Sources of the Great Moderation: A Time-Series Analysis of GDP Subsectors

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Abstract

Recent work finds evidence that the volatility of the U.S. economy has fallen dramatically since the mid-1980s. We trace the timing of this so-called "Great Moderation" across many subsectors of the economy in order to better understand its root cause. We find that the interest rate sensitive sectors generally experience a much earlier volatility decline than other large sectors of the economy. The changes in financial deregulation and Federal Reserve stabilization policies that occurred during the early 1980s support the view that improved monetary policy may have played an important role in stabilizing real economic activity.

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1. Introduction

Recent work finds evidence that the volatility of the U.S. economy fell dramatically in the mid-1980s. Kim and Nelson (1999), McConnell and Quiros (2000) and Blanchard and Simon (2001) are among the first to recognize and analyze this phenomenon. Stock and Watson (2002) report that the standard deviation of real U.S. GDP growth during the 1984 – 2002 period was 61% smaller than that during the 1960 – 1983 period. Moreover, the volatility reduction seems to be wide-spread in that the growth rates of many macroeconomic variables stabilized during the 1980s. A number of papers call this phenomenon the "Great Moderation" and set the timing of the reduction in early 1984.[1]

Despite abundant evidence documenting the Great Moderation, the debate remains open regarding the root cause of the stabilization. The existing literature has largely focused on three possible explanations: good luck, improved monetary policy, and technological change. The essence of the "good luck" argument is that the macroeconomy has experienced a relatively small number of large shocks since the 1980s. For example, Blanchard and Simon (2001) estimate the growth rate of real GDP (Δy_t) as the AR(1) process: $\Delta y_t - \mu = \phi_1(y_{t\text{-}1} - \mu) + \varepsilon_t$ which implies $Var(\Delta y) = Var(\varepsilon)/(1-\phi_1^2)$. They find a significant decline in $Var(\varepsilon)$ but do not find a change in the propagation parameter ϕ_1. Similarly, Stock and Watson (2002) find that real GDP growth in a number of other countries stabilized at roughly the same time as the U.S. economy. As such, they conclude that "… monetary policy can take credit for only a small fraction of the great moderation." Instead, they argue that a fortuitous decrease in the size of the common international shocks accounts for the volatility reductions in the G7 countries. The counterfactual

[1] Also see McConnell, Mosser and Quiros (1999), Chauvet and Potter (2001), Sensier and van Dijk (2004), and Kim, Nelson and Piger (2004).

analyses conducted by Ahmed, Levin and Wilson (2004), and Kim, Morley and Piger (2008) further strengthen the impression that the stabilization of U.S. economy was due to good luck in the sense that smaller and less frequent shocks hit the economy.

Bernanke (2004) argues that a better monetary environment has stabilized inflationary expectations and mitigated price level fluctuations. In such an environment, the Federal Reserve is better able to influence economic activity and the economy is better able to absorb outside shocks. In a slightly different vein, Romer (1999) constructs very long time series of several measures of aggregate U.S. output and shows that the frequency and duration of recessions have declined while the duration of expansions has increased. As such, she argues that better demand management policies have acted to mitigate downturns in the economy and, hence, to stabilize real GDP. Ramey and Vine (2004) study the behavior of U.S. automobile industry and their finding implies that the monetary policy may be the key to understanding the volatility reduction of the aggregate economy.

The notion that improved technology has resulted in a more stable economy has been championed by McConnell and Quiros (2000) and Kahn, McConnell and Quiros (2002). Using somewhat disaggregated data, they trace the Great Moderation to a reduction in the production of durable goods but not in the sales of durables. As such, they argue that better inventory management (due to better technology) best explains the Great Moderation.

In this paper, we measure the timing and magnitudes of the volatility reductions in highly disaggregated subsectors of the economy. Although such measurement is interesting for its own sake, our ultimate aim is to provide some indirect evidence regarding the causes of the Great Moderation. The five panels of Figure 1 suggest that the volatility reduction did not occur uniformly across all sectors of the economy. Note that residential investment and the export of goods seem to experience volatility reductions earlier than the services and durable goods sectors. Using more formal techniques, we find that the volatility in a number of important interest rate sensitive sectors declined prior to 1984:1. There was also an early and sizable volatility reduction in the export of goods, but not in the export of services or in any of the import sectors. Moreover, many sectors that one would think are inventory-sensitive did not experience any significant volatility changes surrounding 1984:1 and a direct study of the change in private inventory even finds an (insignificant) increase of volatility in the early 80s. It is possible that the volatility decline first occurred in the interest rate sensitive sectors and then spread out to the whole economy.

We use two different methods of detecting the timing of the volatility breaks in various subsectors of the U.S. economy. In Section 2, we describe how an AR(p)-ARCH(q) model can be modified so as to estimate the break dates in volatility. Since inference in such a model is nonstandard, we develop a Monte Carlo procedure to show the significance of volatility breaks and the precision of the estimated break dates. Section 3 presents our key finding that interest rate sensitive sectors generally experienced a much earlier volatility decline than the other sectors of the economy. We also provide the posterior odds ratio by following Mankiw, Miron and Weil (1987) to give an additional measure about the precision of the estimated break dates. Section 4 provides further evidence on the timing of the volatility reduction for several important GDP subsectors based upon the Markov regime-switching model. Section 5 discusses the extent to which our findings are consistent with the proposed explanations for the Great Moderation.

2. The General Methodology

In this section, we describe a general methodology that can be used to detect a volatility break in a large number of sectors. To avoid being *ad hoc,* and potentially overfitting the data, we apply the identical methodology to each of the 51 different series examined in this paper. The method has the advantage that it is not residual-based in that the equations for the mean and the variance are simultaneously estimated using maximum likelihood techniques. For now, we ignore the problem of estimating the appropriate lag lengths and consider a simple modification of a standard AR(1)–ARCH(1) model:

$$y_t = a_0 + a_1 y_{t-1} + \varepsilon_t; \quad \varepsilon_t \sim N(0, h_t) \tag{1}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 D_t \tag{2}$$

where: y_t = quarterly growth rate of output for the industry in question, $D_t = 0$ if $t < t^*$ and $D_t = 1$ otherwise. The parameter values are such that $-1 < a_1 < 1$, $\alpha_0 > 0$, $\alpha_1 \geq 0$, and $\alpha_0 + \gamma_1 > 0$.

The important feature in (1) and (2) is that the conditional variance, h_t, is augmented by a structural break in the intercept term. The intercept of h_t is α_0 prior to t^* and is $\alpha_0 + \gamma_1$ beginning at t^*. Hence, if γ_1 is negative, there is a volatility reduction at t^* equal to -γ_1 in the short-run and -$\gamma_1/(1 - \alpha_1)$ in the long-run.

