just-in-time' techniques, have brought about the reduced share of durables inventory and the associated stability of aggregate output.[14] While we do not test this hypothesis here, we highlight a number of patterns in the data that are suggestive of improved

[14] Discussion of just-in-time techniques can be found Freeland (1991), Morgan (1991), Bechter and Stanley (1992), Norris et al. (1994) Allen (1995), Filardo (1995), Flood and Lowe (1995), Hirsch (1996), Ramey and West (1997). Not surprisingly, there is also much discussion of improved inventory management in trade journals and the business press, examples include *Business Week* (April 4, 1994), *Supply Management* (July 16, 1998), *Barron's* (May 25, 1998), and *Purchasing* (September 1, 1998).

Figure 5: Inventory to Sales Ratios: 1953:2 to 1997:2



inventory management.

For example, inventory-to-sales ratios in durables, as shown in Figure 5, have been declining almost steadily since the early 1980's. Interestingly, no such change in trend is evident in the nondurable goods sector. Perhaps more striking is evidence from a monthly survey conducted by the National Association of Purchasing Managers, which prompts respondents to report how many days in advance they order production materials. Though not reported here, we find a statistically significant increase in the early 1980's in the proportion of respondents ordering their production material hand-to-mouth (15 days or less), as well as in those ordering 30 days or less. In addition, the average lead time across all respondents for the period from January 1961 to December 1983 was seventy-two days, while it was only forty-nine days for the 1984-98 period.

Though our discussion of inventories has concentrated on the durables goods sector, we undertake one final test to illustrate the importance of changes in inventory behavior for aggregate GDP volatility. In particular, we subject final sales to domestic purchasers (FSD), defined as GDB minus imported as well as domestically produced inventories, to a structural break test of the form conducted throughout this paper. In the bottom row of Table 4, we see that FSD does not have a volatility break. Thus, the volatility break is eliminated from domestic purchases by subtracting purchases of inventories from total purchases. In other words, there has been no change in the volatility of non-inventory purchases. Clearly some aspect of inventory investment in the U.S. has changed in such a way as to have had a strong effect of the volatility of U.S. output fluctuations.

A complete characterization of the mechanism by which inventories are an important factor in producing the lower volatility surely requires the use of disaggregate data. Industry-level data should allow one to distinguish a scenario in which the source of stability is improved inventory management techniques from one in which the declining share of inventory investment reflects a shift toward less inventory-intensive industries. Similarly, one could investigate whether shifts in the composition of goods by stage of processing has effected a reduction in the fraction of inventories held in the aggregate.

4 Conclusions

This paper identifies a structural decline in the volatility of quarter-to-quarter fluctuations in U.S. GDP growth in the early 1980's. We trace the source of the reduction in aggregate volatility to a decline in the volatility of durables output and provide evidence that the timing of the drop in durables volatility corresponds to a reduction in the share of durables output accounted for by inventory investment.

This break in volatility has important implications for widely used theoretical and empirical techniques, examples of which include the estimation of state-space models of business cycle fluctuations, model calibration exercises and the estimation of structural vector autoregression models over periods spanning the break. In addition, since the break implies that we are now much less likely to see extreme movements in GDP growth, it affects the interpretation policymakers place on particular growth rate realizations.

Finally, while the evidence in this paper points only to a change in quarter-to-quarter rather than cyclical fluctuations in output, one interesting aspect of the cycle that we have not explicitly considered is that documented in Sichel (1994). In particular, Sichel finds that there are typically three phases of a business cycle; recessions, high growth recoveries and moderate growth periods following recoveries. He attributes this three phase pattern for the post-war period to swings in inventory investment. Moreover, he points out that there was not a high growth recovery following the recession of 1990-91 and attributes this to a combination of both weak inventory investment and weak final sales. The question of why sales growth was so weak following this recession not withstanding, one would like to know whether inventory investment tracked sales more closely during the early years of this recovery than during other recoveries, thus rendering the recovery more sluggish than it otherwise might have been. The diminished role of inventories documented here may serve to substantially weaken the high growth recovery phase.

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