Essays on the Volatility of Macroeconomic and Financial Time Series

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Abstract

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The essays are comprised of three chapters to investigate the structural changes and reasons of Japanese postwar macroeconomic dynamic, the structural changes and nature of exchange rate realized volatility, and the relationship between macroeconomic and financial market volatility, respectively. For each chapter, we apply advanced time-series econometrics techniques, including unknown structural break tests, Markov-switching model, long memory model, and factor model using principal component method to analyze a sequence of volatility issues with emphasis on output dynamics, monetary policy and financial market variables. In the first chapter, we exam the rising volatility of Japan's real output and its relationship with monetary policy. A few lessons we learn from Japan's case could be useful for most central bankers.

In the second chapter, using high-frequency data, we explore the possibilities of structural changes and regime switching in the realized volatility of the Deutschemark/Dollar, Yen/Dollar and Yen/Deutschemark spot exchange rates with their observed long-memory property. We find the substantial reduction of persistence of realized volatility after removing the breaks and the VAR-RV-Break model provides the superior predictive ability compared to most of the forecasting models. However, the VAR-RV-I(d) long memory model is still the best forecasting model even when the true financial volatility series are created by structural breaks and we have little knowledge about break dates and size. In the third chapter, we find mixed evidence on volatility destabilization for the financial market. Twelve static factors and eight dynamic factors are calculated and explored from 140 time series data set in the U.S.

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DEDICATION

To my parents and Sophia.

Chapter 1: Output Volatility Regime and Monetary Policy Rule: Evidence from Japan

1.1 Introduction

Over the past twenty years or so, one of the most striking economic activities has been the substantial global decline in macroeconomic volatility, including real output and inflation. A number of recent studies have sought to characterize this widespread decline in volatility, also called "the Great Moderation," across sectors within the U.S. as well as most of the G7 countries. Researchers, for example, Kim and Nelson (1999a), McConnell and Perez-Quiros (2000), both documented the sharply reduced volatility of U.S. real GDP growth since 1984:1. Others, such as Blanchard and Simon (2001), Stock and Watson (2003, 2005a), explored other major industrial countries and found similar declines in the volatility of real output. They both documented Japan as the only country with a different evolution. Nevertheless, they didn't analyze this abnormity in more detail.

There has been a great interest in the issue of Japan's great recession in the 1990s. However, most of this literature focuses on Japanese deflation with low average GDP growth for the past decade. Rather, this chapter focuses on the recent increase in observed output volatility in Japan. This could be shown in the plot of quarter-to-quarter growth rate of real GDP in the late 1990s for Japan in Figure 1.1. Higher volatility of output implies more volatile employment and an increase in economic uncertainty for households and firms. The rising volatility of output means that recessions have become more frequent and more severe. Hence, this chapter wants to answer three questions: First, have there been one or more structural breaks in postwar Japanese real GDP toward stabilization or destabilization? Second, if so, when? Third, the nature and source of the output volatility dynamics.

This chapter employs both classical and Bayesian approaches to identify the structural break for the mean and volatility of real output at an unknown change point. Empirical results suggest two breaks - the first break occurred in 1974:1 toward stabilization and the second break in 1994:4 toward destabilization for the aggregate GDP growth and many disaggregate components of GDP as well. Furthermore, this chapter uses three-state Markov-switching model and find three regimes for the Japan's postwar GDP growth: high growth and high volatility regime - 1955:3 to 1973:2; medium growth and low volatility regime – 1975:2 to

1992:4; and low growth and high volatility regime – 1993:1 to 2001:1. The identification of breaks or regimes for volatility has important implications for policy decision and research modeling such as model calibration and estimation of vector autoregression.

Another goal of this research is to determine the causes of the observed opposite direction of variations for Japan. Many explanations have been proposed for the reduction of volatility in the U.S., with the three main classes of explanations. First, improved policies: specifically monetary policy, such as Clarida, Gali, and Gertler, henceforth CGG, (1998, 2000), and Bernanke (2004). Second, better practices: particularly improved management of business inventories, such as McConnell and Perez-Quiros (2000). Third, good luck: smaller and less frequent shocks hitting the economy, such as Ahmed, Levin, and Wilson (2004), and Stock and Watson (2003, 2005a).

Although these three classes of explanations probably all exist at the same time, the relative importance of these explanations is still a major concern for the evaluation of policy effectiveness. What was the main source of the latest structural break in Japan? Bad policies, bad practices, or just bad luck? This chapter mainly focuses on the policy hypothesis, especially monetary policy. Although enormous literature has investigated in Japanese monetary policy, few has considered about parameter stability issue, which has been assessed and overcome in this chapter. Using monetary reaction function by Generalized Method of Moments (GMM) model, the research concludes that the passive monetary policy was the most likely explanation for this unwelcome structural break in output volatility. Furthermore, Andrade and Divino (2005) suggested that Japanese monetary policy has emphasized on exchange rate targeting instead of inflation rate targeting. However, CGG (1998) found evidences in favor of the inflation targeting. This chapter's results support the former and against the latter.