If the break date t^* is known, it is possible to construct the variable D_t and estimate (1) and (2) using standard maximum likelihood methods. Inference on the estimate of γ_1 can be conducted using a standard *t*-distribution. However, when we use actual economic data, the break dates are unknown so that a different methodology is necessary. A straightforward way to estimate t^* is to use a grid search procedure to find the most likely break date. Specifically, for each value of t^* in the interval 1981:1 – 1986:4, we estimate a model in the form of (1) and (2).[2] The value of t^* yielding the largest value of the likelihood function is taken to be the best

[2] Although it would be possible for us to begin the search prior to 1981:1, it is highly unlikely that the cause of the Great Moderation began before 1981:1. Moreover, to our knowledge, no one has claimed that the source of the Great Moderation started as late as 1986:4.

estimate of the break date. Although other reasonable methods to find volatility breaks are available, this method has the advantage that it is easily applicable to all of the series we analyze below. The downside of the method is that the use of a grid search means that the usual t–statistic for the null hypothesis $\gamma_1 = 0$ does not have a standard distribution.

In order to obtain a reasonable idea of the distribution of t-statistic for the null hypothesis $\gamma_1 = 0$, we conducted a simple Monte Carlo experiment. Specifically, setting $\gamma_1 = 0$ and for various values of a_1 and α_1, we generated 5000 Monte Carlo replications of (1) and (2) with T = 151 observations (Note: As discussed below, our data set contains 151 observations covering the period 1970:1 – 2007:3). Every generated series was estimated for each value of t* in the interval 45 – 68 (Note: With 151 observations, t^* = 45 corresponds to 1981:1 and t^* = 68 corresponds to 1986:4). The value of t^* yielding the greatest value of the likelihood function was designated as the most likely break date for that particular series. The t-statistic for the null hypothesis $\gamma_1 = 0$ was saved so that we have a total of 5000 t-statistics for the null hypothesis $\gamma_1 = 0$. Table 1 shows the upper and lower limits of the t-statistics that can be used to implement 10%, 5% and 1% tests for the null hypothesis $\gamma_1 = 0$. Note that we report the upper and lower limits for combinations of a_1 and α_1 such that a_1 = (0.0, 0.1, 0.2, 0.3, 0.4, and 0.5) and α_1 = (0.0, 0.2, 0.4, and 0.6). For example, given that $a_1 = \alpha_1 = 0$, 95% of the t-statistics fell within the interval – 2.115 to 2.686.

Notice that the quantile intervals of the t-statistic in Table 1 are wider than those from a standard t-distribution because we are searching for the break date. Since the interval 1981:1 to 1986:4 is near the early portion of the data set, the resulting quantile intervals are not symmetric around zero. The key points to note about the quantile intervals are that they are relatively insensitive to the values of a_1 and α_1 in the data-generating process. As such, we can get a reasonable idea about the significance of the break using the values in the table corresponding to the estimated values of a_1 and α_1. A more conservative approach is to use the t-statistics associated with the values of $a_1 = \alpha_1 = 0$. This set of values gives the widest possible quantile intervals and is analogous to a supremum test. Hence, suppose that a researcher estimates a series generated by (1) and (2) and finds that the t-statistic for the null hypothesis $\gamma_1 = 0$ is –1.96. As such, it would be reasonable to maintain that there is a break in the volatility of the series with 90% confidence, but not 95% confidence.

A second issue pertains to the accuracy of the estimation of the break dates. Since each break date will be estimated with error, we wanted to get a notion about the precision of our methodology in estimating t^*. As such, we performed a second Monte Carlo experiment. Specifically, we generated 2500 series in the form of (1) and (2) for various values of a_1, α_1, and γ_1. The difference between this and the Monte Carlo experiment reported in Table 1 is that each generated series actually contains a break at the sample point corresponding to t^* = 1983:1 or 1984:1. The selection of t^* = 1984:1 is based on our finding that the most likely break date for the volatility reduction in real GDP growth is 1984:1. And the selection of t^* = 1983:1 reflects the most likely break date for several important GDP subsectors as we shall see in the next section. In each case (*i.e.*, t^* = 1983:1 and t^* = 1984:1), we estimated each generated series for all possible break dates in the interval 1981:1 to 1986:4 and recorded the break date providing the largest value of the likelihood function. The distribution of these estimated break dates can be used to show whether the estimated break date for any series is statistically different from a true break date of 1983:1 or of 1984:1.

The results are shown in Table 2 for various values of a_1, α_1 and break sizes. All of the series are constructed such that the intercept for the post-break volatility ($\alpha_0 + \gamma_1$) is unity.

Hence, the first column in the table (labeled γ_1) measures the break size relative to the post-break intercept. Unfortunately, the results shown in the table are a bit disappointing in that the break dates for small volatility breaks are poorly estimated. For example, when the true break date is 1983:1 and for the case of $-\gamma_1 = 2$ and $a_1 = \alpha_1 = 0$, 90% of the estimated break dates occurred within the 1981:1 – 1985:3 period and 95% occurred within the 1981:1 – 1986:2 period. As such, for small volatility breaks, the precision of the estimated break date is poor. However, the dates for large breaks can be reasonably well estimated. For example, for $t^* = 1983{:}1$, $a_1 = \alpha_1 = 0$, and $-\gamma_1 = 5$, 90% of the estimated break dates occurred in the interval 1983:1 – 1984:1. Not surprisingly, the precision of the estimated date is largest when the ARCH effect is small and the persistence of autoregressive parameter a_1 is small.

Before proceeding, it is necessary for us to remind the reader that the Monte Carlo results only yield a rough estimate of the confidence intervals for γ_1 and t^* for the actual sectoral data analyzed below. Bootstrapping each series would very likely yield more accurate confidence intervals.

3. GDP Subsectors: Estimation Results and Discussions

In this section, we obtain the estimates of most likely break dates for the various subcomponents of private sector spending. Unlike the simple AR(1)–ARCH(1) model discussed above, we need to estimate the lag lengths in the mean and conditional variance equations. Consider the following generalization of (1) and (2):

$$y_t = a_0 + \sum_{i=1}^{p} a_i y_{t-i} + \varepsilon_t \tag{1'}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \gamma_1 D_t \tag{2'}$$

Notice that the model of the mean has p lags and that the model of the conditional variance has two lags.[3] For each estimated series, we selected the lag length p using the general-to-specific method. Beginning with a lag length of 5, we estimated an equation in the form of (1'). If the value of a_p was not significant at the 5% level, we re-estimated the model using $p - 1$ lags. This procedure was repeated until the last lag was significant or we reached $p = 0$. Conditional on this lag length, for each value of t^* in the interval 1981:1 – 1986:4, we estimated (1') and (2') as an ARCH(2) process. The value of t^* yielding the largest value of the likelihood function was taken to be the consistent estimate of the break date. As for the model of the volatility, if α_q was not significant at the 5% level, we reestimated the series as an ARCH(q-1) process for $q = 2$ or 1.

3.1. Private Sector Expenditures

The results of the estimations for various categories of private spending are reported in Table 3. We use every one of the quarterly series in Table 1.5.3 of the seasonally adjusted Real GDP data set (in expanded detail) obtained from the website of the Bureau of Economic Analysis[4]. The sample period is from the first quarter of 1970 to the third quarter of 2007. Notice that for real GDP, the estimated break date is 1984:1. Since the estimated intercept term (α_0) is 1.339 and the estimated magnitude of the break (γ_1) is −1.117, it follows that the estimate of the post-break intercept ($\alpha_0 + \gamma_1$) is 0.222. The t-statistic for the null hypothesis $\gamma_1 = 0$ is −4.732. If we compare this value to the relevant "pseudo-critical value" from Table 1, it is clear that the

[3] As in Hamilton and Susmel (1994), the ARCH effects are small once the break in the intercept of h_t is controlled for. Also, Ma, Nelson and Startz (2007) show that inference in a GARCH model may be spurious in these circumstances.

