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Cross-Country Evidence on Output Growth Volatility: Nonstationary Variance and GARCH Models

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Abstract

This paper revisits the issue of conditional volatility in real GDP growth rates for Canada, Germany, Italy, Japan, the United Kingdom, and the United States. Previous studies find high persistence in the volatility. This paper shows that this finding largely reflects a nonstationary variance. Output growth in the six countries became noticeably less volatile over the past few decades. In this paper, we employ the modified ICSS algorithm to detect structural change in the variance of output growth. One structural break exists in each of the six countries after identifying outliers and mean shifts in the growth rates. We then use generalized autoregressive conditional heteroskedasticity (GARCH) specifications, modeling output growth and its volatility with and without the break in volatility. The evidence shows that the time-varying variance falls sharply in Canada and Japan, and disappears entirely in Germany, Italy, the U.K. and the U.S., once we incorporate the break in the variance equation of output for the six countries. That is, the integrated GARCH (IGARCH) effect proves spurious and the GARCH model demonstrates misspecification, if researchers neglect a nonstationary variance. Moreover, we also consider the possible effects of our more correct measure of output volatility on output growth as well as the reverse effect of output growth on its volatility. The conditional standard deviation possesses no statistical significance in all countries, except a significant negative effect in Japan. The lagged growth rate of output produces significant negative and positive effects on the conditional variances in Germany and Japan, respectively. No significant effects exist in Canada, Italy, the U.K., and the U.S.

Journal of Economic Literature Classification: C32; E32; O40

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1. Introduction

The Great Moderation captured the attention of macroeconomists, especially since the decline in volatility of real GDP growth occurs in numerous developed countries. Kim and Nelson (1999), McConnell and Perez-Quiros (2000), and Blanchard and Simon (2001), among others, document a structural change in the volatility of U.S. GDP growth, finding a rather dramatic reduction in GDP volatility since the early 1980s. Mills and Wang (2003), Summers (2005), and Stock and Watson (2005) discover a structural break in the volatility of the output growth rate for the G7 countries and Australia, although the break occurs at different times. Kent *et al.* (2005) show a considerable decline in the volatility of real output around the developed world. That is, on average, across 20 selected OECD countries, the standard deviation of the annual growth rate of GDP fell by more than one percentage point since 1970s. Cecchetti *et al.* (2005) examine shifts in the volatility of growth in 25 developed and less-developed countries. They find at least one break in all but 9 countries and at most two breaks in 6 of the 25 countries. Among the 22 breaks, only one takes place in the 1970s, 12 are in the 1980s, and another 9 are in the 1990s.

Several important issues emanate from this phenomenon. First, what caused the decline in volatility? Analysts offer several hypotheses, including better macroeconomic policies, structural change, or good luck.[1] Second, how does one model the decline in volatility? Researchers frequently employ some form of a generalized autoregressive conditional heteroskedasticity (*GARCH*) modeling strategy to capture the movement in volatility under the assumption of a stable

[1] Bernanke (2004) organizes his thinking by using the most efficient inflation and output volatilities frontier, the so-called Taylor curve (trade-off) (Taylor, 1979, 1994; Cecchetti, 1998). Fuhrer (1997) and Lee (1999, 2002) estimate the Taylor trade-off for the U.S. Inefficient monetary policy leaves the economy above the frontier, whereas changes in the volatility of random shocks will shift the lower-bound frontier. Stock and Watson (2003, 2005) attribute the Great Moderation to good luck, implying that the frontier shifted toward the origin. Bernanke (2004) argues that a substantial portion of the Great Moderation reflects better monetary policy, implying a movement toward the frontier. The distinction proves important. Good luck can turn into bad luck and the frontier can shift back to a more unfavorable trade-off, or maintaining good policy can continue the benefits of the Great Moderation.

variance process. Third, does the reduction in output growth volatility affect the real GDP growth rate and/or does the output growth rate affect its volatility? The existing empirical evidence on this third question provides mixed evidence.

Our paper focuses on the latter two questions, putting aside the issue of what precipitated the decline in macroeconomic volatility. First, we argue that the extant methods of modeling the time-series properties of the volatility of the real GDP growth rate contain misspecifications associated with structural shifts. We address such misspecifications by introducing structural shifts in the volatility process. Second, given our improved specification of output growth volatility, we reconsider the effect of the real GDP growth rate volatility on the real GDP growth rate and the effect of the output growth rate on its volatility. In addressing both questions, we examine six countries – Canada, Germany, Italy, Japan, the United Kingdom, and the United States. [2]

Most research on the various aspects of output volatility, such as asymmetry or its effect on the growth rate, assumes a stable *GARCH* process governing conditional growth volatility. The neglect of structural breaks in the variance of output leads to higher persistence in the conditional volatility. For example, in Hamori (2000), the *GARCH* persistence of volatility equals 0.972 for Japan, 0.857 for the U.K., and 0.987 for the U.S. Caporale and McKiernan (1996) and Speight (1999) conclude near unitary persistence of 1.09 and 0.9889, respectively, for the U.K., and Fountas *et al.* (2004) find volatility persistence of 0.982 for Japan. In Ho and Tsui (2003), the exponential *GARCH* (*EGARCH*) persistence of volatility equals 0.848 for Canada, 0.834 for the U.K., and 0.916 for the U.S. In sum, all the persistence measures fall close to one.

Economic growth involves long-run phenomena. For longer sample periods, structural

[2] We exclude France, another G7 country. When the Lagrange multiplier (LM) test of Engle (1982) checks for conditional heteroskedasticity, insignificant LM statistics suggest no need of *GARCH* modeling for France. Cecchetti *et al*. (2005) report that France experiences no breaks in persistence and volatility of GDP growth.

changes in volatility will occur with a higher probability. Hamilton and Susmel (1994) and Kim *et al*. (1998) suggest that the long-run variance dynamics may include regime shifts, but within a regime it may follow a *GARCH* process. Kim and Nelson (1999), Mills and Wang (2003), Bhar and Hamori (2003), and Summers (2005) apply this approach of Markov switching heteroskedasticity with two states to examine the volatility in the growth rate of real GDP. The *GARCH* modeling approach provides an alternative to deal with this issue, but relaxing the implicit assumption of a constant variance process.

Diebold (1986) raises the concern that structural changes may confound persistence estimation in *GARCH* models. He notes that Engle and Bollerslev's (1986) integrated *GARCH* (*IGARCH*) may result from instability of the constant term of the conditional variance, that is, nonstationarity of the unconditional variance. Neglecting such changes can generate spuriously measured persistence with the sum of the estimated autoregressive parameters of the conditional variance heavily biased towards one. Lamoureux and Lastrapes (1990) explore Diebold's conjecture and provide confirming evidence that not accounting for discrete shifts in unconditional variance, the misspecification of the *GARCH* model, can bias upward *GARCH* estimates of persistence in variance. Including dummy variables to account for such shifts diminishes the degree of *GARCH* persistence. Mikosch and Stărică (2004) argue theoretically that the *IGARCH* model makes sense when non-stationary data reflect changes in the unconditional variance. Hillebrand (2005) shows that in the presence of neglected parameter change-points, even a single deterministic change-point, *GARCH* inappropriately measures volatility persistence. More recently, Kramer and Azamo (2007) argue that the changes in the variance could arise from changes in the mean. They demonstrate that the estimated persistence parameter in the *GARCH(1,1)* model contains upward bias when researchers ignore structural changes in the mean.

The evidence of declining output volatility combined with finding an *IGARCH* in conditional volatility motivates us to revisit conditional volatility in real GDP growth rates for Canada, Germany, Italy, Japan, the U.K., and the U.S. We first examine outliers and breaks in the mean growth rates, and then employ the iterated cumulative sum of squares (ICSS) algorithm, newly modified by Sansó, *et al.* (2004) to detect sudden changes in the variance of output growth. Then we apply *GARCH* specifications, modeling output growth and its volatility with and without breaks in volatility. The evidence shows that the time-varying variance falls sharply or disappears entirely, once we incorporate the breaks in the variance equation of output for the six countries. That is, the *IGARCH* effect proves spurious due to nonstationary variance.

The rest of the paper unfolds as follows. Section 2 discusses the data, outliers, and structural changes in the mean and its volatility. Section 3 presents the methodology and the empirical results. Section 4 considers additional evidence on the relationship between the output growth rate and its volatility. Finally, Section 5 concludes.

2. Data and Structural Change in Variance

Output growth rates (y_t) equal the percentage change in the logarithm of seasonally adjusted quarterly real GDP (Y_t) in Canada, Germany, Italy, Japan, the U.K., and the U.S., that come from the IMF *International Financial Statistics* (*IFS*) over the period 1957:1 to 2006:3. The identification of change points will occur endogenously in the data generating process. We employ the modified ICSS algorithm, proposed originally by Inclán and Tiao (1994) and adjusted recently by Sansó, *et al.* (2004) to detect structural changes in the variance. The analysis assumes that the time series of output growth displays a stationary variance over an initial period, and then a sudden change in variance occurs. The variance then exhibits stationarity again for a time, until the next sudden change. The process repeats through time, yielding a time series of observations with an unknown number of changes in the variance.[3]

In Inclán and Tiao (1994), the ICSS tests for changes in the unconditional variance of a stochastic process, assuming that the disturbances prove independent with Gaussian distributions. Let $\{\varepsilon_t\}$ denote a series of independent observations from a normal distribution with mean zero. When N variance changes occur in T observations, $1 < k_1 < k_2 < ... < k_N < T$ equal the set of change points. Let C_k equal the cumulative sum of the squared observations from the start of the series to the k[th] point in time (i.e., $C_k = \sum_{t=1}^{k} \varepsilon_t^2$, k = 1,…,T). Then, define D_k as: $D_k = (C_k / C_T) - k/T$, $k = 1,...,T$ with $D_0 = D_T = 0$. If no changes in variance occur over the sample period, the D_k statistic oscillates around zero. If one or more sudden variance changes exist in the series, then the D_k values drift either up or down and away from zero. Critical values based on the distribution on D_k under the null hypothesis of homogeneous variance provide upper and lower boundaries to detect a significant change in variance with a known level of probability. When the maximum of the absolute value of D_k exceeds the critical value, we reject the null hypothesis of no changes. Let k^* equal the value of k for which $\max_k |D_k|$ occurs. If $\max_k (T/2)^{0.5} |D_k|$ exceeds the predetermined boundary, then k provides an estimate of the change point. The factor $(T/2)^{0.5}$ standardizes the distribution. Under the null, D_k asymptotically behaves as a Brownian bridge.

Economic and financial time series, however, usually show distributions with fat tails (leptokurtic) and persistence in the conditional variance. Sansó, *et al.* (2004) find size distortions

[3] Aggarwal, Inclán, and Leal (1999) apply Inclán and Tiao's (1994) ICSS algorithm to identify the points of sudden changes in the variance of returns in ten emerging stock markets, in addition to Hong Kong, Singapore, Germany, Japan, the U.K., and the U.S. Rapach and Strauss (2007) employ Sansó, *et al.*'s (2004) modified ICSS to detect structural breaks in the unconditional variance of eight U.S. dollar exchange rate return series. Fang and Miller (2008)

for the ICSS test when the series are leptokurtic as well as conditionally heteroskedastic, which produce spurious changes in the unconditional variance. To overcome these problems, they adjust the test by explicitly considering the fourth moment properties of the disturbances and the conditional heteroskedasticity, using a nonparametric adjustment based on the Bartlett kernel. The modified statistic equals $\max_k T^{-0.5}|G_k|$, where $G_k = [\hat{\gamma}_0 + 2\sum_{l=1}^{m}[1-l(m+1)^{-1}]\hat{\gamma}_l]^{-0.5}[C_k - (k/T)C_T]$, $\hat{\gamma}_l = T^{-1}\sum_{t=l+1}^{T}(\varepsilon_t^2 - C_T/T)(\varepsilon_{t-1}^2 - C_T/T)$, and the procedure in Newey and West (1994) generates the lag truncation parameter m. Under general conditions, the modified ICSS statistic $\max_k T^{-0.5}|G_k|$ exhibits the same asymptotic distribution as that of $\max_k (T/2)^{0.5}|D_k|$, and simulations generate finite-sample critical values.