The chapter proceeds as follows: section 1.2 does the data set overview and characterizes the stationarity and linearity of postwar Japanese real GDP growth by structural stability test. Section 1.3 specifies a series of models to explore the nature and timing for both aggregate and disaggregate output fluctuations. Section 1.4 examines the sources of volatility structural change. Section 1.5 concludes.

1.2 Data Overview and Stability Test

1.2.1 Data Overview

This chapter uses quarterly Japanese real GDP data from 1955:2 to 2001:1 provided by Economic and Social Research Institute (ESRI)[1]. Table 1.1 reports the sample standard deviation of major macroeconomic time series for Japan by decade (1955 to 1959 are included in the 1960s; 2001:1 is included in 1990s). Each decade's standard deviation is shown relative to the full-sample standard deviation, so a value more than one means a period of relatively high volatility. Most series were less volatile in the 1980s than over the full sample while more volatile in the 1990s than over the full sample. It is worth noting that inflation (0.3) and short-term interest rate (0.62) were both less volatile in the 1990s because the liquidity trap and zero lower bound of nominal interest rate happened in Japan.

The observed changes in the volatility of output shown in Figure 1.1 could arise from the change in the variance of output shocks (conditional variance), changes in the dynamic process through which these shocks affect output (changes in the autoregressive coefficient; that is, conditional mean), or both. The research estimates the instantaneous variance using nonGaussian smoother based on the stochastic volatility model with heavy tails and time-varying autoregressive coefficients. Equation (1.1) – (1.3) represent the model,

$$y_t = \mu_t + \sum_{j=1}^{4} \phi_{jt} y_{t-j} + \sigma_t e_t \tag{1.1}$$

$$\phi_{jt} = \phi_{jt-1} + \gamma_t v_{jt} \tag{1.2}$$

$$\ln \sigma_t^2 = \ln \sigma_{t-1}^2 + \omega_t \tag{1.3}$$

Figure 1.2 presents graphical evidence on the declined volatility in the 1980s and increased volatility in the 1990s for the major series shown in Table 1.1. The solid line is a raw estimate of the volatility of the series, that is, the absolute value of the deviation of each series from its unconditional mean. The dash line is a two-sided estimate of the instantaneous time-varying standard deviation of the series based on equation (1.1) to (1.3). The model is discussed in more detail in Appendix A.

The results in Figure 1.2 reveal a more accurate picture of the dynamics in volatility. The volatility of GDP declined in the mid 1970s and rose in the mid 1990s. The volatility of

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[1] ESRI only provides real GDP data based on SNA63 (System National Account) from 1955:2 to 2001:1 (benchmark year 1990). ESRI also provides real GDP data SNA93 from 1980:1 to date, but the measurement components are different for SNA68 and SNA93; that is, two data sets are not consistent.

consumption seems to have risen in the mid 1990s. The volatility of investment seems to have declined in mid 1960s. The volatility of change in inventories declined in mid 1970s. The volatility of government spending rose sharply in the mid 1990s. The volatility of the inflation rate declined since the mid 1970s. The volatility of short rates declined since the early 1980s. Most series for the volatility showed different dynamics from those of the U.S. or other industrial countries. Moreover, from Figure 1.1, we were unable to find the fewer and shorter recessions like those found in the U.S. since 1980s[2].

1.2.2 Stationary and Stability Tests

Our approaches focused on whether there was a parameter (structural) stability of the real output growth, which is the first-difference of the real GDP. First, this chapter considered and examined the possibility of linear (deterministic) trend process of Japan real GDP. We used different unit root tests for real GDP and its components as well. The test statistics displayed in Table 1.2 all fail to reject the hypothesis of a stochastic trend of Japanese real GDP and its components (except inflation), which means that I(1) process due to frequent permanent shocks can explain the Japanese macroeconomic process better. Following Zivot and Andrews (1992) and Lumsdaine and Papell (1997), we also considered the unit root tests that allow one and two unknown-timing structural breaks respectively. Using the crash model, with an assumption of the structural change in the intercept of the Japanese real GDP trend, the minimum t statistics for one and two breaks are -2.37 and -3.15 respectively. Therefore, we still could not reject the null of I(1) process for real GDP. Consequently, GDP and its component variables were transformed to annual growth rate ($100 \times \ln(X_t / X_{t-4})$). Others were transformed to first differences ($X_t - X_{t-4}$).

Before specifying the appropriate models (nonlinear or state-space) for Japanese real GDP growth, we needed to detect the parameter stability for the linear model. We used Nyblom's L test as described in Hansen (1992). The research specified the model by using ARIMA (1, 1, 0) for log of the real GDP to test model stability.