[4] The series 'change in private inventory' is absent from the Table 1.5.3 but extracted from the Table 1.4.6.

implied volatility reduction is highly significant.[5] This is true even if the conservative supremum 97.5% confidence interval of −2.401 to 2.974 is used. As reported in column six of the table, the pre-break estimate of the mean level of volatility is about six times its post-break level (i.e., as shown in the table, the ratio of h_2/h_1 = 16.6%) [6]

The remaining portions of Table 3 examine the subcomponents of real GDP. The last column labeled by '%' reports the percentage share of each examined subsector in GDP at the time 1984:1 which gives a rough idea about the contribution of each subcomponent to GDP overall since the contribution is largely stable throughout the sample period. If we use the approximate critical values in Table 1, it is clear that Personal Consumption Expenditures (PCE), which constitutes nearly two-thirds of the GDP, experience a significant volatility reduction (the t-statistic for the null hypothesis $\gamma_1 = 0$ is −3.292) in 1986:3. Although the volatility falls to 24.8% of its original level, the break occurs far later than that for real GDP volatility. If we examine the subcategories of PCE, it appears that durable goods volatility falls at the same time as overall PCE volatility. Furthermore, within the durable goods sector, the most relevant subsector appears to be the motor vehicles and parts subsector which has a significantly volatility reduction by about 70% in 1986:3. The volatility of nondurables is estimated to occur at the boundary of our search, 1981:1, so that it is quite possible that the volatility reduction of nondurables actually occurred prior to 1981:1. The volatility reduction in services is estimated to occur in 1985:1. Among the subsectors of services, it appears that housing services have a

[5] For real GDP the estimated values of α_1 and a_1 are 0.00 and 0.25, respectively. From Table 1, if $\alpha_1 = 0.0$ and $a_1 = 0.20$, the lower and upper critical values for a 95% confidence interval are −2.082 to 2.550.

[6] The estimates in column six report the estimated ratio of the post-break unconditional variance, $(\alpha_0 + \gamma_1)/(1 - \alpha_1 - \alpha_2)$ to the pre-break unconditional variance, $\alpha_0/(1 - \alpha_1 - \alpha_2)$.

volatility decline as late as 1986:3. But interestingly, medical care has a large volatility reduction as early as 1981:4. The point is that the volatility reduction of the whole economy is not likely to have occurred due to a reduction in personal consumption expenditures. Most subsectors experienced a volatility reduction either as late as 1986:3 or a reduction far earlier than any of the standard explanations allow. Within the class of durables, only "Other" seems to have a significant volatility break prior to 1984:1.

Next, we examine Gross Private Domestic Investment (*GPDI*) and its subcomponents. Regarding the overall level of *GPDI*, the absolute value of the *t*-statistic for the null hypothesis $\gamma_1 = 0$ is large relative to those in Table 1 and the magnitude of the reduction is sizable. The key point to note is that the volatility reduction in this sector was concurrent with that of real GDP. The estimates of the subcomponents are such that the break in Fixed Investment occurs at almost the same time as the break in real GDP, whereas the reduction in Residential Investment is estimated to occur at 1983:1. Relative to the entries in Table 1, Nonresidential Investment seems to have had a marginally significant volatility reduction in 1983:4. Finally, contrary to the hypothesis of improved inventory management, the change in private inventory did not experience a volatility reduction but instead an (insignificant) increase.

Exports of Goods experienced a volatility reduction prior to 1984:1, but the break in the export of services is estimated to occur in 1986:3. Volatility reductions in the imports of goods and services are estimated to have occurred in 1986:2 and 1986:3, respectively.

3.2. Government Expenditures

It is possible that the volatility reduction in GDP occurred because of a reduction in the volatility of government spending. Table 4 reports the results of our methodology applied to the various subcomponents of government spending. Notice that total government spending

(Government Consumption plus Investment) experienced a large volatility decline in 1985:4; far later than the slowdown in GDP volatility. At the Federal level, only National Defense Investment expenditures show a large volatility reduction prior to 1984:1 in that the intercept term falls from 176.301 to 29.011 (176.301 – 147.290) at 1981:2. The *t*-statistic for the null hypothesis $\gamma_1 = 0$ is quite large relative to those shown in Table 1. Otherwise, Defense related consumption experienced a volatility increase in 1986:1 and none of the *t*-statistics on any of the other estimates of γ_1 appear to be statistically significant. Interestingly, Gross Investment by state and local governments also experienced a large and significant volatility reduction in 1982:2. Thus, two components of government investment spending experienced a significant volatility reduction prior to 1984:1.

3.3. Discussion of the Estimation Results

The GDP subsectors with "statistically significant" volatility reductions occurring within the interval 1981:2 – 1986:3 (so that the break does not occur on the boundary) are shown in Figure 2. Note that the quarter of the break is in parentheses. We compare only subsectors at the same level of disaggregation since larger sectors are simply the agglomeration of the smaller sectors. For example, we do not report the break for Fixed Investment since we report the breaks for both Residential Investment and Nonresidential Investment.

Besides the Monte Carlo simulation results in Table 2, we also calculate the posterior odds ratio for each subsector reported in Figure 2 to provide an additional measure of the precision of these estimated break dates by following Mankiw, Miron and Weil (1987). The results are given in Table 5. We assign all dates within the search interval an equal probability to have a volatility reduction, *a priori*, then for such a diffuse prior the posterior odds ratio is approximately the ratio of the profile likelihood values calculated for all possible break dates.

The posterior odds ratio tells us how likely the volatility reduction happens at a date other than the estimated break date.

A visual inspection of Figure 2 along with the help of Table 5 clearly indicates two significantly different groups of the subsectors. One group appears to have had an earlier volatility decline during the period of 1981:4 to 1983:4. This group consists mainly of interest rate sensitive sectors: Federal National Defense Gross Investment, State and Local Gross Investment, Other Durables, Residential Investment and Nonresidential Investment. The other group that seems to have had a much later volatility reduction near the end of 1986 includes various services and the import sectors.

4. Further Evidence Using a Markov Regime-Switching Model

In order to provide additional evidence regarding our findings, we apply the Markov regime-switching model of Kim and Nelson (1999) and Kim, Nelson and Piger (2004) to a few important subsectors identified in the above section. As one may see below, the advantage of this method is that it can easily estimate the nonlinearity in both mean and volatility equations jointly and is able to produce an explicit switching probability of volatility reduction for each date. Consider the following setting-up:

$$(1-\phi(L))(y_t-\mu_{D_t})=\varepsilon_t;\varepsilon_t\sim N(0,\sigma^2_{D_t}) \tag{3}$$

$$\mu_{D_t}=\mu_0\cdot(1-D_t)+\mu_1\cdot D_t$$

$$\sigma^2_{D_t}=\sigma^2_0\cdot(1-D_t)+\sigma^2_1\cdot D_t$$

Where y_t represents the growth rate for each of relevant GDP subsectors; $\phi(L)=\sum_{i=1}^{p}\phi_i L^i$ and the lag length p is identified using the general-to-specific principle discussed in the above section; dummy variable $D_t = 0$ if $t < t^*$ and $D_t = 1$ otherwise; and t^* is the break date. Hence, this model allows for a potential break in the mean growth rate as well as in the volatility process. Note that σ_0^2 is the variance before the break and that σ_1^2 is the variance after the break. If there is a volatility decline we should find $\sigma_1^2 < \sigma_0^2$.