For longer periods, outliers will also occur with higher probability in addition to structural breaks in the output growth rates. An outlier observation appears inconsistent with other observations in the data set. That is, a low probability exists that on an outlier originates from the same statistical distribution as the other observations in the data set. Franses and Haldrup (1994) prove that outliers may produce spurious stationarity. In a recent study, Rodrigues and Ruhia (2007) show that the CUSUM-type tests for detecting structural breaks in variance such as the ICSS method in Inclán and Tiao (1994) and Sansó, *et al.* (2004) are sensitive to outlier observations. That is, neglected outliers bias the ICSS test towards finding a larger number of breaks. To rectify this issue, we first detect outliers from each series of the growth rate, using the extreme studentized deviate (ESD) test (see Walfish, 2006, who reviews statistical outlier methods). In a step-wise fashion, we remove an identified outlier and then repeat the procedure. We find no outliers in Canada, five outliers (i.e., 1991:1, 1963:1, 1968:2, 1969:2, and 1963:2) in Germany, three outliers

use this approach to determine the change point in the variance of U.S. output growth.

(i.e., 1970:1, 1966:1, and 1974:4) in Italy, two outliers (i.e., 1974:1 and 1960:1) in Japan, six outliers (i.e., 1973:1, 1979:2, 1963:2, 1958:2, 1974:1, and 1979:3) in the U.K., and three outliers (i.e., 1958:1, 1978:2, and 1980:2) in the U.S.[4] Most outliers were in the 1960s and 1970s. Stock and Watson (2005) and Levin and Piger (2006) replace outliers with the series-specific full-sample median growth rate and the median of the six adjacent observations, respectively. In this study, we replace the outliers with interpolated values as the median of the six adjacent observations that are not themselves outliers.

Then, we begin our analysis by looking for structural changes in the volatility for GDP growth in a series of steps. First, following Stock and Watson (2002, 2005) and Herrera and Pesavento (2005), we construct *AR* models for the growth rate series. Based on the Schwarz information criterion (*SIC*), the *AR(1)* process proves adequate to capture growth dynamics and produces white-noise residuals for Canada and Italy, *AR(4)* for Germany, Japan and the U.K., and *AR(2)* for the U.S. The general mean growth rate equation equals the following: [5]

$$y_t = a_0 + \sum_{i=1}^{4} b_i y_{t-i} + \varepsilon_t , \tag{1}$$

where the growth rate $y_t \equiv 100 \times (\ln Y_t - \ln Y_{t-1})$, $\ln Y_t$ equals the natural logarithm of real GDP, and ε_t equals the white-noise random error.

Second, we estimate equation (1) allowing for the possibility of structural breaks in its coefficients. Specifically, we use the statistical techniques of Bai and Perron (1998, 2003) to estimate multiple break dates without prior knowledge of when those breaks occur. After finding

[4] The order of listing data in parentheses reflects the order of identification, with the first data corresponding to the first outlier identified, and so on.

[5] We assume that the growth rates of each series are stationary, subject to breaks (see Garcia and Perron, 1996, for discussion). We corroborate this assumption with Augmented Dickey-Fuller (ADF) tests performed on each series.

any breaks in the parameters of y_t, we use that model specification for each country to obtain series of estimated residuals, $\hat{\varepsilon}_t$. To allow for the conditional mean and variance to possibly experience breaks at different dates, we proceed to the third step of the modified ICSS algorithm, which tests for breaks in the squared value of estimated residuals, $\hat{\varepsilon}_t^2$. [6]

Bai and Perron (1998, 2003) propose several tests for multiple breaks. We adopt one procedure and sequentially test the hypothesis of m breaks versus m+1 breaks using a $\sup F(m+1|m)$ statistics, which detects the presence of m+1 breaks conditional on finding *m* breaks and the supremum comes from all possible partitions of the data for the number of breaks tested. In the application of the test, we search for up to five breaks in the coefficients of the following *AR* model:

$$y_t = a_0 + \sum_{j=1}^{m} a_j D_j + \sum_{i=1}^{4} b_i y_{t-i} + \sum_{i=1}^{4} \sum_{j=1}^{m} c_{ij} y_{t-i} D_j + \varepsilon_t, \qquad (2)$$

where $D_j = 1$ if $t > k$ and zero otherwise, k equals the date of the break in the conditional mean. If we reject the null of no break at a 5-percent significance level, we then proceed to estimate the break date using least squares, to divide the sample into two subsamples according to the estimated break date, and to perform a test of parameter constancy for both subsamples. We repeat this process by sequentially increasing *m* until we fail to reject the hypothesis of no additional structural change. In the process, rejecting *m* breaks favors a model with *m+1* breaks, if the overall minimal value of the sum of squared residuals over all the segments, including an additional break, is sufficiently smaller than the sum of squared residuals from the model with *m* breaks. The break

[6] Alternatively, we test for parameter constancy in the conditional mean of the absolute value of the residuals $\hat{\varepsilon}_t$, using the Bai and Perron (1998, 2003) approach as in Cecchetti *et al*. (2005) and Herrera and Pesavento (2005), Very similar results are obtained as compared with using the modified ICSS algorithm. That is, we find the same date of the break in the conditional variance for Canada, Germany, and Japan, and only few-quarter difference for Italy, the U.K., and the U.S.

dates selected are the ones associated with this overall minimum. We search for multiple breaks in the series of output growth using the GAUSS code made available by Bai and Perron (2003).

Table 1 displays the results of testing for breaks in the mean growth rate as well as critical values at the 5-percent significance level (in parentheses). The value of the $\sup F(5|0)$ test proves significant for *m=5* in Canada, Germany, Italy, Japan, and the U.K., suggesting the existence of at least one break in the growth rate series of Canada, Germany, Italy, Japan, and the U.K., but not in the U.S. The sequential $\sup F(m+1|m)$ exhibits significance up to *m=2* in Japan. That is, given the existence of one break, $\sup F(2|1) = 25.0691$ suggests that a second break exists. The next test, $\sup F(3|2) = 7.6779$ falls below the critical value, suggesting that only two breaks exist for the output growth series in Japan. Given the significant $\sup F(5|0)$ test, the $\sup F(m+1|m)$ results suggest that only one break exists in the mean growth rates of Canada, Germany, Italy, and the U.K. The break dates occur at 1974:1 for Canada, 1971:1 for Germany, 1979:4 for Italy, 1973:1 and 1989:3 for Japan, and 1976:1 for the U.K. Using the same approach, but assuming a simple *AR(1)* model and testing for multiple breaks in the persistence coefficient (i.e., only b_i), Cecchetti *et al*. (2005) find one break in the persistence of GDP growth for Canada at 1980:4 and for Italy at 1979:4, and no breaks for Germany, Japan, the U.K., and the U.S. Our results more closely approximate those in Stock and Watson (2005), who use *AR(4)* models for the G7 countries over the period 1960:1 to 2002:4. That is, one break occurs at 1972:4 in Canada, 1979:4 in Italy, 1973:1 in Japan, 1980:1 in the U.K., and no breaks, in Germany and the U.S. The existing literature supports the view that no change in the mean growth rate occurs in the U.S. (e.g., McConnell and Perez-Quiros, 2000, among many others).

To test for breaks in volatility of output growth, the modified ICSS algorithm successively evaluates G_k at different parts of the squared value of estimated residuals, $\hat{\varepsilon}_t^2$, in equation (2), dividing consecutively after finding a possible change point.[7] In our application, the procedure identifies a single structural break in the variance of growth rates for each of the six countries. Thus, change in the *GARCH* process governs volatility. Different countries experience different break dates, that is, 1987:1 in Canada, 1993:1 in Germany, 1996:1 in Italy, 1975:1 in Japan, 1991:1 in the U.K., and 1983:2 in the U.S. [8]

On the one hand, Mills and Wang (2003) fit Hamilton's Markov chain model to post-war quarterly output growth that allows for a one-time structural break and find the break around 1976 in Canada, 1974 in Germany, 1982 in Italy, 1976 in Japan, 1993 in the U.K., and 1984 in the U.S. Summers (2005) uses the probability that GDP volatility in any particular quarter is high or low and reports the date of the switch from high to low volatility at 1988:1 in Canada, 1971:3 in Germany, 1980:2 in Italy, 1975:2 in Japan, 1982:2 in the U.K., and 1984:4 in the U.S. Cecchetti *et al*. (2005), on the other hand, search for multiple breaks in growth series based on Bai and Perron (1998, 2003). Using quarterly data of real GDP growth starting in 1970, they find one break in volatility at 1987:2 in Canada, at 1993:3 in Germany, at 1983:3 in Italy, at 1984:2 in the U.S., two breaks at 1981:2 and 1991:4 in the U.K., and none in Japan. Stock and Watson (2005) test for changes in the variance of *AR(4)* innovations using the Quandt likelihood ratio and report the break dates of 1991:2 in Canada, 1993:1 in Germany, 1980:1 in Italy, 1980:1 in the U.K., 1983:2 in the U.S., and no break date in Japan.

Different approaches and sample periods may lead to different findings of the break dates

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[7] We implement the modified ICSS algorithm using the GAUSS procedures available from Andreu Sansó's web page at http://www.uib.es/depart/deaweb/personal/profesores/personalpages/andreusanso/we.

[8] Alternatively, using the Bai and Perron (1998, 2003) approach, we find break dates in the conditional variance at 1987:1 for Canada, 1993:1 for Germany, 1982:4 in addition to 1997:3 for Italy, 1975:1 for Japan, 1990:4 for the U.K., and 1984:1 for the U.S.

in a country. Generally, the evidence indicates that the U.S. break date occurs some time in the early to mid-1980s. But for Canada, Germany, Italy, Japan, and the U.K., the timing of the decline seems much more controversial. For Canada, our break date, 1987:1, comes close to the 1988:1 break date in Summers (2005), 1987:2 in Cecchetti *et al*. (2005), and 1991:2 in Stock and Watson (2005), but relatively far from the 1976 break date in Mills and Wang (2003). For Germany, our break date, 1993:1, occurs nearly twenty-years later than the 1974 break date in Mills and Wang (2003) and 1971:3 in Summers (2005), but almost the same as the 1993:3 break date in Cecchetti *et al.* (2005) and 1993:1 in Stock and Watson (2005). For Italy, our one break date, 1996:1, differs from the 1982 break date in Mills and Wang (2003), 1980:1 in Summers (2005), 1983:3 in Cecchetti *et al*. (2005), and 1980:1 in Stock and Watson (2005). As noted in footnote 7, however, using Bai and Perron (1998, 2003) test, we find two break dates, 1982:4 and 1997:3. For Japan, our break date, 1975:1, appears close to the 1976 break date in Mills and Wang (2003) and 1975:2 in Summers (2005), but both Cecchetti et al. (2005) and Stock and Watson (2005) find no break. For the U.K., our break date, 1991:1, comes closer to the 1993 break date in Mills and Wang (2003) and 1991:4 in Cecchetti *et al*. (2005) than to the 1982:2 break date in Summers (2005) and 1980:1 in Stock and Watson (2005).

Figure 1 plots the series of real GDP growth rates and marks the break dates for the mean as well as the variance with a gray area. We further conduct structural stability tests for the unconditional mean and variance of the growth rate by splitting the sample into sub-periods according to the break dates in each country. For the unconditional mean, a t-statistic tests for the equality of means under unequal variances for two different samples, while a variance-ratio statistic tests for the equality of the unconditional variances.

Table 2 reports preliminary statistics for the data and the results of the structural stability tests. In Panel A, Japan shows the highest mean growth rate of 1.1142 percent for the full 50-year sample. The U.K. exhibits the lowest of 0.5877. Canada, Germany, Italy, and the U.S. fall between at 0.8589, 0.6256, 0.9054, and 0.8248, respectively. Moreover, Japan also displays the highest output volatility, represented by the standard deviation of 1.6472, and the U.K. possesses the lowest of 0.7873. Skewness statistics support symmetric distributions for all countries except Japan. Kurtosis statistics exhibit leptokurticity with fat tails for Germany and the U.K. Consequently, Jarque-Bera tests reject normality for Germany, Japan, and the U.K., but cannot reject normal distributions in Canada, Italy, and the U.S. The ADF unit-root test implies that the growth rate exhibits stationarity for each of the six samples. Particularly, Canada, Germany, Italy, Japan, and the U.K. are broken trend-stationary, the U.S. is trend-stationary, according to the tests suggested in Lumsdaine and Papell (1997) and Papell and Prodan (2004).[9] Valid inferences for *GARCH* estimation require stationary data series.