From Table 1.3, we rejected both the hypothesis of the stability or homoskedasticity of intercept term (μ) and variance (σ^2) and reject the hypothesis of the joint stability of the parameters. Although we failed to reject the null for the autoregressive coefficient, this does not mean we can rule out instability in the autoregressive parameter. As Hansen (1992)

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[2] There is a latest recession from 2000: 4 to 2002: 1, which cannot be seen in Figure 1.

mentioned, if both the autoregressive and error variance have shifted, the power of the L test for the autoregressive parameter is low. In summary, the result explains the possibility of heteroskedasticity of mean and variance.

1.3 Model Specifications for Output Growth and Volatility Regime

In this section, we will exam whether the instability of real GDP is associated with a single or multiple distinct structural breaks in the mean and volatility. If so, we then estimate the timing of the structural change in the process of the data. Alternative Markov-switching model would be presented as well.

1.3.1 Benchmark Method – Single Structural Break Test on Mean and Variance

We use the following model to test if there is a structural break in the conditional mean and variance proposed by Stock and Watson (2002a). To test a break in the conditional variance, we let $\varepsilon_t(\tau)$ denote the errors in the autoregression in equation (1.4), which is the same as equation (1.1),

$$y_t = \mu_t + \phi(L)y_{t-1} + \varepsilon_t \tag{1.4}$$

where

$$\mu_t + \phi_t(L) = \begin{cases} \mu_1 + \phi_1(L), & t \le \tau_1 \\ \mu_2 + \phi_2(L), & t > \tau_1 \end{cases} \quad \text{and } \mathrm{E}(\varepsilon^2) = \begin{cases} \sigma_1^2, & t \le \tau_2 \\ \sigma_2^2, & t > \tau_2 \end{cases} \tag{1.5}$$

where $\phi(L)$ denotes a lag polynomial, τ_1 is the break date for conditional mean (constant and AR coefficients) and τ_2 (innovation variance) is the break for the conditional variance. Equation (1.5) implies conditional mean and variance might change at different dates. We use supremum of the sequence of Wald test statistics, $W_T(\pi)$, which tests the null hypothesis that the parameters are constant against the alternative that they have a single break at a fraction π through the sample. The break date is treated as an unknown priori so that the tests compute the sequence W_T for $t = t_0 + \ldots, t_1$ and then computing a supremum of the sequence. This method is called Quandt likelihood ratio (QLR[3]) proposed by Quant (1960) and also referred to sup-Wald statistic proposed by Andrews (1993).

[3] We use heteroscedasticity-robust version of the QLR statistics where $W_T(\pi)$ is computed by using White (1980) heteroscedasticity-robust covariance matrix, in which the residuals were computed under the null rather than each of the alternatives for computational convenience.

First, the QLR statistic is used to test for a break in equation (1.5) in the central 70% of the whole sample. Then we test for a break in the variance at an unknown date τ_2 by computing the QLR statistic for a break in the mean of the absolute value of the residuals from the estimated AR model (1.4), where the autoregression allows for a break in the AR parameter at the estimated break date τ_1. For the break test in the conditional variance, under the null hypothesis that there is no break in the variance; E($\varepsilon_t^2(\tau_1)$) is constant. Under the alternative hypothesis that there is a break at date τ_2, E($\varepsilon_t^2(\tau_1)$) is σ_1^2, when $t \le \tau_2$; is σ_2^2, when $t > \tau_2$. We report the break dates at the 5% significant level and compute 67% confidence intervals by Bai (1997)[4]. The p-values associated with these statistics are computed using the approximation proposed by Hansen (1997). Although the QLR is for the single-break model, it has the power against other forms of time variation. Rejection of the no-break null by the QLR statistic is evidence of time variation, which may have single or more than one break in equation (1.5). In order to check another potential break, we choose the sub-sample period 1975:2 to 2001:1.

Table 1.4 shows the results for the full sample period 1955:3 to 2001:1. There was a structural break of conditional mean for Japanese real GDP growth in 1973:1 and a structural break of conditional variance for Japanese real GDP growth in 1974:1. The former result explains the slowdown in the average growth rates of real output widespread across major industrial countries by the first oil crisis.

Table 1.5 reports the results for the subsample period 1975:2 to 2001:1. There is one structural break of conditional mean for Japan real GDP growth in 1991:1 since the burst of the Japanese "bubble economy" and another structural break of conditional variance for Japanese real GDP growth in 1994: 4. The former dates the beginning of Japan's persistent economic stagnation, which is also called "Great Recession."

1.3.2 Single Structural Break Test on Variance

McConnell and Perez-Quiros (2000) attributed the possibility of the structural break of observed residual variance for U.S. GDP growth to mean or innovation separately. To provide the robustness analysis for the structural break date that we got from the benchmark

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[4] 95% intervals are too wide and uninformative since the break estimator has a non-normal, fat-tailed distribution. Hence, we report 67% confidence intervals rather than 95%, conventional intervals.

method, we estimate a break point by their method by using the innovation break test only:

$$y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \varepsilon_t, \quad \varepsilon_t \sim N(0,\sigma_t^2) \tag{1.6}$$

where $\sigma_t^2 = \sigma_1^2$ if $t \le \tau$, and $\sigma_t^2 = \sigma_2^2$ if $t > \tau$. As reported in Table 1.6, we still find the same result of break date: 1974:1 for the whole sample period and 1994:4 for the subsample period.