Following Chib (1998), we treat D_t as a discrete latent variable with the following transition probabilities to allow for, at most, one break:

$$\Pr(D_{t+1} = 0 \mid D_t = 0) = q$$
$$\Pr(D_{t+1} = 1 \mid D_t = 1) = 1$$
$$0 < q < 1$$

We estimate such a regime-switching model for the growth rates of GDP, Residential Investment, Nonresidential Investment, Exports of Goods, Motor Vehicles and Parts (MVP), and Housing Services. The estimation is done using standard maximum likelihood technique. Since our preliminary estimations find the shift in mean unimportant, we report results from the restricted model with no break in the mean.

In constructing the six panels of Figure 3, we used Kim's (1994) algorithm to obtain the smoothed probability of staying in the high volatility regime for each considered series. The shaded vertical line indicates the first date this probability falls below 0.5. The sharp decline of this probability for Residential Investment during the early 1980s adds to the evidence that this sector seems to have experienced an early volatility decline. On the other hand, the switching of the probability for Nonresidential Investment seems to be much more gradual. The smoothed probability for both Exports of Goods and Medical Care show a sharp decline during the early 1980s. But for both MVP and the Housing Services, the probability of switching into the low volatility regime happens much later. Overall, the results based on the Markov regime-switching model further strengthen our findings in Section 3.

5. Conclusion

We presented strong evidence that the Great Moderation did not occur uniformly across the various sectors of the economy. It is particularly interesting that various subcomponents of investment (i.e., Residential Investment, Nonresidential Investment, National Defense Investments Expenditures, and State and Local Government Investment) all declined prior to 1984:1. In contrast, the volatility declines of the services and import sectors generally occurred much later. This seems to be generally consistent with the arguments presented by Clarida, Gali and Gertler (2000) and Bernanke (2004) that better monetary policy helped to stabilize the economy. After all, monetary policy is most likely to affect the interest rate sensitive sectors. It is also possible that the relaxation of Regulation-Q in the early 1980s allowed for Residential Investment to respond more directly to changes in market interest rates.

It seems to be an anomaly that the volatility of MVP did not decline until 1986:3. It is generally agreed that this sector is quite responsive to interest rates. However, President Reagan's voluntary export restraints on Japanese automobiles went into effect in May 1981. Initially, only 1.68 million Japanese cars were allowed to enter the U.S. each year. The cap was raised to 1.85 million cars in 1984, and to 2.30 million in 1985. It is possible that the relaxation of the restraints subjected U.S. automobile makers to more foreign competition and ultimately stabilized sales.

We find little support for the notion that improved inventory management techniques were responsible for the Great Moderation. Transportation Equipment, Industrial Equipment, Other Equipment, and MVP all use large inventories. It is probably true that better inventory management practices have played an important role in these sectors. However, the important point is that we did not find early volatility reductions in these sectors. A direct study of the change in private inventory even reveals an (insignificant) increase in its volatility.

Another interesting finding is that the Exports of Goods had a volatility decline as early as 1982:4. Note that the post-break volatility is only about 1/6 of that of the pre-break volatility. On the surface this seems to be consistent with Stock and Watson's (2002) view that common international shocks stabilized demand. However, it is difficult to attribute the Great Moderation to the stabilization of foreign demand since the Exports of Services did not experience a volatility reduction until 1986:3. Moreover, we estimate that the U.S. Imports of Goods and the U.S. Imports of Services did not experience volatility declines until 1986.

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Table 1: Confidence Intervals for the Null Hypothesis $\gamma_1 = 0$

a_1	α_1	L 90%	U 90%	L 95%	U 95%	L 97.5	U 97.5
0.00	0.00	-1.8715	2.381	-2.115	2.686	-2.401	2.974
0.00	0.20	-1.9094	2.277	-2.146	2.545	-2.348	2.858
0.00	0.40	-1.8860	2.292	-2.131	2.553	-2.345	2.866
0.00	0.60	-1.8929	2.311	-2.125	2.557	-2.341	2.879
0.10	0.00	-1.8303	2.312	-2.099	2.571	-2.312	2.899
0.10	0.20	-1.8714	2.279	-2.128	2.520	-2.298	2.816
0.10	0.40	-1.8613	2.266	-2.100	2.543	-2.257	2.788
0.10	0.60	-1.8575	2.254	-2.116	2.529	-2.292	2.836
0.20	0.00	-1.8602	2.269	-2.082	2.550	-2.259	2.772
0.20	0.20	-1.8622	2.210	-2.072	2.479	-2.239	2.776
0.20	0.40	-1.8539	2.210	-2.075	2.495	-2.233	2.820
0.20	0.60	-1.8456	2.220	-2.068	2.506	-2.241	2.783
0.30	0.00	-1.8541	2.211	-2.065	2.484	-2.276	2.752
0.30	0.20	-1.8398	2.226	-2.070	2.503	-2.239	2.755
0.30	0.40	-1.8243	2.215	-2.051	2.489	-2.219	2.747
0.30	0.60	-1.8280	2.221	-2.055	2.490	-2.230	2.713
0.40	0.00	-1.8782	2.155	-2.069	2.457	-2.284	2.722
0.40	0.20	-1.8254	2.200	-2.031	2.472	-2.195	2.755
0.40	0.40	-1.8235	2.201	-2.017	2.469	-2.181	2.738
0.40	0.60	-1.8099	2.180	-2.017	2.484	-2.180	2.741
0.50	0.00	-1.9005	2.110	-2.101	2.397	-2.282	2.631
0.50	0.20	-1.8130	2.204	-2.002	2.459	-2.192	2.753
0.50	0.40	-1.8011	2.187	-1.975	2.461	-2.139	2.678
0.50	0.60	-1.7792	2.188	-1.981	2.441	-2.131	2.718