Panel B reports diagnostic checks for the *AR* models (i.e., equation 1) constructed for the six growth series. The Ljung-Box Q statistics test for autocorrelations in the residuals up to 6 lags. The test indicates none for the six countries. The Lagrange multiplier (LM) test of Engle (1982) checks for conditional heteroskedasticity of the residuals. The significant LM statistics suggest the

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[9] In performing the unit-root tests, we take special care, since structural changes in the mean growth rates occur (i.e., one in Canada, Germany, Italy, and the U.K., and two in Japan). Following Papell and Prodan (2004), we specify augmented Dickey-Fuller (ADF) tests for a unit-root with and without shifts in the deterministic trend as follows: $\Delta y_t = a_0 + \delta_1 D_1 + \delta_2 D_2 + d\ t + a_1 y_{t-1} + \sum_{i=1}^{k} \beta_i \Delta y_{t-i} + \varepsilon_t$, where $D_1 = 1$ for t > 1974:1, 0 otherwise for Canada; $D_1 = 1$ for *t > 1971:1, 0* otherwise for Germany; $D_1 = 1$ for *t > 1979:4, 0* otherwise for Italy; $D_1 = 1$ for *t >1973:1*, and $D_2 = 1$ for *t >1989:3,* 0 otherwise for Japan; and $D_1 = 1$ for *t > 1976:1, 0* otherwise for the U.K. When not specified $D_1 = 0$ and $D_2 = 0$ for all *t*, such as in the U.S. for both D_1 and D_2. The standard ADF test sets $\delta_1 = \delta_2 = 0$ and tests the null of a unit root in favor of the alternative of trend-stationarity. When allowing for two breaks in the intercept of the trend function and the model tests the null of a unit root in favor of the alternative of broken trend-stationarity. We reject the null, if a_1 significantly differs from zero. Papell and Prodan (2004) prove that the rejections of the unit-root null in favor of broken trend-stationarity are not subject to the heterogeneity present in the data.

need of *GARCH* modeling for each of the six growth rates. That is, the *GARCH* models implies that the mean-corrected growth rate is serially uncorrelated, but dependent.

Panel C splits the full sample into sub-samples at the break dates in the mean growth rate. For Canada, Germany, Italy, and Japan, the t-statistics that test for structural change in the mean between the sub-samples reject the null hypothesis of equal means. Canada exhibits a significant drop in the mean growth rate from 1.1364 in the pre-1974 sample period to 0.7138 in the post-1974 period. German growth rate falls from 0.9917 in the pre-1971 period to 0.5121 in the post-1971 period. Italy shows a decline from 1.4171 in the pre-1979 period to 0.5293 in the post-1979 period. Japan experiences two sharp drops, first, from 2.3821 in the pre-1973 sample period to 0.8517 in the period between 1973 to 1989, second, a further drop to 0.1758 in the post-1989 period. For the U.K., although the Bai and Perron's (1998, 2003) method detects one structural break, the insignificant t-statistic suggests equality between the two mean growth rates before and after 1976:1. A further examination (in Table 4) shows that the U.K. does experience structural changes in the *AR(4)* process. The decrease in the constant term, however, tends to offset the increase in the persistency parameter, leading to unchanged mean values (see footnote 13). The U.S. experiences no change in the growth rate average for the full sample.

Panel D splits the full sample into two sub-samples at the break date in the variance. A clear decline in the standard deviation of the growth rate occurs for all the six countries. The p-values for the variance-ratio F-test significantly reject the null of variance equality between the two samples. The decline equals 41 percent in Canada, 58 percent in Germany, 55 percent in Italy, 41 percent in Japan, 61 percent in the U.K., and 47 percent in the U.S. The large decline in the U.K. appears in Figure 1 as compared to other five countries. As noted in the introduction, economists call the substantial drop in the variance of output growth in the period after the break as the Great

Moderation. Most research focuses on the causes of the Great Moderation such as good policies, structural change, good luck, or output composition shifts, as discussed in McConnell and Perez-Quiros (2000), Blanchard and Simon (2001), Stock and Watson (2003, 2005), Ahmed *et al.* (2004), Bernanke (2004), Summers (2005), Kent *et al.* (2005), Cecchetti *et al.* (2005), and Eggers and Ioannides (2006). This paper examines the effect of the Great Moderation on the time-series specification of output-growth volatility in *GARCH* models (i.e., Section 3) as well as the effects, if any, of our output-growth volatility measure on output growth and of output growth on its volatility (i.e., Section 4).

3. Time-Series Specification of Output Growth Volatility

The *GARCH(1,1)* model proves adequate to represent the volatility process of most financial and economic time series. Caporale and McKiernan (1996), Speight (1999), Hamori (2000), Henry and Olekalns (2002), Ho and Tsui (2003), Fountas *et al*. (2004), and Fountas and Karanasos (2006) apply this specification to parameterize the time-varying conditional variance of output growth for the countries studied. Five of the six countries in our sample experience drops in their growth rates. To capture the mean shifts, we include dummy variables in the mean equation, which equal unity from the break date forward, zero otherwise, as follows:

$$y_t = a_0 + \sum_{j=1}^{2} a_j MD_j + \sum_{i=1}^{4} b_i y_{t-i} + \sum_{i=1}^{4}\sum_{j=1}^{2} c_{ij} y_{t-i} MD_j + \varepsilon_t , \tag{3}$$

where the dummy variable $MD_1 = 1$ for $t > 1974:1$, 0 otherwise, for Canada; $MD_1 = 1$ for $t > 1971:1$, 0 otherwise, for Germany; $MD_1 = 1$ for $t > 1979:4$, 0 otherwise, for Italy; $MD_1 = 1$ for $t > 1976:1$, 0 otherwise, for the U.K.; two dummy variables $MD_1 = 1$ for $t > 1973:1$, 0 otherwise, and $MD_2 = 1$ for $t > 1989:3$, 0 otherwise, for Japan. Once again, the U.S. does not experience breaks in the growth process.

To consider the effect of the Great Moderation on the variance of output in the *GARCH* process, a dummy variable enters into the conditional variance equation, which equals unity from the break date forward, zero otherwise, for our six sample countries as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \gamma\ VD_j\,,\ j = C, G, I, J, U.K., and\ U.S., \qquad (4)$$

where VD_C =1 for $t > 1987:1$, 0 otherwise, for Canada, VD_G =1 for $t > 1993:1$, 0 otherwise, for Germany, VD_I =1 for $t > 1996:4$, 0 otherwise, for Italy, VD_J =1 for $t > 1975:1$, 0 otherwise, for Japan, VD_{UK} =1 for $t > 1991:3$, 0 otherwise, for the U.K., VD_{US} =1 for $t > 1983:2$, 0 otherwise, for the U.S., and σ_t^2 equals the conditional variance of the growth rate, given information available at time t-1. The conditions that $\alpha_i \geq 0$, $\beta_i \geq 0$, and $\alpha_1 + \beta_1 < 1$ ensure positive and stable conditional variances of ε_t. The sum, $\alpha_1 + \beta_1$, measures the persistence of shocks to the conditional variances. Evidence of an *IGARCH*, or, in general, evidence of high persistence proves analogous to a unit root in the mean of a stochastic process. This persistence may also result from occasional level shifts in volatility. The dummy variable accommodates such extraordinary changes. If β_1 equals zero, the process reduces to an *ARCH(1)*. When α_1 and β_1 both equal zero, the variance equals a constant. We estimate each of the models employing Bollerslev and Wooldridge's (1992) quasi-maximum likelihood estimation (QMLE) technique, assuming normally distributed errors and using the Berndt *et al*. (1974) (BHHH) algorithm.

We first estimate the *GARCH(1,1)* models without structural breaks in the mean and the variance equations. That is, we consider model specifications without structural breaks as counterfactual experiments. Table 3 reports the estimation results with standard errors in parentheses, p-values in brackets, and statistics for the standardized residuals. Each estimate in the variance equation exceeds zero. The volatility persistence measures of 0.9912 in Canada, 0.9738 in Germany, 0.9882 in Italy, 0.9840 in Japan, 0.9968 in the U.K., and 0.9422 in the U.S. All estimates of persistence nearly match those reported in Caporale and McKiernan (1996), Speight

(1999), Hamori (2000), Ho and Tsui (2003), and Fountas *et al*. (2004) and prove high. The likelihood ratio (LR) tests for $\alpha_1 + \beta_1 = 1$ in the *GARCH* process do not reject the null hypothesis of an *IGARCH* effect at the 5-percent level for all specifications. The model assumes that positive and negative shocks generate the same effect on volatility for each country. We employ Engle and Ng's (1993) diagnostic test to detect asymmetry in variance of the growth rates. The null hypothesis assumes no asymmetric effect in volatility. The joint test statistics (Engle-Ng) indicate insignificance at the 5-percent level, supporting the symmetric *GARCH* models specified for the sample countries, except Japan. The fitted models adequately capture the time-series properties of the data in that the Ljung-Box Q-statistics for standardized residuals ($LB\ Q$) and standardized squared residuals ($LB\ Q^2$), up to 6 lags, do not detect remaining autocorrelation and conditional heteroskedasticity. The standardized residuals exhibit symmetric distributions in all countries, and significant excess kurtosis exists in Canada and the U.K., but not in Germany, Italy, Japan and the U.S. Thus, Canada and the U.K. do not exhibit the characteristics of a normal distribution.

The empirical results raise two issues. First, the structural changes in the mean and the Great Moderation in the volatility of GDP growth identified by the Bai and Perron (1998, 2003) method and the modified ICSS algorithm suggest that the volatility persistence estimated in the *GARCH* models may prove spurious, since researchers do not incorporate these structural changes. Lastrapes (1989) shows that changes in the unconditional variance should receive consideration when specifying *ARCH* models. In his study, for instance, the persistence of volatility in exchange rates decreases after incorporating three U.S. monetary policy regime shifts between 1976 and 1986, diminishing the likelihood of integration-in-variance. Tzavalis and Wickens (1995) find strong evidence of a high degree of persistence in the volatility of the term premium of bonds. Once they allow for the monetary regime shift between 1979 and 1982, however, the high persistence in the *GARCH(1,1)-M* model disappears. More recently, using U.S. output growth data, Fang and Miller (2008) discover that the time-varying conditional variance falls sharply or disappears completely in *GARCH-M* or *ARCH-M* specifications, once they incorporate a structural break in the variance of output growth in 1982 or 1984. Kramer and Azamo (2007) argue that structural changes in the mean may lead to high persistence parameter in *GARCH* models.

Second, the significant statistical property of excess kurtosis in Canada and the U.K. provides a cautionary note. Kurtosis for the standardized residuals (i.e., ε_t / σ_t) should vanish. According to the distributional assumptions in the *GARCH* specification, the standardized residuals should reflect a normal distribution, if the *GARCH* model totally captures the leptokurtic unconditional distribution. Blanchard and Simon (2001) note that the distribution of output growth exhibits excess kurtosis (or skewness), if large and infrequent shocks occur. This suggests that the evidence of excess kurtosis may also reflect the mean changes and the Great Moderation. We argue that the higher moments of the standardized residuals provide important diagnostic information regarding accurate model specification and the true data generating process, particularly when structural change in mean and variance may occur.

Thus, we expect to resolve the two puzzles by modeling the mean changes and the non-stationarity variance arising from the Great Moderation. First, the high persistence of output volatility decreases after accounting for the mean change and the Great Moderation, diminishing the likelihood of biasing the sum of the estimated autoregressive parameters toward one. Second, leptokurtosis in the distribution of output growth vanishes after adjustment for *GARCH* with the structural breaks.

Canada, Germany, Italy, Japan, and the U.K. require special attention because structural changes occur in the mean. Japan also displays the significant Engle-Ng statistic, the only country that faces this complication among the six countries studied. Table 4 reports estimation results where we include dummy variables in the mean equation, but exclude the shift dummy variable from the variance equation for the five countries.