1.3.3 Multiple Structural Breaks Test on Mean

Even though we found two structural breaks above, the method is based on an ad hoc choice of sample period. To do a robustness check and overcome the drawbacks from single structural break test, we use a multiple-structural-breaks test that allows one to test the null hypothesis of n breaks versus the alternative hypothesis of n+1 breaks, as proposed by Bai and Perron (1998, 2003) using least squares. We consider the linear regression with *n* breaks:

$$y_t = x_t'\beta + z_t'\delta_j + \varepsilon_t \qquad t = T_{j-1}+1,\ldots,T_j \tag{1.7}$$

where j =1,...., n +1. y_t is the observed dependent variable at time *t*; $x'(p \times 1)$ and $z'(q \times 1)$ are vectors of covariates; β and δ_j are the vectors of coefficients; ε_t is the disturbance at time t. We specify the model by p = 0 where all the coefficients are subject to change. The variance of ε_t needs not to be constant. Breaks in variance are permitted at the same dates as the breaks in means of the regression.

Table 1.7 reports the results. For the determination of the numbers of breaks, the $\sup F_T$ tests are all significant for *n* between 1 and 5. The $F_T\,(2|1)$ is 11.6 and significant but $F_T\,(3|2)$ is 4.08, which is not significant. Therefore, the sequential procedure using 5% significance level selects 2 breaks. Finally, the break dates on means are estimated in 1973:1 and 1991: 2, which are almost the same as the break dates found in the benchmark method.

1.3.4 Multivariate Structural Break Test on Variance - VAR Method

In theory, a common break date could be estimated more precisely by using multiple equations. Bai, Lumsdaine and Stock (1998) used a low-dimensional VAR to estimate common breaks across multiple series. We use their method except for keeping VAR coefficients constant. The hypothesis of no break was tested against the alternative of a common break in VAR equations by the QLR statistic, which was computed using the absolute values of the VAR residuals. We also use 67% confidence interval proposed in the same chapter.

VAR components are the first difference of the logarithm of consumptions, investment, export, import, and government spending. Table 1.8 reports the result that there is a break date in 1975:2 for the whole sample period and another break date in 1994:3 for the subsample period. The break date results from univariate methods mentioned above are all in the confidence interval here.

1.3.5 The Long and Declining Trend Method on Variance

Blanchard and Simon (2001) argue that a large decline in U.S. output volatility is not a recent development but rather a steady long trend, starting in the 1950s, interrupted in the 1970s and early 1980s, with a return to trend in the late 1980s and 1990s. To investigate this possibility for Japan (an increase in output volatility since middle 1990s is a temporary deviation from the declining trend, as shown in Figure 1.3.A), we conduct additional specification in which the innovation variance is modeled as a time-trend linear function with a discrete jump at an unknown break date. The QLR test in equation (1.5) was modified as a model to include a time trend as well as the break.

$$|\varepsilon_t| = \gamma_0 + \gamma_1 t + \gamma_2 D_t(\tau) + e_t \tag{1.8}$$

where $D_t(\tau)$ is a binary variable that equals 1 if $t \geq \tau$ and equals 0 otherwise and e_t is an error term. We also choose the central 70% of the sample for value τ . The results are reported in the final block of Table 1.4. For the real GDP in the full sample, we reject the null hypothesis of no trend as well as no break. The break date is in 1994:2. Namely, we can interpret that there was a declining trend in volatility for Japanese real output prior to 1994 but a break occurred in 1994:2 towards rising volatility regime, which is shown in Figure 1.3.B. For the subsample, we could not reject the null hypothesis for most of the macroeconomic series because sample size is not big enough. In sum, the break model mentioned above performs better than the trend model.

1.3.6 Markov-Switching Model

Hamilton (1989) used a Markov-switching model to explain postwar U.S. business fluctuations, and the turning point was treated as a structural event that is inherent in the data-generating process. Parameter changes are thought to be recurrent and governed by a Markov process, which is different from the structural break test detecting nonrecurrent changes. This model can capture a particular form of nonlinear dynamics or asymmetry in the business cycle. The model allows the mean rate of GDP growth to switch between two states to show the boom with a high probability that output growth remains high if it is initially high and recession as well if output growth is initially low.