Table 2: Confidence Intervals for t^*

$-\gamma_1$	α_1	a_1	L 90%	U 90%	L 95%	U 95%	L 97.5	U 97.5	L 90%	U 90%	L 95%	U 95%	L 97.5	U 97.5
			Break Date = 1983:1						**Break Date = 1984:1**					
2	0.0	0.0	1981:1	1985:3	1981:1	1986:2	1981:1	1986:3	1981:2	1985:4	1981:1	1986:3	1981:1	1986:4
2	0.0	0.4	1981:1	1985:2	1981:1	1986:1	1981:1	1986:3	1981:2	1985:4	1981:1	1986:3	1981:1	1986:4
2	0.0	0.6	1981:1	1985:2	1981:1	1986:1	1981:1	1986:3	1981:2	1985:4	1981:1	1986:2	1981:1	1986:4
2	0.3	0.0	1981:1	1986:1	1981:1	1986:3	1981:1	1986:4	1981:1	1986:2	1981:1	1986:4	1981:1	1986:4
2	0.3	0.4	1981:1	1986:1	1981:1	1986:3	1981:1	1986:4	1981:1	1986:2	1981:1	1986:4	1981:1	1986:4
2	0.3	0.6	1981:1	1986:1	1981:1	1986:3	1981:1	1986:4	1981:1	1986:2	1981:1	1986:4	1981:1	1986:4
2	0.5	0.0	1981:1	1986:2	1981:1	1986:4	1981:1	1986:4	1981:1	1986:3	1981:1	1986:4	1981:1	1986:4
2	0.5	0.4	1981:1	1986:2	1981:1	1986:4	1981:1	1986:4	1981:1	1986:3	1981:1	1986:4	1981:1	1986:4
2	0.5	0.6	1981:1	1986:2	1981:1	1986:4	1981:1	1986:4	1981:1	1986:3	1981:1	1986:4	1981:1	1986:4
5	0.0	0.0	1981:3	1984:1	1981:2	1984:4	1981:1	1985:2	1982:2	1985:1	1981:4	1985:3	1981:2	1986:1
5	0.0	0.4	1981:3	1984:1	1981:2	1984:3	1981:1	1985:2	1982:2	1985:1	1981:4	1985:3	1981:2	1986:1
5	0.0	0.6	1981:3	1984:1	1981:2	1984:3	1981:1	1985:2	1982:2	1985:1	1981:4	1985:3	1981:2	1985:4
5	0.3	0.0	1981:2	1984:4	1981:1	1985:3	1981:1	1986:2	1982:1	1985:3	1981:3	1986:2	1981:1	1986:3
5	0.3	0.4	1981:2	1984:3	1981:1	1985:3	1981:1	1986:1	1982:1	1985:3	1981:2	1986:2	1981:1	1986:3
5	0.3	0.6	1981:2	1984:3	1981:1	1985:3	1981:1	1986:1	1982:1	1985:3	1981:3	1986:2	1981:1	1986:3
5	0.5	0.0	1981:2	1985:2	1981:1	1986:1	1981:1	1986:3	1981:4	1985:4	1981:2	1986:2	1981:1	1986:4
5	0.5	0.4	1981:2	1985:2	1981:1	1986:1	1981:1	1986:3	1981:4	1985:4	1981:2	1986:3	1981:1	1986:4
5	0.5	0.6	1981:2	1985:2	1981:1	1985:4	1981:1	1986:3	1981:4	1985:4	1981:2	1986:2	1981:1	1986:4
10	0.0	0.0	1982:1	1983:3	1981:4	1984:1	1981:2	1984:2	1983:1	1984:3	1982:3	1985:1	1982:1	1985:2
10	0.0	0.4	1982:1	1983:4	1981:4	1984:1	1981:2	1984:2	1983:1	1984:3	1982:3	1985:1	1982:2	1985:2
10	0.0	0.6	1982:1	1983:4	1981:3	1984:1	1981:2	1984:2	1983:1	1984:3	1982:3	1984:4	1982:1	1985:2
10	0.3	0.0	1981:4	1984:1	1981:3	1984:3	1981:1	1985:2	1982:4	1985:1	1982:2	1985:3	1981:4	1985:4
10	0.3	0.4	1981:4	1984:1	1981:2	1984:3	1981:1	1985:2	1982:4	1985:1	1982:2	1985:3	1981:4	1985:4
10	0.3	0.6	1981:4	1984:1	1981:3	1984:3	1981:2	1985:2	1982:4	1985:1	1982:2	1985:3	1981:4	1985:4
10	0.5	0.0	1981:4	1984:3	1981:2	1985:2	1981:1	1985:4	1982:3	1985:2	1982:1	1985:4	1981:3	1986:2
10	0.5	0.4	1981:4	1984:3	1981:2	1985:2	1981:1	1985:4	1982:3	1985:3	1982:1	1985:4	1981:2	1986:2
10	0.5	0.6	1981:4	1984:3	1981:2	1985:1	1981:1	1985:3	1982:3	1985:3	1982:1	1985:4	1981:2	1986:2

Table 3: Components of Private Sector Expenditures

	Date	α_0	γ_1	*t*-stat	h_2/h_1	Σa_i	$\Sigma \alpha_i$	%
Gross domestic product	1984:1	1.339	-1.117	-4.732	0.166	0.25	0.00	100
Personal consumption expenditures	1986:3	0.662	-0.498	-3.292	0.248	0.49	0.00	62.7
Durable goods	1986:3	16.138	-10.368	-2.631	0.358	0.00	0.00	8.1
Motor vehicles and parts	1986:3	60.810	-42.338	-3.244	0.304	-0.30	0.00	3.5
Furniture and household equip.	1981:4	3.215	-2.015	-1.739	0.373	0.42	0.28	3.1
Other	1982:3	6.332	-4.582	-2.716	0.276	0.00	0.55	1.5
Nondurable goods	1981:1	0.760	-0.512	-3.045	0.326	0.37	0.00	24.9
Food	1981:1	0.967	-0.613	-3.015	0.366	0.00	0.00	12.7
Clothing and shoes	1984:3	2.035	-0.923	-2.006	0.547	0.00	0.24	3.8
Gasoline, fuel oil, & other energy	1981:1	6.559	-4.737	-1.463	0.278	0.00	0.00	3.7
Other	1982:1	0.868	-0.509	-1.948	0.413	0.33	0.23	4.6
Services	1985:1	0.202	-0.140	-2.964	0.308	0.33	0.29	29.7
Housing	1986:3	0.098	-0.048	-2.217	0.505	0.68	0.00	9.0
Household operation	1986:1	2.404	-0.262	-0.457	0.891	-0.53	0.00	4.0
Electricity and gas	1981:1	8.936	-0.307	-0.120	0.966	-1.28	0.00	1.9
Other household operation	1982:1	0.640	-0.070	-0.500	0.890	0.42	0.00	2.0
Transportation	1986:1	1.628	-1.284	-1.814	0.211	0.56	0.47	2.3
Medical care	1981:4	0.794	-0.687	-3.654	0.135	0.51	0.00	6.4
Recreation	1983:1	0.935	-0.366	-1.946	0.609	0.30	-0.06	1.5
Other	1985:1	1.669	-1.018	-2.963	0.390	0.37	0.00	6.5
Gross private domestic investment	1984:1	41.692	-34.621	-2.789	0.170	0.06	0.00	18.5
Fixed investment	1983:4	6.692	-4.684	-2.838	0.300	0.52	0.00	18.2
Nonresidential	1983:4	5.432	-2.818	-2.261	0.481	0.62	0.00	13.3
Structures	1981:3	5.650	2.302	0.944	1.408	0.49	0.00	4.9
Equipment and software	1984:1	8.267	-4.446	-2.699	0.462	0.55	-0.07	8.4
Info. equipment and software	1983:4	8.455	-4.176	-2.303	0.506	0.55	0.00	2.4
Computers and equipment	1986:3	97.673	-75.408	-4.054	0.228	0.27	0.00	0.4
Software	1983:1	5.273	-2.339	-1.542	0.557	0.58	0.00	0.3
Other	1982:1	5.380	2.372	1.188	1.441	0.45	0.00	1.7
Industrial equipment	1981:3	7.275	-0.767	-0.376	0.895	0.44	-0.08	2.2
Transportation equipment	1986:3	36.344	-0.870	-0.085	0.976	0.05	0.06	1.9
Other equipment	1983:4	22.446	-16.098	-2.932	0.283	0.00	0.00	1.9
Residential	1983:1	25.144	-22.484	-3.694	0.106	0.61	0.33	4.9
Change in Private Inventory	1981:4	426.01	238.26	1.620	1.559	0.533	0	0.4
Exports	1983:1	11.352	-9.370	-3.286	0.175	0.27	0.26	9.9
Goods	1982:4	18.214	-15.008	-3.031	0.176	0.25	0.23	8.0
Services	1986:3	14.481	-8.898	-2.074	0.386	-0.23	0.00	1.9
Imports	1985:4	14.614	-12.707	-4.050	0.130	0.22	0.24	11.2
Goods	1986:2	17.417	-14.979	-3.465	0.140	0.00	0.28	9.5
Services	1986:3	10.231	-5.560	-2.539	0.457	0.00	0.00	1.9