Different countries exhibit different change behaviors. In Canada the coefficients of the dummy variable, both for the intercept and the persistency, are significant, at the 5-percent level. The negative estimate of the intercept-shift dummy variable dominates the positive estimate of the persistency parameter, explaining the drop of the mean growth analyzed in Table 2.[10] In Germany, the fall in growth comes largely from the persistency parameters due to the insignificance of the intercept dummy variable. For the persistency parameters, negative changes must dominate positive changes to reflect the drop in the growth rate in Table 2.

In Italy and Japan, however, all persistency parameters of the dummy variables prove insignificant. We then estimate the model for a parsimonious version with the insignificant persistency estimates (i.e., c_{11} in Italy and c_{11} through c_{42} in Japan) deleted. The advantages of parsimony include higher precision of estimates from reduced multicollinearity, increased degrees of freedom, more reliable estimates, and greater power of tests. The insignificant likelihood ratio statistic (LR(1)=1.2606 in Italy and LR(8) =3.4072 in Japan), at the 5-percent level, suggests no explanatory difference between the general and the parsimonious models for the two countries. Additionally, modified Akaike Information Criterion (*AIC*) and *SIC* model selection criteria choose the simple models for each of them.[11] [12] In the simple model the coefficients of the dummy

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[10] That is, under the stationarity condition of an *AR(p)* process, when allowing for mean changes, the mean of the growth rate equals $y = \dfrac{a_0 + \sum_{j=1}^{m} a_j}{1 - \sum_{i=1}^{p}\sum_{j=1}^{m}(b_i + c_{ij})}$, where $\dfrac{\partial y}{\partial a_j} > 0$ and $\dfrac{\partial y}{\partial c_{ij}} > 0$.

[11] Conventional *AIC* and *SIC* measure squared deviations of the model of the mean. In this study, we test how well the model of the variance fits the data. Brooks and Burke (2003) suggest the following modified *AIC* and *SIC* for assessing models of the variance. That is, *AIC*= $\sum_{i=1}^{T}\log(\sigma_t^2) + 2n$ and *SIC*= $\sum_{i=1}^{T}\log(\sigma_t^2) + n\ln(T)$, where σ_t^2 equals

variables are significantly negative at the 5-percent level, suggesting that the source of the drop of the mean growth rates comes from the shift in the constant term in the *AR* process. For Japan, the insignificant Engle and Ng's (1993) joint test statistic (3.6644) now suggests no asymmetric volatility at the 5-percent level. This result matches that of Hamori (2000), Ho and Tsui (2003), and Fountas *et al.* (2004), who find no asymmetry between output volatility and growth for Japan. We thus proceed by focusing on the effect of nonstationary variance on conditional volatility, using the simple symmetric *GARCH* specification.

In the U.K. the significant estimates of a_1 and c_{11} suggest changes in the constant term and persistency of the first *AR* term in the *AR(4)* process. The effects of the negative and positive changes must just offset each other to lead to unchanged mean growth rate in Table 2.[13] The highly significant LR statistic (28.1476) does not suggest the elimination of the three insignificant persistence estimates of the dummy variable (i.e., c_{21}, c_{31}, and c_{41}) in the *AR* model.

In Table 4 the *GARCH* model estimates nearly match those in Table 3 for Canada, Germany, Italy, Japan, and the U.K. In particular, the high volatility persistence (0.9776 in Canada, 0.9951 in Germany, 0.9963 in Italy, 0.9865 in Japan, and 0.9932 in the U.K.) remains, meaning that the mean shift does not explain the *IGARCH* effect. This result readdresses the point made by Sensier and van Dijk (2004, p.835) in that "The main effect of allowing for a structural change in mean appears to be that…the break in volatility is dated somewhat later…The distribution of percentage changes

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estimated values of the conditional variance, *T* equals the number of usable observations, and *n* equals the number of estimated parameters in the mean and variance equations.

[12] For Germany, Italy, and Japan, the positive values of *AIC* and *SIC* reflect the high standard deviations (1.1147, 1.2234, and 1.6472, respectively) in Table 2 or the high conditional volatility in Figure 2. For Canada, the U.K., and the U.S., the standard deviation or conditional volatility falls below one in Table 2 and Figure 2, leading to negative values of either the *AIC* or the *SIC*.

[13] We test for the null hypothesis that $\frac{a_0}{1-\sum_{i=1}^{p} b_i} = \frac{a_0 + a_1}{1-\sum_{i=1}^{4}\sum_{j=1}^{1}(b_i + c_{ij})}$. The insignificant F-statistic (0.4766) suggests no difference between the two average mean growth rates.

in standard deviation is largely unaffected." Intuitively, mean shifts capture changes in the intercept or the persistency parameter, and not the volatility. In other words, the mean-shift dummy variables affect the distributional behavior of the residuals such as the interaction between the dummy variable and the excess kurtosis in Canada and the U.K., which previously proved significant in Table 3, now proves insignificant, but not the *IGARCH* process, which reflects the nonstationary variance. The Engle and Ng (1993) asymmetric test exhibits some sensitivity to the *GARCH* model specification. Although Japan passes the Engle-Ng test, now German specification suggests that positive and negative shocks may affect the volatility differently.

Table 5 reports the estimates with the variance break, showing that the structural dummy proves highly significant in the variance equation in all six cases along with significant structural dummies in the mean equation in Canada, Germany, Italy, Japan, and the U.K. The negative estimate (γ) of the dummy variable in the variance equation reflects exactly the Great Moderation for each country. Following the work of Brooks and Burke (2003) and Fountas and Karanasos (2006), the modified *AIC* and *SIC* rank the various *GARCH* type models. The improvement of the value (i.e., smaller value) of each of the two model selection criteria (see Tables 3 and 5) indicates that including the dummy variables in the mean and variance equations provides a better specification. The Ljung-Box Q-statistics of the standardized residuals and the squared standardized residuals show no evidence of autocorrelation and heteroskedasticity, providing support for these specifications. The Engle-Ng diagnostic statistics suggest no need for an asymmetric model at the 5-percent level, except Germany. The coefficients of skewness and excess kurtosis prove insignificant, although Canada experiences significant skewness at the 10-percent level. The standardized residuals, however, conform to a normal distribution in all six countries.

One important consequence emerges by allowing for a structural change in the conditional variance. That is, a large decline occurs in the estimated degree of persistence in the conditional variance. Each estimate in the variance equation in Table 5 falls below the similar model without the dummy variable in Tables 3 and 4. The significant LR statistic at the 5-percent level in Table 5 proves no *IGARCH* effect in each of the six countries. In addition, the estimates of α_1 and β_1 not only fall in size but also become insignificant in the specification that includes the variance dummy variable in Japan, Germany, Italy, and the U.K., indicating no *ARCH* or no *GARCH* effects. That is, the dummy variable replaces the *GARCH* effect. Moreover, the *GARCH(1,1)* model reduces to *ARCH(1)* in Canada and the U.S.

Since the *AR* term (i.e., the β_1 estimate) in the variance equation is insignificant for all countries, the *GARCH(1,1)* process reduces to a parsimonious *ARCH(1)* at most. Table 6 reports the *ARCH(1)* estimates. The omission of the insignificant β_1 leads to a lower value of *AIC* or *SIC* for the models, except the U.S. The insignificant likelihood ratio statistic (0.6848), which follows a χ^2 distribution with one degree of freedom, suggests no difference between the *GARCH(1,1)* and the *ARCH(1)* models at the 5-percent level for the U.S. In the *ARCH(1)* model, most of the dummy variables in the mean and variance equations are significant at the 5-percent level. The *ARCH* effect is stable and significant at the 10-percent level for Canada, Germany, and Japan. Italy, the U.K., and the U.S. reduce to constant variance models. The diagnostic tests suggest no autocorrelation, heteroskedasticity, skewness, or excess kurtosis, but a normal distribution in the residuals at the 5-percent significance level, supporting this parsimonious specification. Accordingly, we argue that the *ARCH(1)* model appropriately and adequately captures volatility of real GDP growth in Canada, Germany, and Japan, whereas homoskedasticity exists for Italy, the U.K., and the U.S. The *GARCH* effect generally reflects the effect of the Great Moderation.

Figure 2 plots the conditional variances with (i.e., Table 6) and without (i.e., Table 3) dummy variables for the six models, respectively. The solid line includes the dummy variable while the dashed line excludes the dummy variable. One common characteristic appears in the diagrams for the six countries -- a clear shift in the variance. The high volatility appears in the period before the break date in each of the six countries.

4. Output Growth Volatility and Output Growth

The prior section considers the appropriate time-series specification of the volatility of the growth rate of real GDP. A number of authors examine the issue of how this volatility affects the growth rate of GDP. That is, does decreased real GDP growth rate volatility cause a higher or lower real GDP growth rate? Alternative theoretical models give mixed results -- negative, positive, or no relationship between output growth volatility and output growth. For example, the misperceptions theory, proposed originally by Friedman (1968), Phelps (1968), and Lucas (1972), argues that output fluctuates around its natural rate, reflecting price misperceptions due to monetary shocks. The long-run growth rate of potential output, however, reflects technology and other real factors. The standard dichotomy in macroeconomics implies no relationship between output volatility and its growth rate. Martin and Rogers (1997, 2000) argue that learning-by-doing generates growth whereby production complements productivity-improving activities and stabilization policy can positively affect human capital accumulation and growth. One natural conclusion, therefore, implies a negative relationship between output volatility and growth. In contrast, Black (1987) argues that high output volatility and high growth coexist. According to Blackburn (1999), a relative increase in the volatility of shocks increases the pace of knowledge accumulation and, hence, growth, implying a positive relation between output volatility and growth.

Applying a *GARCH* in mean (*GARCH-M*) model (Engle *et al*., 1987), Caporale and McKiernan (1996, 1998) find a positive relationship between output volatility and growth for the U.K. and the U.S., whereas Fountas and Karanasos (2006) find a positive relationship for Germany and Japan. Speight (1999) and Fountas and Karanasos (2006), however, conclude that no relationship exists in the U.K and the U.S. In contrast, Macri and Sinha (2000) and Henry and Olekalns (2002) discover a negative link between volatility and growth for Australia and the U.S. While these empirical studies employ post-war data, no one explicitly considers the effect of the Great Moderation on this relationship. Fang and Miller (2008) find a weak *GARCH* effect and no link between volatility and growth for the U.S. with a structural break in the volatility process. To provide more evidence on this issue, this section pursues this question with our more appropriate time-series specification of the real GDP growth rate volatility, employing an *ARCH(1)-M* model to examine the effect of output volatility on the output growth rate for Canada, Germany, Italy, Japan, the U.K., and the U.S.

To examine the effect of output volatility on its growth, the mean growth rate shown in equation (3) translates into the following:

$$y_t = a_0 + \sum_{j=1}^{2} a_j MD_j + \sum_{i=1}^{4} b_i y_{t-i} + \sum_{i=1}^{4}\sum_{j=1}^{2} c_{ij} y_{t-i} MD_j + \lambda\sigma_t + \varepsilon_t \qquad (5)$$

where σ_t equals the standard deviation of the conditional variance, σ_t^2, and λ measures the volatility effect. The estimate of λ may exceed or fall below zero and prove significant or insignificant.

Fountas *et al.* (2006) empirically investigate the possibility of a two-way relationship between output growth and its volatility. They conduct Granger-causality tests in a vector-autoregressive model and find that output growth volatility positively affects output growth in the G7 countries, except Japan, and output growth affects output growth volatility negatively in

Japan, Germany, and the U.S. Although no economic theory explicitly models the effect of output growth on its volatility, these findings raise an issue for *GARCH-M* type modeling strategy. That is, if output growth partly determines its volatility but is excluded in the variance equation, then the conditional variance equation exhibits misspecification and *GARCH-M* estimates prove inconsistent (Pagan and Ullah, 1988). Fountas and Karanasos (2006) and Fang and Miller (2008) incorporate lagged output growth into the conditional variance equation in their *GARCH-M* models. They both find a negative level effect in the variance for the U.S. and Fountas and Karanasos (2006) find no level effect in Japan. Thus, to avoid potential endogeneity bias, we augment the variance equation to include the lagged output growth as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \theta\ y_{t-1} + \gamma\ VD_j\ ,\ j = C, G, I, J, U.K., \text{ and } U.S., \qquad (6)$$

where θ measures the level effect of the output growth on the variance. The sign of θ is unknown, since Fountas *et al.* (2006) show that either a negative or a positive relationship may occur.