We first apply his model in the Japanese real GDP growth (y_t) for the sample 1955:3-2001:1 as follows:

$$\begin{aligned} &(y_t - \mu_{St}) = \phi_1(y_{t-1} - \mu_{St-1}) + \ldots + \phi_4(y_{t-4} - \mu_{St-4}) + \varepsilon_t \\ &e_t \sim i.i.d.N(0, \sigma^2) \\ &\mu_{St} = \mu_0(1 - S_t) + \mu_1 S_t \\ &\Pr[S_t = 1 \mid S_{t-1} = 1] = p, \quad \Pr[S_t = 0 \mid S_{t-1} = 0] = q \end{aligned} \tag{1.9}$$

From Figure 1.4.A, without considering the structural change on means and variance Hamilton's model would perform too poorly to explain the recession and expansion, especially between 1970s and 1990s. To improve this situation, Kim and Nelson (1999a) proposed a modified model in which μ and/or σ^2 are subject to a one-time structural break.

However, we use an alternative model, proposed by Garcia and Perron (1996), which is three-state rather than two-state. This model allows three possible regimes affecting both the mean (μ_{St}) and variance (σ^2_{St}). We only assume that three states of means with $\mu_1 < \mu_2 < \mu_3$ to present the Japanese postwar GDP growth convergence. There is no restriction on states of variance. Furthermore, based on this model, we use the Bayesian approach by Gibbs-sampling procedure proposed by Kim and Nelson (1999b) to estimate the regime switching. It is worth noting that Bayesian approach has an advantage over classical tests for treating both model's hyperparameters and the state variable random variables. In contrast to the classical approach, which treats the state variable conditional on the estimated values of the hyperparameters, the Bayesian approach make inference on state variables based on joint distribution of state variables and hyperparameters.

$$\begin{aligned} &(y_t - \mu_{St}) = \phi_1(y_{t-1} - \mu_{St-1}) + \phi_2(y_{t-2} - \mu_{St-2}) + \varepsilon_t \\ &\varepsilon_t \sim i.i.d.N(0, \sigma^2_{St}) \\ &\mu_{St} = \mu_1 S_{1t} + \mu_2 S_{2t} + \mu_3 S_{3t}, \quad \text{where } \mu_1 < \mu_2 < \mu_3 \\ &\sigma_{St}{}^2 = \sigma_1^2 S_{1t} + \sigma_2^2 S_{2t} + \sigma_3^2 S_{3t} \\ &\Pr[S_t = j \mid S_{t-1} = i] = p_{ij}, \quad \sum_{j=1}^{3} p_{ij} = 1, \quad i, j = 1,2,3 \quad S_{kt} = 1 \; if \; S_t = k \end{aligned} \tag{1.10}$$

The first 2,000 draws of Gibbs-sampling are discarded, and the analysis is based on the next 10,000 draws. Table 1.9 reports the marginal posterior distributions of each of the model's parameters. We find three regimes as shown in Figure 1.4: high growth (quarterly: 2.20; annual: 8.8) and high volatility (quarterly: 1.77; annual: 7.08) regime – 1955:3 to 1973:2; medium growth (quarterly: 0.95; annual: 3.8) and low volatility (quarterly: 0.42; annual: 1.68) regime – 1975:2 to 1992:4; and low growth (quarterly: 0.10; annual: 0.4) and high volatility (quarterly: 1.90; annual: 7.6) regime – 1993:1 to 2001:1[5] by three-state Markov-switching model. The regime-switching points are very close to the structural break points.

1.4 Sources of the Change in Output Volatility

There have been three major explanations proposed for the sources of the decline of U.S. output volatility since 1984. The first hypothesis is *the good macroeconomic policy*, i.e. that better monetary policy that has tamed the business cycle. If monetary policy changes, it has a direct effect on the propagation mechanism of the shocks. If agents are rational, policies changes will be incorporated into the private sector's forecasts. The second one is *the good practice*, i.e. just-in-time inventory management coming from computation and communication technology improvement, increased depth and sophistication of financial markets, deregulation in industries, and a shift away from manufacturing toward services. The last one is *the good luck*, which simply reflects a decline in the variance of exogenous shocks hitting U.S. economy[6]. It is interesting to explore why Japan reduced their output and inflation volatility a decade earlier than U.S. (1974:1 versus 1984:1) but has had rising output volatility of late. Which hypothesis can mostly contribute to the Japan medium growth – low volatility regime from 1975:2 to 1992:4?

1.4.1 Bad Luck Hypothesis

Since the real exogenous shocks are difficult to identify, this chapter uses VAR forecast errors (impulse) to represent the shocks. Using the reduced-form VAR method mentioned in Section 1.3.4 with three variables: real GDP growth, call rate, and inflation rate, we only found one common structural break date of absolute value of VAR residuals occurred

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[5] Another short period of low growth and high volatility regime occurred between 1973:3 and 1975:1.