Table 4: Components of Government Expenditures

	Date	α_0	γ_1	t-stat	h_2/h_1	Σa_i	$\Sigma \alpha_i$	%
Govt. cons. and gross investment	1985:4	1.014	-0.447	-2.174	0.559	0.33	0.00	20.1
Federal	1982:4	2.326	0.689	0.964	1.296	0.40	0.00	8.5
Nondefense	1981:1	2.189	1.475	1.421	1.674	-0.33	0.78	5.9
Consumption expenditures	1984:2	6.109	-2.881	-1.069	0.528	-0.43	0.64	5.0
Gross investment	1983:3	20.059	-3.323	-0.674	0.834	-0.71	0.25	0.9
National defense	1985:1	3.253	1.838	1.526	1.565	0.53	0.00	2.6
Consumption expenditures	1986:1	1.979	2.944	3.217	2.488	0.61	0.00	2.2
Gross investment	1981:2	176.301	-147.290	-3.479	0.165	-0.30	0.00	0.4
State and local	1986:1	0.946	-0.685	-3.236	0.276	0.25	0.05	11.6
Consumption expenditures	1986:1	0.171	-0.061	-1.378	0.642	0.62	0.00	9.1
Gross investment	1982:1	21.252	-17.291	-2.805	0.186	0.00	0.23	2.4

Notes for Table 3 and 4: Data in all subsectors but change in private inventory are from the National Income and Accounts Table 1.5.3. Data of change in private inventory is from Table 1.4.6. The last column "%" denotes the percentage share of each subsector in GDP at the time 1984:1.

Table 5: Estimated Break Dates for Some Important Subsectors and the Corresponding Posterior Odds Ratios

Date	GDP	Motor	Dur_ Other	House	Med_ Care	Ser_ Other	Non_ resi	Resi	Ex_ Goods	Exp_ Ser	Im_ Goods	Imp_ Ser	Fed_Nat _Def_Inv	State_L ocal_Inv
1/1/1981	0.03	0.03	0.11	0.00	0.10	0.03	0.09	0.01	0.03	0.00	0.00	0.01	0.60	0.00
4/1/1981	0.08	0.04	0.10	0.00	0.07	0.02	0.07	0.00	0.02	0.00	0.00	0.01	**1.00**	0.02
7/1/1981	0.07	0.03	0.08	0.01	0.07	0.02	0.06	0.02	0.11	0.00	0.00	0.01	0.47	0.02
10/1/1981	0.13	0.10	0.85	0.01	**1.00**	0.02	0.05	0.02	0.07	0.00	0.00	0.01	0.28	0.01
1/1/1982	0.31	0.07	0.76	0.01	0.70	0.01	0.13	0.02	0.41	0.00	0.01	0.00	0.15	**1.00**
4/1/1982	0.24	0.05	0.53	0.01	0.65	0.02	0.26	0.01	0.31	0.00	0.01	0.01	0.57	0.38
7/1/1982	0.24	0.02	**1.00**	0.01	0.31	0.02	0.25	0.00	0.55	0.00	0.01	0.01	0.34	0.61
10/1/1982	0.14	0.05	0.82	0.01	0.29	0.16	0.19	0.34	**1.00**	0.00	0.02	0.00	0.37	0.06
1/1/1983	0.11	0.03	0.56	0.01	0.14	0.18	0.15	**1.00**	0.75	0.00	0.02	0.00	0.18	0.03
4/1/1983	0.93	0.07	0.32	0.00	0.06	0.17	0.15	0.82	0.47	0.00	0.10	0.01	0.15	0.02
7/1/1983	0.90	0.07	0.45	0.07	0.03	0.20	0.36	0.77	0.20	0.00	0.14	0.01	0.09	0.03
10/1/1983	0.89	0.07	0.49	0.06	0.01	0.15	**1.00**	0.43	0.17	0.00	0.12	0.00	0.09	0.01
1/1/1984	**1.00**	0.06	0.55	0.06	0.01	0.20	0.73	0.17	0.17	0.01	0.50	0.07	0.05	0.03
4/1/1984	0.78	0.04	0.51	0.05	0.02	0.14	0.69	0.06	0.09	0.01	0.41	0.07	0.03	0.02
7/1/1984	0.39	0.02	0.42	0.40	0.01	0.46	0.49	0.04	0.06	0.01	0.12	0.07	0.02	0.04
10/1/1984	0.18	0.01	0.35	0.35	0.01	0.45	0.36	0.02	0.03	0.01	0.05	0.07	0.13	0.02
1/1/1985	0.08	0.02	0.25	0.49	0.00	**1.00**	0.29	0.01	0.05	0.01	0.78	0.06	0.07	0.01
4/1/1985	0.03	0.01	0.22	0.55	0.00	0.80	0.21	0.00	0.04	0.20	0.73	0.05	0.13	0.02
7/1/1985	0.05	0.03	0.15	0.45	0.00	0.50	0.30	0.00	0.03	0.01	0.52	0.18	0.11	0.01
10/1/1985	0.02	0.06	0.09	0.34	0.00	0.39	0.27	0.00	0.02	0.01	0.46	0.14	0.07	0.01
1/1/1986	0.01	0.04	0.06	0.41	0.00	0.40	0.30	0.00	0.01	0.51	0.43	0.13	0.04	0.02
4/1/1986	0.01	0.03	0.04	0.48	0.00	0.26	0.44	0.00	0.01	0.40	**1.00**	0.82	0.04	0.01
7/1/1986	0.00	**1.00**	0.14	**1.00**	0.00	0.17	0.33	0.00	0.00	**1.00**	0.55	**1.00**	0.47	0.00
10/1/1986	0.00	0.83	0.66	0.00	0.31	0.12	0.00	0.00	0.69	0.26	0.83	0.29	0.01	0.01

Note: The subsectors reported here are selected based on Figure 2. For each subsector, the posterior odds ratio for each date is the probability that the volatility reduction occurred at that date relative to the probability that the volatility reduction occurred at the estimated break date, that is, the date with the highest likelihood.