Table 7 reports the *ARCH(1)-M* estimation results, where we include the mean and variance structural breaks along with the lagged output growth in the variance equation. The coefficient of the conditional standard deviation (λ) possesses no statistical significance in all countries, except the negative significance at the 5-percent level for Japan. The effect of the lagged growth rate of output on its conditional variance proves significantly negative for Germany and significantly positive for Japan. The effect proves not significant in Canada, Italy, the U.K., and the U.S. All other estimates and diagnostic statistics mirror those in the models without the in-mean and level effects.

The insignificant estimate of λ in the mean equation implies no relationship between output volatility and its growth in Canada, Germany, Italy, the U.K., and the U.S. This result conforms to the misperceptions hypothesis and the previous empirical findings, using *GARCH-M* models, of Fountas and Karanasos (2006) and Fang and Miller (2008) for the U.S. and Speight (1999) for the U.K. This finding, however, proves inconsistent with the discovery of a positive relationship by Caporale and McKiernan (1996, 1998) for the U.K. and the U.S., as well as the discovery of a negative relationship by Henry and Olekaln (2002) for the U.S. and by Macri and Sinha (2000) for Australia. Japan experiences the highest mean growth rate and standard deviation in Table 2 and alone sees a significantly negative volatility in-mean effect. Bernanke (1983) and Pindyck (1991) demonstrate that irreversibility makes investment especially sensitive to various forms of risk. Output volatility generates risk about future demand that impedes investment, leading to a negative relationship between output volatility and growth. Martin and Rogers (2000) argue that learning-by-doing generates growth and economic instability impedes human-capital accumulation and, thus, growth. Japanese evidence supports these hypotheses, which counters the positive finding in Fountas and Karanasos (2006). Regarding the level effect, Fountas and Karanasos (2006) report a significant negative effect for Germany and the U.S., but an insignificant effect for Japan. We discover identical results in Germany, but differ in our finding a significant positive effect for Japan and no level effects for the U.S., Canada, Italy, and the U.K.

Generally, evidence on either the volatility-in-mean effect or the level effect proves weak in this paper compared with the existing literature. Different empirical findings may come from several sources. First, our quarterly data spanning 1957:1 to 2006:3 contain much more recent data than the samples in previous studies. The more recent data on growth rate volatility exhibit substantial declines. Reduced volatility may neutralize the effect of volatility on the growth rate or the lagged output effect on its volatility. Second, other studies use monthly IP (industrial production) and annual real GNP or IP to examine the relationship between output volatility and its growth. The data frequency may provide another avenue for different findings. Existing research, however, does not limit the phenomenon of the Great Moderation to quarterly output only. For example, Sensier and van Dijk (2004) find approximately 80 percent of 214 monthly U.S. macroeconomic time series, including *IP*, experience a break in the variance over the period 1959 to 1999, with most breaks occurring after 1980. Third, some researchers use asymmetric *GARCH* models. In our Table 7, the Engle-Ng (1993) diagnostic test shows no asymmetric effect under a symmetric *GARCH* specification, suggesting no need for an asymmetric model. This conclusion also receives support from Hamori (2000), who shows that the *GARCH* version provides the best statistical fit compared to exponential *GARCH* and threshold *GARCH* and that the volatility process proves symmetric for Japan, the U.K., and the U.S. Fourth, and most importantly, most previous studies implicitly assume that a stable *GARCH* process governs conditional growth volatility, using annual, quarterly, or monthly data. The neglect of structural breaks in the variance produces misspecification of the conditional variance, which leads to significant *GARCH* and, thus, the *GARCH-M* effects or level effects. Our *ARCH-M* estimation results prove robust to the Great Moderation.

5. Conclusion

This paper investigates the properties of the variance in quarterly real GDP growth rates and their effects on conditional volatility for Canada, Germany, Italy, Japan, the U.K., and the U.S. during the period 1957:1 to 2006:3 as well as the effects, if any, of output growth volatility on output growth and of the lagged output growth on its volatility. We begin by considering the possible effects, if any, of structural change on the volatility process. Our initial results, based on a *GARCH* model of the conditional variance of the residuals, find strong evidence of volatility persistence in the growth rate. Subsequent analysis reveals that this conclusion does not prove robust to a one-time shift in output volatility, identified by the modified ICSS algorithm. The findings of high volatility persistence measured by the *GARCH* model disappear in the specifications that include a dummy variable for the structural break. That is, the *IGARCH* effect proves spurious. This result demonstrates the misspecification of *GARCH* models, if researchers neglect the nonstationary variance.

Our measure of volatility that corrects for structural shifts in the volatility process leads to different results with respect to how the conditional volatility of output growth affects output growth and the effects of output growth on its volatility. That is, we find substantive differences from those findings of previous studies. The volatility of output growth negatively affects output growth only in Japan. In Canada, Germany, Italy, the U.K., and the U.S., volatility does not significantly affect output growth. Further, output growth negatively affects its volatility in Germany, but positively, in Japan. Output growth does not significantly affect its volatility in Canada, Italy, the U.K., and the U.S.

While this paper focuses on the appropriate specifications of the conditional volatility of real GDP growth rates for the G7 (excluding France) as well as the relationship, if any, between real GDP growth and its volatility, we address the potential implications of our findings for the causes of the Great Moderation. Our first results confirm the basic finding that the output growth volatility declines in each country. The output growth rate itself, however, fell substantially in four of the six countries studied in the 1970s, which preceded the Great Moderation. Later, in our regression analysis, the weak evidence of the level effect implies that the declining growth rate does not cause the Great Moderation. As for the debate on good policy (Cecchetti *et al.* 2005), structural change (Kent *et al.* 2005), or good luck (Stock and Watson 2005), since we do not directly address this issue, the remaining observations represent our conjectures, which require further investigation.

First, our critical finding that the conditional variances of each country experience one-time shifts from high to low volatility with different timing offers a caution for the good luck conclusion. That is, the shift in the volatility processes across countries occurs at different points in time, implying non-synchronization of causes. Good luck could involve worldwide shocks that affect all countries simultaneously of idiosyncratic shocks that affect individual countries. Non-synchronization of the causes of the Great Moderation suggests that idiosyncratic, country-specific shocks must play an important role. On the one hand, Stock and Watson (2005) find that most of the variance of GDP growth in the G7 countries reflects common international shocks and idiosyncratic domestic shocks, but their relative importance varies considerably across countries. Their analysis suggests that, with the exception of Japan, a significant portion of the widespread reduction in volatility associates with a reduction in the magnitude of the common international shocks. Japan experiences a remarkable increase in the fraction of the variance attributed to domestic shocks. That is, international shocks become unimportant and domestic shocks explain nearly all of its volatility after 1984. On the other hand, Hughes Hallett and Richter (2006) report inconclusive convergence results of business cycles from the U.K., the U.S. and the Eurozone, in that countries experience some cycles in common but diverge with respect to other cycles. Thus, our finding of non-synchronized shifts in volatility across countries may argue against good luck.

Second, structural change, such as behavioral changes, better inventory management, the breakdown of the EMS, the coming of the Euro, changes in monetary institutions, the efficacy of macro-policies, financial development, the increasing integration and volatility of financial markets, and structural reforms in markets, probably occurs gradually rather than in one-time dramatic change. Thus, our major finding also argues against the structural change view.

Third, the two oil-price shocks in the 1970s coupled with the ill-advised policy responses created the worldwide buildup of inflation. Those bad shocks riveted the attention of monetary policy authorities around the world. The global movement toward central bank independence and transparency as well as intensified concern about fighting inflation, even inflation targeting, ushered in altered (good) policy. The timing of events in each country reflected the existing institutional structure and internal politics. Moreover, except for Japan, the bad inflation performance in the 1970s preceded the one-time shifts in volatility identified by our analysis.

Finally, the true test of the causes of the Great Moderation may only await the passage of time. The current run up in oil prices may provide the acid test. Thus, future research that incorporates this latest episode of an oil-price shock may produce a more definitive answer to the question.

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Table 1: Structural Break Tests on the Mean Growth Rate

	Canada	Germany	Italy	Japan	United Kingdom	United States
$\sup F(5\|0)$	6.8253*	14.4665*	8.0624*	16.5513*	18.0127*	4.4381
	(5.8500)	(10.5200)	(5.8500)	(10.5200)	(10.5200)	(7.4600)
$\sup F(2\|1)$	2.4822	9.8897	3.7698	25.0691*	5.7094	3.0674
	(12.9500)	(19.9100)	(12.9500)	(19.9100)	(19.9100)	(15.7200)
$\sup F(3\|2)$	2.7613	11.9277	3.7698	7.6779	8.2823	2.0756
	(14.0300)	(20.9900)	(14.0300)	(20.9900)	(20.9900)	(16.8300)
Number of breaks	1	1	1	2	1	0
Break date	1974:1	1971:1	1979:4	1973:1 1989:3	1976:1	—

Note: The $\sup F$ statistics come from the Bai and Perron (1998, 2003) method. Critical values for the 5-percent significance level appear in parentheses. $\sup F(5 \mid 0)$ tests for the existence of at least one break for five breaks. $\sup F(m+1 \mid m)$ provides a sequential test to confirm or disconfirm more breaks, given at least one break.

* denotes 5-percent significance level.

Table 2: Preliminary Statistics for Quarterly Real GDP Growth

Panel A : Moments of full-sample and ADF test

	Canada	Germany	Italy	Japan	United Kingdom	United States
Mean	0.8589	0.6256	0.9064	1.1142	0.5877	0.8248
Standard deviation	0.8854	1.1147	1.2234	1.6472	0.7873	0.8161
Skewness	-0.0182	0.0196	0.2215	0.6137*	-0.1488	-0.2198
	[0.9173]	[0.9135]	[0.2212]	[0.0004]	[0.3961]	[0.2100]
Excess kurtosis	0.4725	0.9618*	0.0182	0.0743	0.7827*	0.3652
	[0.1824]	[0.0085]	[0.9602]	[0.8339]	[0.0272]	[0.3027]
Jacque-Bera normality test	1.8529	7.1824*	1.5235	12.4774*	5.7852**	2.6960
	[0.3959]	[0.0275]	[0.4668]	[0.0019]	[0.0554]	[0.2597]
ADF(n)	-11.4840(0)*	-11.4430(3)*	-26.4462(0)*	-9.1141(1)*	-5.1507(3)*	-6.7743(1)*

Panel B: Mean Equation Specification

	Canada	Germany	Italy	Japan	United Kingdom	United States
AR(p)	**AR(1)**	**AR(4)**	**AR(1)**	**AR(4)**	**AR(4)**	**AR(2)**
LB Q(3)	5.2137	0.3026	1.0395	0.0180	0.1864	0.1737
	[0.1568]	[0.9595]	[0.7916]	[0.9993]	[0.9797]	[0.9817]
LB Q(6)	5.7632	2.5318	5.9558	1.1393	3.4189	3.1725
	[0.4502]	[0.8648]	[0.4281]	[0.9797]	[0.7547]	[0.7869]
LM (3)	15.2981*	7.6516*	6.8982**	15.3712*	12.0784*	19.0800*
	[0.0015]	[0.0537]	[0.0752]	[0.0015]	[0.0071]	[0.0002]
LM (6)	23.8698*	12.4725*	16.7077*	19.5580*	17.3087*	25.1338*
	[0.0005]	[0.0522]	[0.0104]	[0.0033]	[0.0082]	[0.0003]