[6] Ferguson (2006) doubt this hypothesis because the events occurred in the late 1990s and early 2000s such as Russian default crisis, Long Term Capital Management Travails, September 11 attacks, and corporate governance scandals.

in 1980:3 with confidence interval 1979:2 to 1981:4. This simply explains exogenous shocks which changed in 1980:3 have no association with the output structural breaks in 1974:1 or 1994:4. Hence, the bad luck hypothesis would not be the appropriate explanation for changing output volatility regimes. Furthermore, Hamilton (1983) argued that the stagflation period in the 1970s in the U.S. was attributed to cost-push shocks such as union wage pressures, price increases by oligopolistic firms or increase in oil prices, that is, bad luck. But we can not see that Japan's variability of inflation and output was affected by oil shock after 1975:2. It would be difficult for oil shocks to generate unstable real output and inflation for a long time without an accommodating monetary policy. However, we can not exclude the possibility of an influential role of productivity shocks on output volatility in Japanese first and third regime. This chapter leaves this hypothesis open for further research.

1.4.2 Bad Practice Hypothesis

Bad practice is also problematic to be the main cause of rising volatility since there is no obvious evidence to support this hypothesis for Japan. For example, better inventory management occurred not only in the U.S. but also in Japan as shown in Figure 1.2.A. And this better inventory hypothesis may play an important role for the decline in volatility of output in 1975:2 since the volatility for the change of inventory over GDP has a structural break toward stabilization in 1975:2 reported in Table 1.4. It is worthwhile to mention the seriousness of the banking problem in Japan, due to bad loans from the burst of the asset bubble in the early 1990s. Figure 1.5 shows that the M2 multiplier (M2/Monetary base) decreases sharply since 1992. We also get the structural break in mean of M2 in 1990:2 from Table 1.5 due to the difficulty in financing investment projects. This "credit crunch" could explain Japan's slump and its rising variance as well.

It is widely agreed that residential fixed investment has been highly volatile and procyclical. From Table 1.4 and 1.5, the evidence reports that it does not play a central role in explaining rising variability because there is no structural break of residential investment occurred in the 1990s. The services sector is less cyclically sensitive than the manufacturing sector. However, from Figure 1.7, we can see that the Japanese economy is shifting from manufacturing sector towards a service sector, especially in the 1990s. Consequently, this hypothesis is less persuasive to explain the rising volatility totally.

1.4.3 Bad Policies Hypothesis

Finally, it is not surprising to get the result: bad policy is the main source of Japan's high volatile regime since 1993:1. There has been a flood of literature investigating the sources and policy recommendations for Japan's low growth regime, but few of them have explored the association between its policy and rising volatility of output. What did Japan do that cause a rise in output volatility given relatively stable inflation (deflation)?

1.4.3.1 Monetary Policy Rule – Closed Economy Model

CGG (2000) estimated a forward-looking Taylor rule for the monetary policy reaction function using ex-post data and generalized method of moment (GMM). They presented evidence that US monetary policy rule changed from indeterminacy in pre-Volcker period to determinacy in Volcker-Greenspan period. Since evidence was shown two structural breaks between three regimes, we use these three regimes as subsamples to estimate Japanese monetary policy rules. These three regimes correspond to unstable, stable and unstable eras. Following CGG's method, a monetary policy that uses short-term nominal interest rate as an instrument rule affects the real economy in the short run:

$$R_t = \rho R_{t-1} + (1-\rho)(\alpha + \psi_1 E[\pi_{t+4} \mid \Omega_t] + \psi_2 E[x_{t+1} \mid \Omega_t]) + \varepsilon_t \qquad (1.11)$$

where R_t is the short-term nominal interest rate (call rate) set by the Bank of Japan (BOJ), ρ is an indicator of the degree of smoothing of interest rate changes, π_{t+4}[7] is the rate of inflation in one year (the percent change in the price level between period *t* and *t + 4*) measured by the four-quarter percent change of the GDP deflator, and x_{t+1} is the output gap[8] in period t + 1 (the deviation of real GDP from potential real GDP, calculated by HP-filter). E is the expectation operator, and Ω_t is the information set at the time the interest rate is determined. The instrument set includes lags of the call rate, inflation, the output gap, and the log of real exchange rate. Generally speaking, interest rate rules with $\psi_1 > 1$ and $\psi_2 > 0$

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[7] The central bank is assumed to have a target horizon of one year for its inflation target since the horizon roughly fits the conventional wisdom about the lag with which monetary policy affects inflation. Target horizon of 4 quarter is more realistic than one or two quarters. (CGG 2000)

[8] Although some economists point out that Japan's output gap is seriously undervalued in 1990s (Krugman 1998), it is still hard to accurately measure and predict the true productivity process. Given the limited information, we use HP filter to calculate Japan's output gap as shown in Figure 6.

will tend to be stabilizing[9]. For example, famous Taylor rule suggests ψ_1 =1.5 (for the current inflation) and ψ_2 =0.5 (for the current output gap) proposed by Taylor (1993). On the other hand, those with $\psi_1 \leq 1$ and $\psi_2 \leq 0$ are likely to be destabilizing or, at best, accommodative of shocks to the economy.