Figure 1: Growth Rates of GDP and Four Key Subsectors

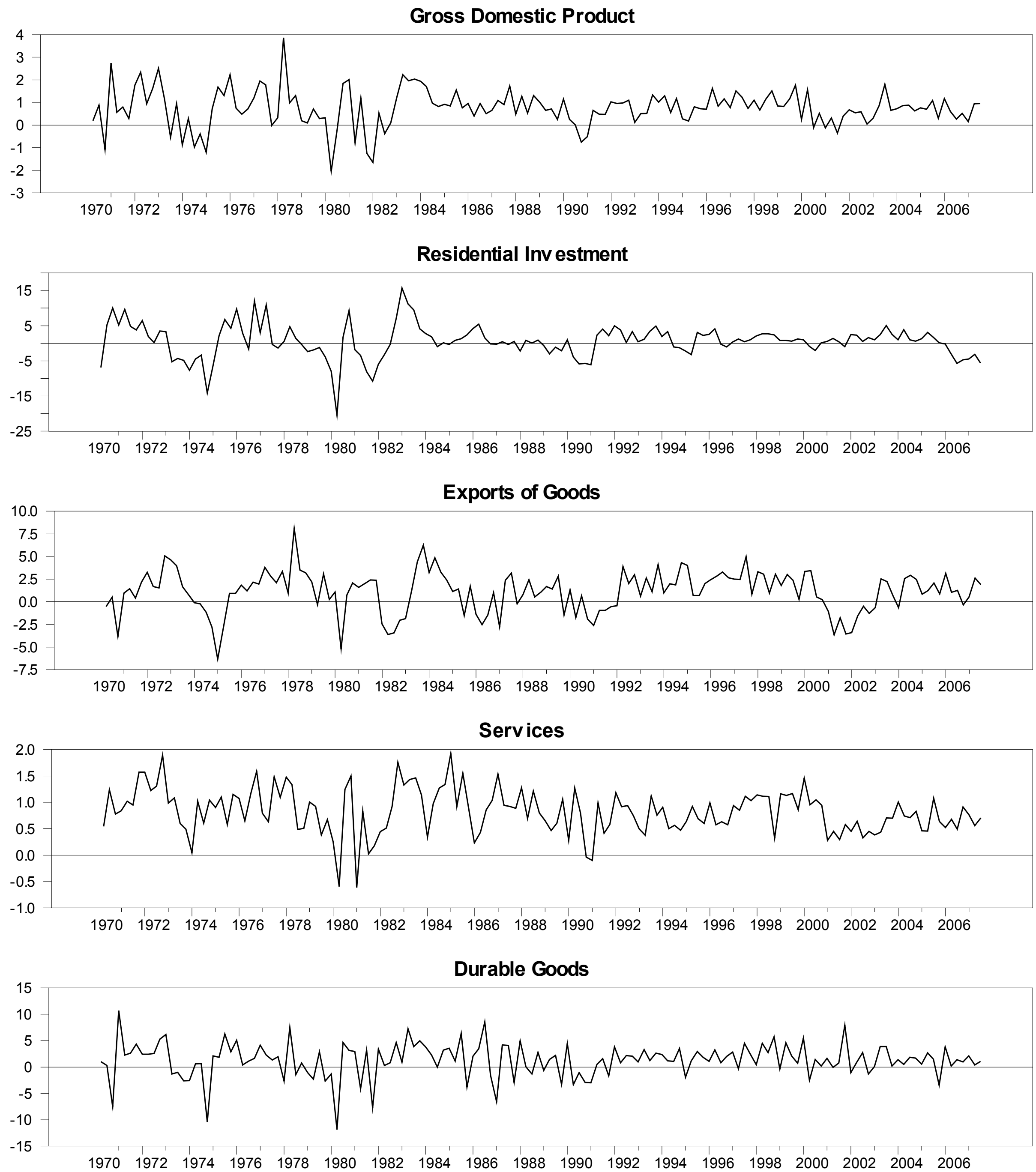


Figure 2: Estimated Break Dates

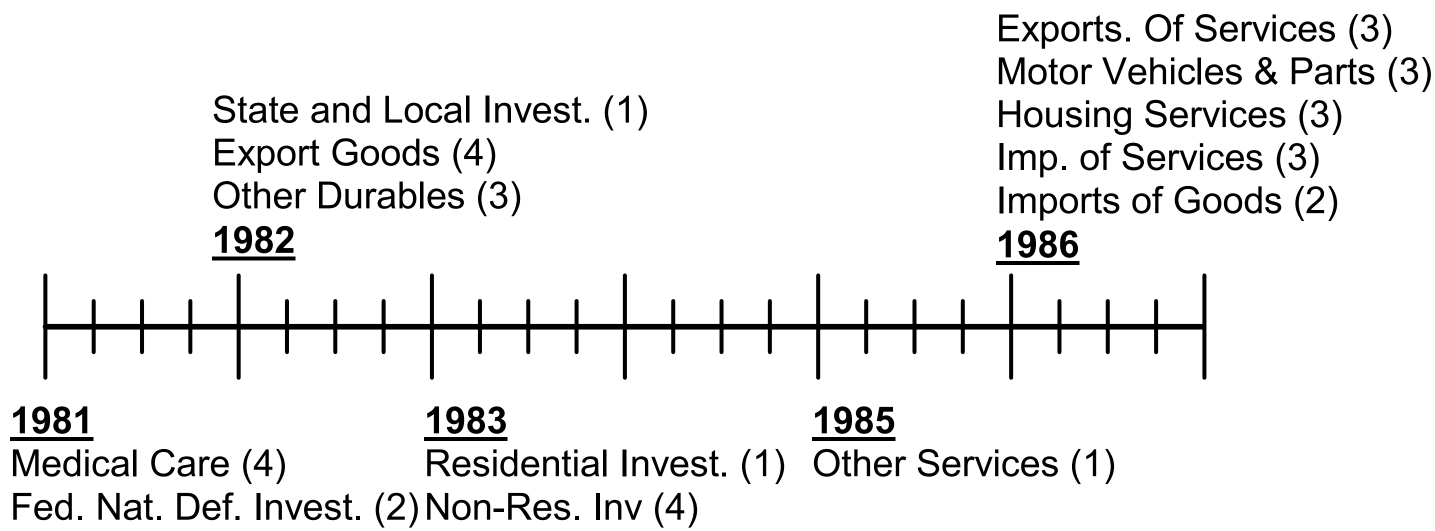
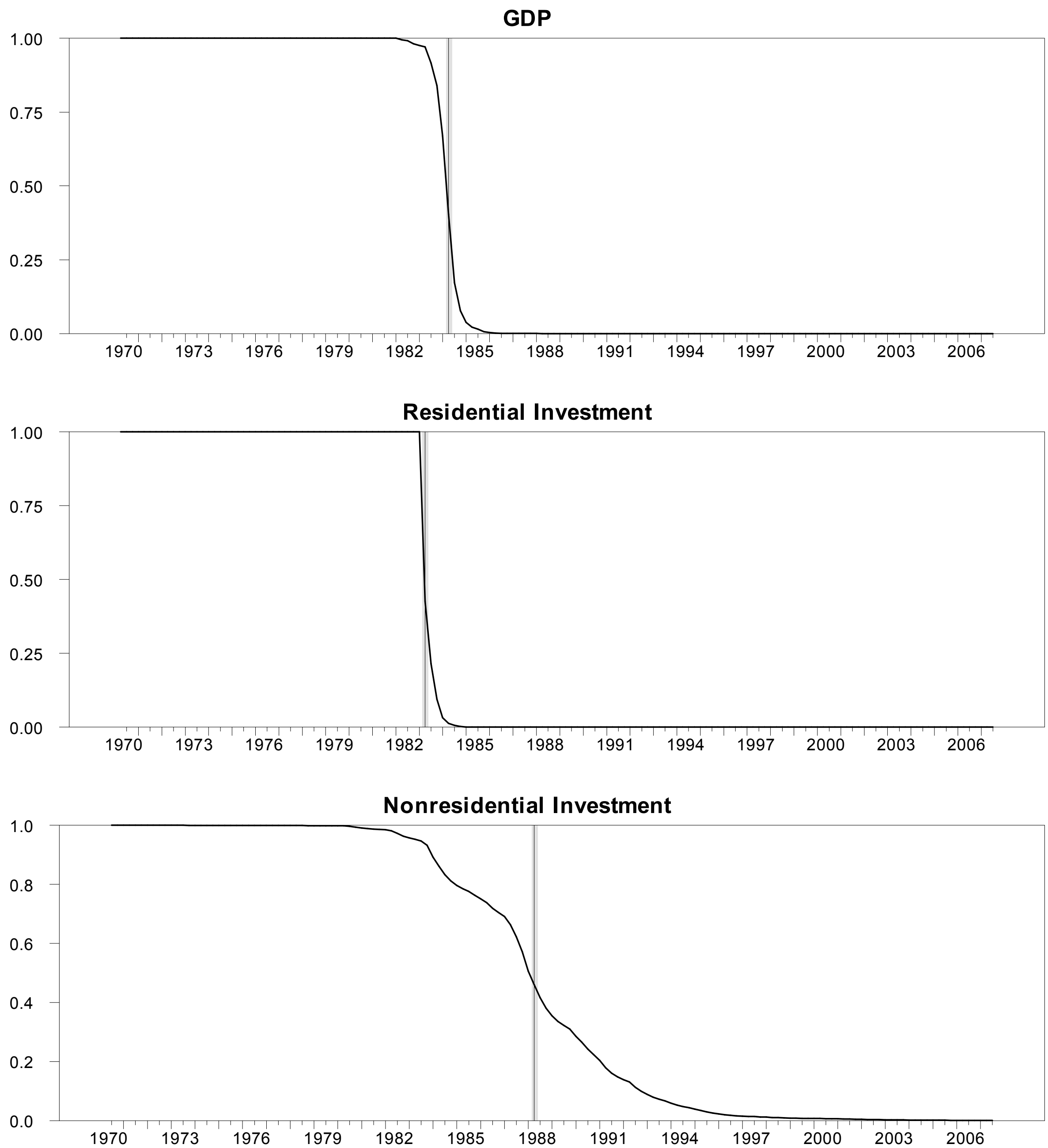