Panel C: Breaks in Mean and Structural stability test

	Break date	Period	Mean	Structural stability test: Sub-sample 1 v.s. Sub-sample 2	Sub-sample 2 v.s. Sub-sample 3	Sub-sample 1 v.s. Sub-sample 3
Canada	1974:1	1957:1-1974:1	1.1364	2.9031*	-	-
		1974:2-2006:3	0.7138	[0.0045]		
Germany	1971:1	1960:1-1971:1	0.9917	1.9838*	-	-
		1971:2-2006:3	0.5121	[0.0524]		
Italy	1979:4	1960:1-1979:4	1.4171	4.9676*	-	-
		1980:1-2006:3	0.5293	[0.0000]		
Japan	1973:1	1957:1-1973:1	2.3821	5.5828*	3.5685*	8.6633*
	1989:3	1973:2-1989:3	0.8517	[0.0000]	[0.0005]	[0.0000]
		1989:4-2006:3	0.1758			
United Kingdom	1976:1	1957:1-1976:1	0.6181	0.3910	-	-
		1976:2-2006:3	0.5688	[0.6964]		
United States	-	1957:1-2006:3	0.8248	-	-	-

Panel D: Breaks in Variance and Structural stability test

	Break date	Period	Standard deviation	Structural stability test: Sub-sample 1 v.s. Sub-sample 2
Canada	1987:1	1957:1-1987:1	1.0170	2.8656*
		1987:2-2006:3	0.6008	[0.0000]
Germany	1993:1	1960:1-1993:1	1.2680	5.6399*
		1993:2-2006:3	0.5339	[0.0000]
Italy	1996:4	1960:1-1996:4	1.3144	4.9888*
		1997:1-2006:3	0.5885	[0.0000]
Japan	1975:1	1957:1-1975:1	1.8894	2.8417*
		1975:2-2006:3	1.1208	[0.0000]
United Kingdom	1991:1	1957:1-1991:1	0.9194	6.7068*
		1991:2-2006:3	0.3550	[0.0000]
United States	1983:2	1957:1-1983:2	1.0062	3.5964*
		1983:3-2006:3	0.5305	[0.0000]

Note: The p-values appear in brackets; 0.0000 indicates less than 0.00005. The measures of skewness and kurtosis are normally distributed as $N(0,6/T)$ and $N(0,24/T)$, respectively, where T equals the number of observations. ADF(n) equals the augmented Dickey-Fuller unit-root test with lags n selected by the recursive t-statistic procedure (Ng and Perron 1995). Critical values at the 5-percent level equal -3.60 for no break, -6.10 for two breaks (Papell and Prodan, 2004), and -3.87 for one break (Perron, 1989). $LB\,Q(k)$ and *LM (k)* equal Ljung-Box Q-statistic and Lagrange multiplier statistic, respectively, testing for residuals and squared residuals for autocorrelations up to k lags. A t-statistic under unequal variances tests for structural change in the unconditional mean between the different regimes. The F test equals the unconditional variance ratio test between the samples i and j, and is asymptotically distributed as $F(df_i, df_j)$, where df denotes degrees of freedom.

* denotes 5-percent significance level.

** denotes 10-percent significance level.

Table 3: AR-GARCH(1,1) Estimates without Structural Break

$$y_t = a_0 + \sum_{i=1}^{4} b_i y_{t-i} + \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

	Canada	Germany	Italy	Japan	United Kingdom	United States
a_0	0.5326*	0.3867*	0.6372*	0.1940**	0.3907*	0.4890*
	(0.0761)	(0.0955)	(0.1047)	(0.1085)	(0.0872)	(0.0844)
b_1	0.3224*	-0.0908	0.1343**	0.0336	0.0624	0.1791*
	(0.0802)	(0.0756)	(0.0815)	(0.0771)	(0.0725)	(0.0768)
b_2		0.0844		0.2486*	0.0563	0.2487*
		(0.0688)		(0.0701)	(0.0833)	(0.0699)
b_3		-0.0329		0.1150**	0.1042	
		(0.0758)		(0.0657)	(0.0739)	
b_4		0.3213*		0.2801*	0.1600*	
		(0.0723)		(0.0586)	(0.0765)	
α_0	0.0199	0.0258	0.0106	0.0180	0.0047	0.0320**
	(0.0170)	(0.0403)	(0.0251)	(0.0372)	(0.0059)	(0.0185)
α_1	0.2280*	0.0568	0.0484	0.0791**	0.0822*	0.2224*
	(0.0750)	(0.0486)	(0.0316)	(0.0449)	(0.0430)	(0.0769)
β_1	0.7632*	0.9170*	0.9398*	0.9049*	0.9146*	0.7208*
	(0.0620)	(0.0832)	(0.0416)	(0.0539)	(0.0472)	(0.0849)
LR	0.0506	0.4248	0.3716	0.4463	0.0513	1.7710
	[0.8222]	[0.5154]	[0.5429]	[0.5049]	[0.8210]	[0.1849]
AIC	-32.2869	15.1432	29.0132	59.2089	-38.8493	-51.1186
SIC	-30.8145	17.2238	29.8148	61.5113	-36.5469	-49.3650
LB Q (3)	3.3208	1.0719	3.2623	0.0779	0.7538	0.6081
	[0.3447]	[0.7838]	[0.3529]	[0.9943]	[0.8604]	[0.8945]
LB Q (6)	4.2957	2.4783	9.1565	1.4149	3.2777	1.1353
	[0.6367]	[0.8708]	[0.1649]	[0.9649]	[0.7732]	[0.9799]
LB Q^2 (3)	0.8552	2.7007	2.9165	5.5626	0.7057	0.4805
	[0.8362]	[0.4401]	[0.4046]	[0.1349]	[0.8718]	[0.9231]
LB Q^2 (6)	3.0656	5.0552	5.6389	8.9620	3.0756	1.9163
	[0.8005]	[0.5367]	[0.4648]	[0.1757]	[0.7993]	[0.9272]
Engle-Ng	1.5069	2.8006	0.6858	8.2779*	1.7631	1.7344
	[0.6806]	[0.4233]	[0.8765]	[0.0406]	[0.6229]	[0.6292]
Skewness	-0.1298	-0.1573	0.0341	-0.0577	0.0557	0.0399
	[0.4603]	[0.3902]	[0.8508]	[0.7446]	[0.7530]	[0.8208]
Excess kurtosis	1.1503*	0.1602	0.0442	-0.2267	0.9215*	-0.2736
	[0.0012]	[0.6651]	[0.9040]	[0.5266]	[0.0100]	[0.4424]
Jacque-Bera	11.4153*	0.9453	0.0510	0.5233	6.9652*	0.6634
	[0.0033]	[0.6233]	[0.9748]	[0.7697]	[0.0307]	[0.7176]

Note: Standard errors appear in parentheses; p-values appear in brackets; $LB\,Q(k)$ and $LB\,Q^2(k)$ equal Ljung-Box Q-statistics, testing for standardized residuals and squared standardized residuals for autocorrelations up to k lags. LR equals the likelihood ratio statistic, following a χ^2 distribution with one degree of freedom that tests for $\alpha_1 + \beta_1 = 1$. The modified *AIC* and *SIC* select models from the *GARCH* family. Engle-Ng equals the TR^2 statistics, which follows a χ^2 distribution with 3 degrees of freedom and tests for asymmetric volatility.

* denotes 5% significance level.

** denotes 10% significance level.

Table 4: AR-GARCH(1,1) Estimates with Mean Structural Break

$$y_t = a_0 + \sum_{j=1}^{2} a_j MD_j + \sum_{i=1}^{4} b_i y_{t-i} + \sum_{i=1}^{4}\sum_{j=1}^{2} c_{ij} y_{t-i} MD_j + \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

where MD_1 =1 for t >1974:1; 0 otherwise for Canada

MD_1 =1 for t >1971:1; 0 otherwise for Germany

MD_1 =1 for t >1979:4; 0 otherwise for Italy

MD_1 =1 for t >1973:1 and MD_2 =1 for t >1989:3; 0 otherwise for Japan

MD_1 =1 for t >1976:1; 0 otherwise for the U.K.

	Canada	**Germany**	**Italy**		**Japan**		**United Kingdom**
			General	**Simple**	**General**	**Simple**	
a_0	1.3464* (0.1817)	0.7227** (0.4219)	1.1849* (0.2052)	1.2627* (0.1968)	2.1814* (0.4818)	2.1639* (0.3961)	0.7093* (0.2060)
a_1	-1.0168* (0.1987)	-0.4481 (0.4254)	-0.6074* (0.2320)	-0.7027* (0.1983)	-1.5121* (0.4963)	-1.4703* (0.3305)	-0.4388* (0.2184)
a_2					-0.5386** (0.2954)	-0.5686* (0.2098)	
b_1	-0.0999 (0.1340)	-0.1433 (0.1560)	0.0351 (0.1197)	0.0065 (0.0815)	-0.0679 (0.1412)	-0.0975 (0.0790)	-0.1140 (0.1195)
b_2		0.0257 (0.1264)			0.1673 (0.1192)	0.1018 (0.0736)	0.0506 (0.1219)
b_3		-0.2139* (0.0961)			-0.0317 (0.1055)	-0.0339 (0.0685)	0.0087 (0.1183)
b_4		0.4863* (0.1273)			0.0385 (0.0985)	0.1328* (0.0609)	0.0822 (0.1210)
c_{11}	0.6152* (0.1583)	0.1529 (0.1736)	-0.0521 (0.1564)		-0.0477 (0.2021)		0.4355* (0.1497)
c_{21}		0.0461 (0.1493)			-0.0799 (0.1727)		-0.0895 (0.1619)
c_{31}		0.2681* (0.1358)			-0.0277 (0.1607)		0.1574 (0.1480)
c_{41}		-0.3033* (0.1571)			0.2112 (0.1483)		0.0341 (0.1487)
c_{12}					0.0007 (0.2087)		
c_{22}					-0.0753 (0.1724)		
c_{32}					0.0789 (0.1860)		
c_{42}					-0.1530 (0.1553)		
α_0	0.0052 (0.0077)	0.0050 (0.0157)	0.0024 (0.0169)	0.0027 (0.0197)	0.0088 (0.0282)	0.0156 (0.0344)	0.0001 (0.0026)
α_1	0.1052* (0.0508)	0.0988** (0.0551)	0.0359 (0.0254)	0.0383 (0.0251)	0.0975* (0.0427)	0.1055* (0.0460)	0.0721* (0.0321)
β_1	0.8724* (0.0597)	0.8963* (0.0648)	0.9588* (0.0328)	0.9580* (0.0344)	0.8933* (0.0499)	0.8810* (0.0576)	0.9211* (0.0341)
LR	1.1502 [0.2849]	0.0508 [0.8218]	0.1635 [0.6864]	0.0633 [0.8016]	0.1791 [0.6727]	0.2730 [0.6019]	0.3299 [0.5664]
AIC	-44.4893	13.4271	35.9275	32.1555	66.4666	51.5480	-48.4257
SIC	-42.4281	16.8080	37.7977	33.7586	71.6470	54.4260	-44.6843
LB Q **(3)**	3.8330 [0.2800]	0.6162 [0.8927]	0.3587 [0.9486]	0.4615 [0.9272]	0.2352 [0.9717]	0.2277 [0.9729]	0.1311 [0.9878]
LB Q **(6)**	5.9522 [0.4285]	2.6078 [0.8562]	3.9257 [0.6867]	3.8717 [0.6940]	0.4862 [0.9980]	0.7400 [0.9935]	1.7555 [0.9407]
LB Q^2 **(3)**	3.6060 [0.3072]	5.3523 [0.1477]	2.4350 [0.4871]	2.9934 [0.3926]	3.4249 [0.3306]	3.4569 [0.3264]	1.0626 [0.7861]
LB Q^2 **(6)**	6.4311 [0.3766]	6.5102 [0.3685]	5.0384 [0.5389]	5.2272 [0.5150]	6.2471 [0.3960]	6.8040 [0.3393]	3.6063 [0.7297]
Engle-Ng	1.7440 [0.6271]	8.1305* [0.0433]	1.2925 [0.7309]	2.1661 [0.5386]	3.1430 [0.3700]	3.6644 [0.3000]	5.3115 [0.1503]
Skewness	-0.1299 [0.4597]	-0.2789 [0.1276]	-0.1103 [0.5432]	-0.1158 [0.5232]	-0.1425 [0.4212]	-0.1460 [0.4098]	-0.0506 [0.7751]
Excess kurtosis	-0.0435 [0.9025]	0.1867 [0.6138]	0.2398 [0.5135]	0.2618 [0.4755]	-0.3785 [0.2905]	-0.3348 [0.3498]	0.4877 [0.1732]
Jacque-Bera	0.5703 [0.7518]	2.6241 [0.2692]	0.8190 [0.6639]	0.9427 [0.6241]	1.8152 [0.4034]	1.5961 [0.4501]	2.0062 [0.3667]

Note: See Table 3.
* denotes 5% significance level.
** denotes 10% significance level.