1.4.3.2 Results in Closed Economy Model

Based on the results from section III, we estimate the model with three subperiods: 1961:1-1975:1, 1975:2-1992:4, and 1993:1-2001:1 using quarterly data[10]. Table 1.10 reports GMM estimates of the interest rate rule parameters ψ_1, ψ_2, α, and ρ. The model specification works well since the J-statistic shows that we cannot reject the overidentifying restrictions. We find significant results of ψ_1 (2.08, with *s.e.* = 0.55) in the second regime, which is stabilizing. In first and third regime, the ψ_1 are destabilizing. (-0.85, with *s.e.* = 0.46; -0.67, with *s.e.* = 0.27, respectively). The estimates of ψ_2 are not significant from zero for the first and second regimes, but it is significant in the third regime.

For robustness check, we also use alternative monthly data to estimate two subperiods[11]: 1979:1-1992:12, 1993:1-2001:12 where π_t is measured by the CPI and x_t is the output gap of industrial production. The instrument set includes 12 lags of the call rate, inflation, the output gap, the difference of the log of real exchange rate, and commodity price inflation. We find the consistent results as quarterly data. In the second regime, ψ_1 is stabilizing and significant (2.04, with *s.e.* = 0.98) and ψ_2 is insignificant (0.83, with *s.e.* = 0.53). In the third regime, ψ_1 is destabilizing and significant (0.32, with *s.e.* = 0.07) and ψ_2 is insignificant (0.02, with *s.e.* = 0.03). The estimate for ρ is high in most cases (except first regime), providing strong evidence for interest rate inertia.

The results in the second regime are similar to those in CGG (1998). Using monthly data, they found ψ_1 is 2.04 (with *s.e.* = 0.19) and ψ_2 is 0.08 (with *s.e.* = 0.03) for BOJ from

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[9] $\psi_1 > 1$ per se is called Taylor principle.

[10] The first regime begins in 1961:1 because of call rate data availability. The third regime begins in 1993:1 instead of 1994:4 because we can have a bigger sample size for the short third regime.

[11] Industrial production data is only available since 1978:1.

1979:4 to 1994:12[12]. They suggested that BOJ appeared to have placed more weight on controlling inflation relative to output stabilization.

Thus, our estimates confirm that CGG (1998) about the monetary policy using inflation targeting that follows Taylor principle with some weight on output stabilization was the main reason for Japanese stable regime (1975:2 – 1992:4). Why would Japan apply stabilizing monetary policy in second regime but used destabilizing policy in the first and third regimes? First, it is worth noting the abandonment of Bretton Woods system of Japan in March 1973, changing from fixed-exchange-rate system to floating-exchange-rate system. It was an important institutional change and source for the structural break from high volatility regime to low volatility regime. Under the Bretton Woods system, Japan maintained a fixed nominal exchange rate of 360 yen per dollar. Monetary policy during this period was limited and passively responded to offset exchange-rate pressures (ψ_1= -0.85, with *s.e.* = 0.46; ρ>1). From the Mundell-Fleming Model, we know that a government that fixes its currency's exchange rate loses control of the domestic money supply. Taylor (1993) also argued that the fluctuations in real output are much larger in the fixed-exchange-rate system than those in the flexible-exchange-rate system. Using a multivariate GARCH-M model, Kim (2000) found that the flexible-exchange-rate system helped the Japanese economy to absorb the foreign shocks.

Second, for the third regime, ψ_1 is passive and destabilizing (ψ_1= -0.67, with *s.e.* = 0.27). Since 1995 (see Figure 8), Japan has fallen into deflation. According to Taylor principle, BOJ has to cut the nominal interest rate or increases monetary base actively (ψ_1>1) to mitigate this deflation gap but they did not or could not. Namely, they used too restrictive of a monetary policy, which is consistent with the findings in McCallum (2000) using different policy rules models. The deflationary environment let Japan fall into liquidity trap in which conventional monetary policy lost its power because the nominal interest rate was close to zero, where the quantity of money became irrelevant since money and bond became perfect substitutes. Figure 9 shows the call rate dropped to 0.25% and then cut to 0.02% since 1999[13]. Using a stochastic simulation, Reifschneider and Williams (2000) found volatility of output and employment increase significantly under the low-inflation environment with a constraint

[12] CGG (1998) mentioned that they pick April 1979 as the appropriate starting date because it is the beginning period of significant financial market deregulation. We think it is not persuasive. The appropriate starting date should be 1975 if data is available.
[13] Even though conventional monetary policy is ineffective in the liquidity trap, Japan still can benefit by expanding monetary base and using open market purchases for long-term government bonds and/or foreign exchanges (Svensson 2004).

of zero bound of nominal interest rate. This is the main reason for the output instability in the third regime.