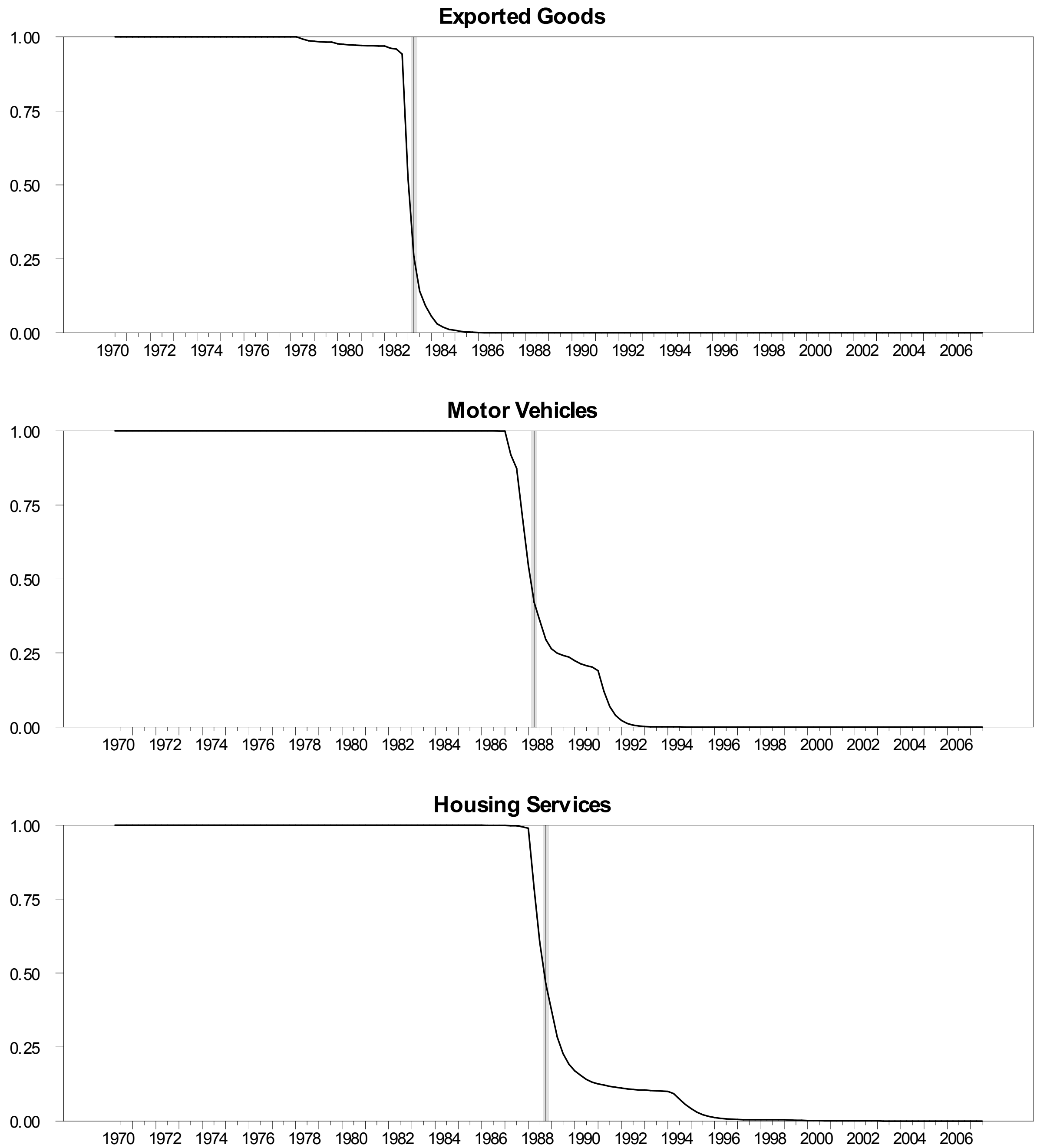


Figure 3 Smoothed Probability of Staying in the High Volatility Regime





Note: The shaded gridline represents the first quarter in which the probability of staying in the high volatility regime drops below 0.5.