Table 5: AR-GARCH(1,1) Estimates with Variance Structural Break

$$y_t = a_0 + \sum_{j=1}^{2} a_j MD_j + \sum_{i=1}^{4} b_i y_{t-i} + \sum_{i=1}^{4}\sum_{j=1}^{2} c_{ij} y_{t-i} MD_j + \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma\ VD_j\ , j = C, G, I, J, U.K., \text{and } U.S.$$

where MD_1 =1 for t > 1974:1 and VD_C =1 for t > 1987:1; 0 otherwise for Canada

MD_1 =1 for t > 1971:1 and VD_G =1 for t > 1993:1; 0 otherwise for Germany

MD_1 =1 for t > 1979:4 and VD_I =1 for t > 1996:4; 0 otherwise for Italy

MD_1 =1 for t > 1973:1, MD_2 =1 for t > 1989:3 and VD_J =1 for t> 1975:1; 0 otherwise for Japan

MD_1 =1 for t > 1976:1 and VD_{UK} =1 for t > 1991:1; 0 otherwise for the U.K.

VD_{US} =1 for t > 1983:2; 0 otherwise for the U.S.

	Canada	Germany	Italy	Japan	United Kingdom	United States
a_0	1.2150*	1.0489*	1.3995*	2.1991*	0.6899*	0.4356*
	(0.1972)	(0.4501)	(0.1829)	(0.4341)	(0.1690)	(0.0768)
a_1	-0.9115*	-0.7185	-0.9260*	-1.4627*	-0.4479*	
	(0.2107)	(0.4550)	(0.1808)	(0.3279)	(0.1827)	
a_2				-0.5832*		
				(0.2116)		
b_1	-0.0599	-0.2402	0.0032	-0.1306	-0.1086	0.2083*
	(0.1223)	(0.1620)	(0.0771)	(0.0821)	(0.1184)	(0.0685)
b_2		-0.0861		0.1369*	0.0547	0.2555*
		(0.1259)		(0.0686)	(0.1015)	(0.0662)
b_3		-0.2435*		-0.0307	-0.0553	
		(0.1232)		(0.0808)	(0.1103)	
b_4		0.4568*		0.1458*	0.0512	
		(0.1121)		(0.0719)	(0.1046)	
c_{11}	0.6229*	0.2473			0.4853*	
	(0.1444)	(0.1827)			(0.1643)	
c_{21}		0.1235			-0.1407	
		(0.1451)			(0.1493)	
c_{31}		0.3075*			0.2906**	
		(0.1422)			(0.1599)	
c_{41}		-0.2934*			0.0335	
		(0.1430)			(0.1428)	
α_0	0.7174*	1.0747*	1.3887*	1.7894*	0.7736*	0.6527*
	(0.2446)	(0.5110)	(0.5719)	(0.8763)	(0.0279)	(0.2622)
α_1	0.1289**	0.0570	0.0970	0.1960	0.0262	0.1617**
	(0.0773)	(0.0920)	(0.0779)	(0.1361)	(0.1229)	(0.0933)
β_1	0.1191	0.0512	0.0100	0.2315	0.0233	0.1375
	(0.2112)	(0.4256)	(0.3245)	(0.3049)	(0.1672)	(0.3084)
γ	-0.5760*	-0.8531*	-1.0766*	-1.2474**	-0.7013*	-0.5170*
	(0.2058)	(0.4100)	(0.4724)	(0.7337)	(0.0395)	(0.2076)
LR	11.4816*	5.2404*	7.9651*	4.8899*	38.5216*	6.3635*
	[0.0009]	[0.0233]	[0.0053]	[0.0283]	[0.0000]	[0.0125]
AIC	-43.4670	5.9714	23.7058	50.9089	-53.1525	-56.0088
SIC	-41.4281	9.6124	25.5761	54.0743	-49.1233	-53.9630
LB Q (3)	3.0169	0.4751	0.5723	1.0279	0.6610	1.1485
	[0.3890]	[0.9243]	[0.9027]	[0.7944]	[0.8823]	[0.7653]
LB Q (6)	3.7040	2.2553	5.0207	1.3253	2.6576	1.9403
	[0.7166]	[0.8947]	[0.5411]	[0.9702]	[0.8504]	[0.9251]
LB Q^2 (3)	4.3788	6.0667	1.5604	1.1528	1.5256	0.4229
	[0.2233]	[0.1084]	[0.6683]	[0.7643]	[0.6763]	[0.9354]
LB Q^2 (6)	7.6243	8.4749	5.7597	2.4457	3.3582	1.7076
	[0.2669]	[0.2053]	[0.4506]	[0.8744]	[0.7627]	[0.9445]
Engle-Ng	2.4183	9.9059*	0.0712	2.3014	5.3579	1.2653
	[0.4902]	[0.0193]	[0.9950]	[0.5122]	[0.1473]	[0.7373]
Skewness	-0.3078**	-0.1390	-0.1877	-0.0328	-0.0540	-0.0048
	[0.0799]	[0.4475]	[0.3012]	[0.8530]	[0.7602]	[0.9780]
Excess kurtosis	-0.0770	-0.2851	-0.0284	-0.3206	-0.2281	-0.4447
	[0.8283]	[0.4411]	[0.9382]	[0.3706]	[0.5241]	[0.2119]
Jacque-Bera	3.1610	1.2030	1.0925	0.8658	0.5152	1.6159
	[0.2058]	[0.5479]	[0.5791]	[0.6486]	[0.7728]	[0.4457]

Note: See Table 3.
* denotes 5% significance level.
** denotes 10% significance level.

Table 6: AR-ARCH(1) Estimates with Variance Structural Break

$$y_t = a_0 + \sum_{j=1}^{2} a_j MD_j + \sum_{i=1}^{4} b_i y_{t-i} + \sum_{i=1}^{4}\sum_{j=1}^{2} c_{ij} y_{t-i} MD_j + \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma\ VD_j\ ,\ j = C, G, I, J, U.K., and\ U.S.$$

where MD_1 =1 for t > 1974:1 and VD_C =1 for t > 1987:1; 0 otherwise for Canada

MD_1 =1 for t > 1971:1 and VD_G =1 for t > 1993:1; 0 otherwise for Germany

MD_1 =1 for t > 1979:4 and VD_I =1 for t > 1996:4; 0 otherwise for Italy

MD_1 =1 for t > 1973:1, MD_2 =1 for t > 1989:3 and VD_J =1 for t> 1975:1; 0 otherwise for Japan

MD_1 =1 for t > 1976:1 and VD_{UK} =1 for t > 1991:1; 0 otherwise for the U.K.

VD_{US} =1 for t > 1983:2; 0 otherwise for the U.S.

	Canada	Germany	Italy	Japan	United Kingdom	United States
a_0	1.1479*	1.2790*	1.4003*	1.9675*	0.6952*	0.4129*
	(0.2004)	(0.4159)	(0.1827)	(0.4053)	(0.1951)	(0.0796)
a_1	-0.8362*	-0.9585*	-0.9263*	-1.2909*	-0.4491*	
	(0.2126)	(0.4204)	(0.1807)	(0.3422)	(0.2037)	
a_2				-0.4974*		
				(0.2008)		
b_1	-0.0367	-0.3034*	0.0028	-0.0975	-0.1019	0.2117*
	(0.1230)	(0.1453)	(0.0771)	(0.0777)	(0.1158)	(0.0705)
b_2		-0.1531		0.1197	0.0364	0.2951*
		(0.1122)		(0.0787)	(0.1250)	(0.0671)
b_3		-0.2504*		0.0130	-0.0598	
		(0.1199)		(0.0650)	(0.1062)	
b_4		0.4277*		0.1520*	0.0412	
		(0.1094)		(0.0618)	(0.1167)	
c_{11}	0.5862*	0.3303*			0.4682*	
	(0.1436)	(0.1669)			(0.1458)	
c_{21}		0.1826			-0.0263	
		(0.1333)			(0.1582)	
c_{31}		0.3185*			0.2534**	
		(0.1376)			(0.1347)	
c_{41}		-0.2632*			0.0289	
		(0.1385)			(0.1399)	
α_0	0.8214*	1.0268*	1.4044*	2.5283*	0.7601*	0.8850*
	(0.1277)	(0.1675)	(0.2026)	(0.4878)	(0.1082)	(0.1130)
α_1	0.1520**	0.1562**	0.0966	0.1721**	0.0091	0.1210
	(0.0858)	(0.0914)	(0.0759)	(0.0950)	(0.0619)	(0.0823)
γ	-0.6698*	-0.7882*	-1.0880*	-1.7257*	-0.6861*	-0.7148*
	(0.1276)	(0.1650)	(0.2023)	(0.4705)	(0.1060)	(0.1124)
LR	97.5379*	85.1422*	141.3015*	75.8266*	256.0659*	113.8015*
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
AIC	-46.6351	6.2083	21.7118	49.9491	-59.0634	-54.6136
SIC	-44.5739	9.5893	23.3148	52.8271	-55.3219	-52.8600
LB Q (3)	2.8412	0.8331	0.5787	0.4650	0.1585	1.1627
	[0.4167]	[0.8415]	[0.9012]	[0.9265]	[0.9839]	[0.7619]
LB Q (6)	3.4861	2.3755	5.0256	1.0401	2.4983	2.0698
	[0.7458]	[0.8821]	[0.5405]	[0.9840]	[0.8686]	[0.9131]
LB Q^2 (3)	4.1888	4.6037	1.5600	3.3591	1.1893	0.5003
	[0.2417]	[0.2032]	[0.6684]	[0.3394]	[0.7555]	[0.9188]
LB Q^2 (6)	7.2880	6.7270	5.7811	5.0552	3.2641	1.6917
	[0.2950]	[0.3468]	[0.4481]	[0.5367]	[0.7750]	[0.9457]
Engle-Ng	2.4097	5.8644	0.0733	3.5196	4.9047	0.8551
	[0.4918]	[0.1183]	[0.9948]	[0.3182]	[0.1789]	[0.8362]
Skewness	-0.3141**	-0.1553	-0.1867	-0.0230	-0.0479	-0.0167
	[0.0740]	[0.3961]	[0.3038]	[0.8964]	[0.7869]	[0.9244]
Excess kurtosis	-0.0780	-0.1551	-0.0306	-0.3183	-0.1625	-0.4349
	[0.8262]	[0.6751]	[0.9335]	[0.3740]	[0.6499]	[0.2221]
Jacque-Bera	3.2909	0.9147	1.0819	0.8365	0.2877	1.5543
	[0.1929]	[0.6329]	[0.5821]	[0.6581]	[0.8660]	[0.4597]

Note: See Table 3.

* denotes 5% significance level.

** denotes 10% significance level.

Table 7: AR-ARCH(1)-M Estimates with structural break and level effect

$$y_t = a_0 + \sum_{j=1}^{2} a_j MD_j + \sum_{i=1}^{4} b_i y_{t-i} + \sum_{i=1}^{4}\sum_{j=1}^{2} c_{ij} y_{t-i} MD_j + \lambda\sigma_t + \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \theta\ y_{t-1} + \gamma\ VD_j\ ,\ j = C, G, I, J, U.K., \text{and } U.S.$$

where MD_1 =1 for t > 1974:1 and VD_C =1 for t > 1987:1; 0 otherwise for Canada

MD_1 =1 for t > 1971:1 and VD_G =1 for t > 1993:1; 0 otherwise for Germany

MD_1 =1 for t > 1979:4 and VD_I =1 for t > 1996:4; 0 otherwise for Italy

MD_1 =1 for t > 1973:1, MD_2 =1 for t > 1989:3 and VD_J =1 for t> 1975:1; 0 otherwise for Japan

MD_1 =1 for t > 1976:1 and VD_{UK} =1 for t > 1991:1; 0 otherwise for the U.K.

VD_{US} =1 for t > 1983:2; 0 otherwise for the U.S.

	Canada	Germany	Italy	Japan	United Kingdom	United States
a_0	0.8859*	0.8719**	1.0536*	3.3966*	0.7422*	0.4421*
	(0.2980)	(0.5185)	(0.3496)	(0.7655)	(0.2357)	(0.1342)
a_1	-0.7171*	-0.7950**	-0.7901*	-1.7538*	-0.5033*	
	(0.2350)	(0.4681)	(0.2066)	(0.4038)	(0.2176)	
a_2				-0.5640*		
				(0.1913)		
b_1	-0.0131	-0.2787**	-0.0057	0.0226	-0.1236	0.2089*
	(0.1234)	(0.1582)	(0.0797)	(0.0914)	(0.1107)	(0.0696)
b_2		-0.1738		0.1613*	0.0115	0.2542*
		(0.1232)		(0.0630)	(0.1227)	(0.0668)
b_3		-0.2915*		0.0102	-0.0818	
		(0.1251)		(0.0639)	(0.1055)	
b_4		0.4284*		0.1618*	0.0364	
		(0.1119)		(0.0568)	(0.1165)	
c_{11}	0.6160*	0.3100**			0.4662*	
	(0.1458)	(0.1726)			(0.1453)	
c_{21}		0.1838			-0.0041	
		(0.1405)			(0.1576)	
c_{31}		0.3324*			0.2678*	
		(0.1443)			(0.1401)	
c_{41}		-0.2997*			0.0334	
		(0.1399)			(0.1418)	
λ	0.2618	0.3541	0.2873	-1.0585*	-0.0006	-0.0136
	(0.2317)	(0.2485)	(0.2538)	(0.4847)	(0.1571)	(0.1984)
α_0	0.8436*	1.1759*	1.3515*	1.5783*	0.7364*	0.8358*
	(0.1287)	(0.1721)	(0.2177)	(0.4324)	(0.1143)	(0.1151)
α_1	0.1075**	0.0795	0.1165	0.2442*	0.0832	0.1083
	(0.0601)	(0.0765)	(0.0780)	(0.0680)	(0.0756)	(0.0798)
γ	-0.6615*	-0.8544*	-1.0514*	-1.0312*	-0.6899*	-0.6488*
	(0.1212)	(0.1623)	(0.1991)	(0.4321)	(0.1084)	(0.1114)
θ	-0.0612	-0.1412*	0.0168	0.3133*	0.0008	-0.0199
	(0.0488)	(0.0745)	(0.0925)	(0.1002)	(0.0315)	(0.0524)
LR	220.4818*	144.4523*	128.2905*	123.4781*	146.7953*	124.7603*
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
AIC	-52.0827	8.5606	25.1690	46.6370	-62.1212	-54.7447
SIC	-49.4325	12.4617	27.3064	50.0906	-57.8042	-52.4067
LB Q(3)	2.9049	1.3321	0.7515	0.4917	0.4812	1.2035
	[0.4065]	[0.7215]	[0.8610]	[0.9207]	[0.9230]	[0.7521]
LB Q(6)	3.9140	4.1269	5.8156	1.7588	2.7947	2.0932
	[0.6883]	[0.6595]	[0.4441]	[0.9404]	[0.8341]	[0.9109]
LB Q^2(3)	3.5009	4.3039	2.3143	1.2965	1.4042	0.5954
	[0.3206]	[0.2304]	[0.5097]	[0.7299]	[0.7045]	[0.8974]
LB Q^2(6)	6.5333	5.7135	5.9435	2.3787	2.8848	1.9207
	[0.3661]	[0.4560]	[0.4295]	[0.8817]	[0.8231]	[0.9268]
Engle-Ng	0.3217	3.8221	0.0480	6.0282	3.6500	1.2267
	[0.9558]	[0.2813]	[0.9972]	[0.1102]	[0.3018]	[0.7465]
Skewness	-0.2704	-0.1798	-0.1638	-0.0387	-0.0420	-0.0402
	[0.1240]	[0.3259]	[0.3668]	[0.8267]	[0.8125]	[0.8194]
Excess kurtosis	-0.2084	-0.2096	-0.0410	-0.4360	-0.0380	-0.4521
	[0.5574]	[0.5711]	[0.9109]	[0.2233]	[0.9154]	[0.2043]
Jacque-Bera	2.7584	1.3143	0.8407	1.5859	0.0687	1.7224
	[0.2517]	[0.5183]	[0.6568]	[0.4525]	[0.9661]	[0.4226]

Note: See Table 3.
* denotes 5% significance level.
** denotes 10% significance level.

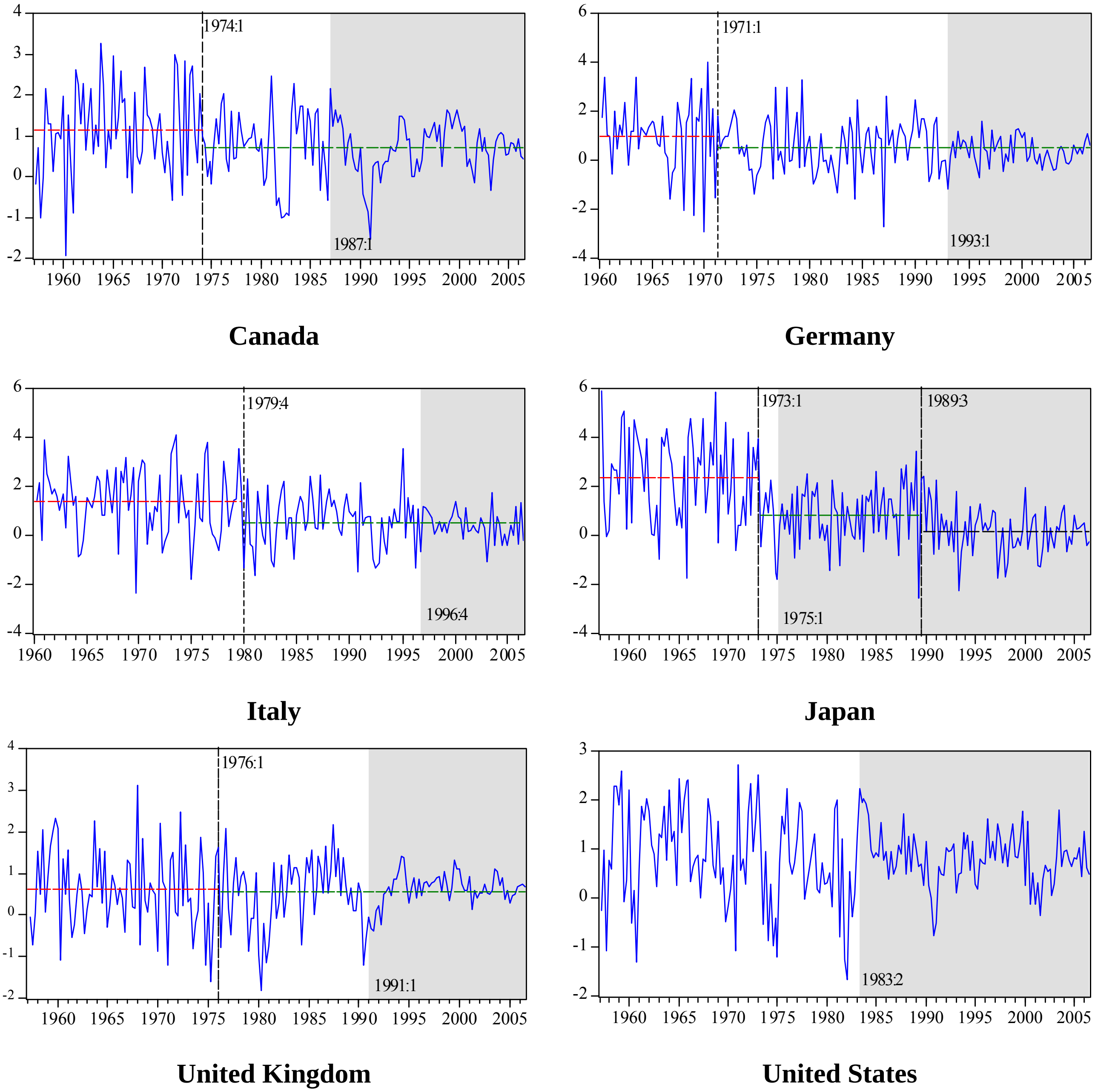

Figure 1.Real GDP Growth Rate

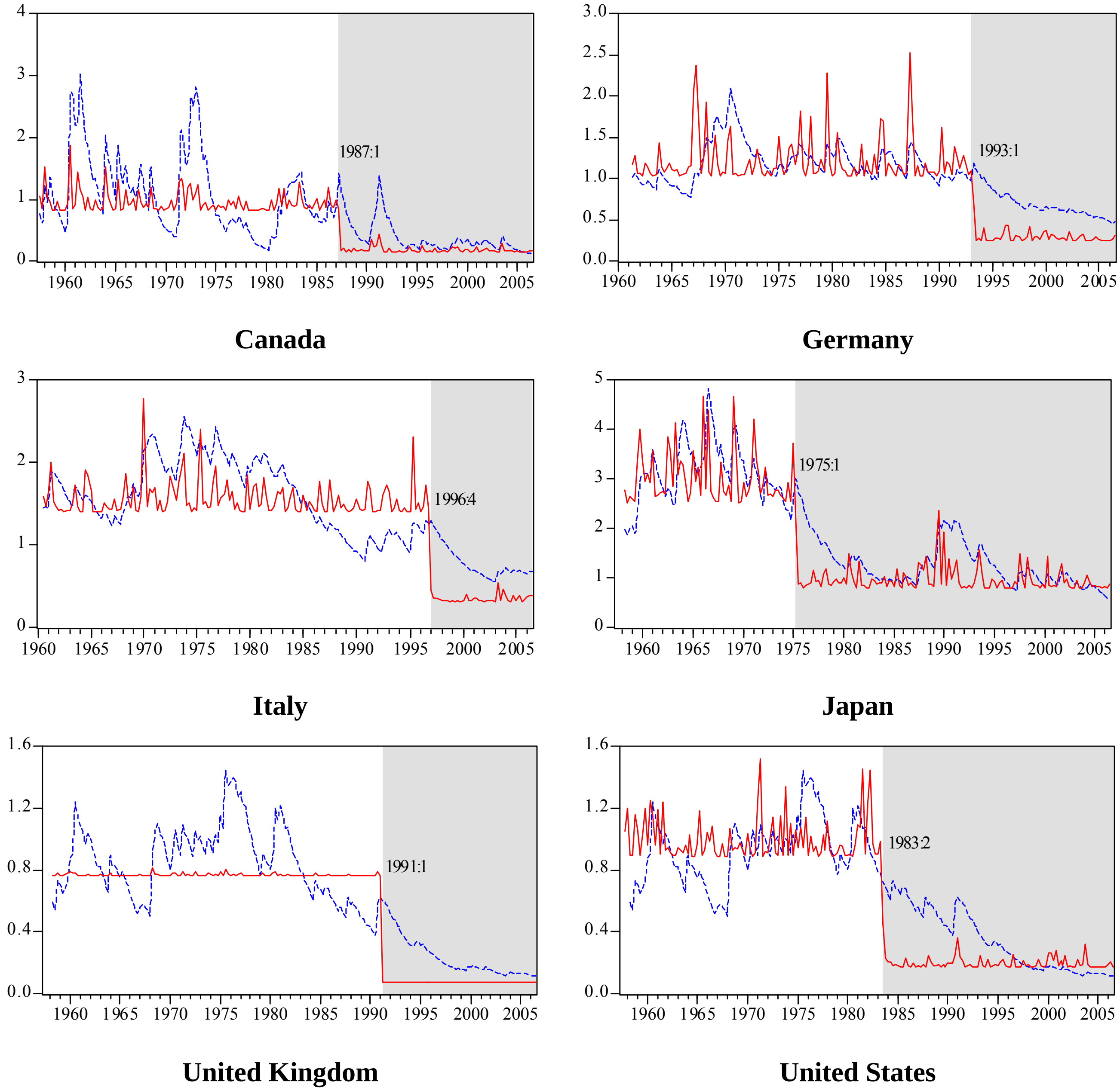

Figure 2. GARCH variance with (Solid Line) and without (Dashed Line) Dummy