1.4.3.3 Monetary Policy Rule – Open Economy Model

As in Ball (1999), in a closed economy, inflation targeting and Taylor rules perform well in stabilizing both output and inflation. In an open economy, however, these policies perform poorly unless they are modified. The policy instrument should be based on both the interest rate and the real exchange rate. Svensson (2000) also mentioned that including the real exchange rate in the monetary policy rule has important consequences. The exchange rate allows an additional channel for the transmission of monetary policy. The real exchange rate will affect the aggregate demand and inflation with lags. For robustness check, we modified and estimated the open - economy monetary policy rule proposed by Taylor (2001) as follows,

$$R_t = \rho R_{t-1} + (1-\rho)(\alpha + \psi_1 E[\pi_{t+4} \mid \Omega_t] + \psi_2 E[x_{t+1} \mid \Omega_t] + \psi_3 E[e_t \mid \Omega_t]) + \varepsilon_t \qquad (1.12)$$

where R_t π_{t+4}, x_{t+1}, are variables as mentioned in (1.7) and e_t is the real exchange rate gap[14] (the deviation from its HP-trend; an increase in e_t is a real appreciation). The model is similar to that in CGG (1998). The difference is that we use HP-trend to get real exchange rate gap rather than linear-trend they used. The reason for different forecast horizons is because of the realistic lags of the different channels for the transmission of monetary policy (Svensson 2000): The direct exchange rate channel to the inflation (through import prices) has the shortest lag, the aggregate demand channel to the output gap has an intermediate lag, and the aggregate demand and expectations channels on inflation have the longest lag. We use quarterly data to estimate the forward-looking model by two subperiods: 1975:2-1992:4, 1993:1-2001:1 and monthly data for two subperiods: 1979:1-1992:12, 1993:1-2001:12 where π_t is measured by the CPI and x_t is the output gap of industrial production. The instrument set includes four lags of the call rate, inflation, the output gap, and the difference of real exchange rate.

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[14] In Obstefel and Rogoff (1995), they pointed out that Japan, with an unusually high differential between productive growth in its tradable- and nontradable-goods, will typically experience a rise in the relative price of nontraded goods and an appreciation of its real exchange rate. Any attempt to use PPP as a guide to monetary policy intervention must allow for productivity-based PPP deviations.

1.4.3.4 Results in Open Economy Model

Table 1.11 presents the results for the open-economy model. Surprisingly, in the second (stable) regime, ψ_1 is 0.54 (with *s.e.* = 0.14), that is, BOJ did not raise the nominal interest rate sufficiently (ψ_1>1) to increase the real rate when inflation moves above its long-run target as reported in CGG (1998). Including real exchange rate data, they found ψ_1 was 1.92 (with *s.e.* = 0.11) for BOJ in the period from 1979:4 to 1994:12[15]. One potential explanation would be that they used inappropriate real exchange data (deviation from linear trend) while real exchange rate is I(1) process as shown in Table 1.2. Using cointegration analysis and impulse response functions for the same period data as in CGG (1998), Andrade and Divino (2005) found BOJ has tried to stabilize exchange rate and the interest rate is counter-cyclical to the exchange rate and the coefficient of inflation is smaller than 1. In the second regime, BOJ responded actively via exchange rate channel (as an indicator of future inflation expectation) rather than inflation channel directly because the exchange rate channel gives the central bank a possibility to stabilize inflation sufficiently.

As argued by Obstfeld and Rogoff (1995), an appreciation of the real exchange rate accompanied by slow output growth would call on the central bank to lower the short-term interest rate to relax the monetary policy. Nonetheless, Japan did not follow this rule of thumb in the third regime. As shown in Table 1.10 and 1.11, either quarterly or monthly data, Japan has all the significant negative policy coefficients in the second regime but positive coefficients in the third regime. This implies that BOJ used relatively passive and destabilizing monetary policy rule in the third regime because of ψ_1<1 and ψ_3>0. This destabilizing interest-rate response to real exchange rate also caused rising volatility in real exchange rate (structural break occurred in 1992:4 toward destabilization) shown in Table 1.4 and 1.5 and Figure 2.B. And more volatile real exchange rate caused larger output fluctuations through IS curve. This would be the reason for the output instability in the third regime in the open-economy model.

1.4.3.5 Reasons for Using Bad Monetary Policy

The results above lead to the following important question: why did BOJ persistently

[15] CGG (1998) mentioned that they pick April 1979 as the appropriate starting date because it is the beginning period of significant financial market deregulation. We think it is not persuasive. The appropriate starting date should be 1975 if data is available.

use clearly inferior monetary policy resulting in high output volatility in the 1990s? Three possible answers for this question are the following.

First, after the asset price bubbled in the late 1980s, BOJ was more concerned about asset price so they were reluctant to use expansionary policy. Bernanke and Gertler (1999) argued that it is neither necessary nor desirable for monetary policy to respond to asset prices cycle, except to the extent that they could help to forecast inflationary or deflationary pressures. Did BOJ conduct excessive monetary easing to generate the asset bubble in the second regime, in particular, 1985-1989? From the results of our open economy model, it is persuasive that BOJ tried to stabilize real exchange rate gap rather than the explanation that BOJ was accommodating asset boom. As in Ueda (1997) using structural VAR, given the reasonable aggregate price level, BOJ's monetary policy could not have been conducted better to avoid the asset bubbles and bursts in the late 1980s and the early 1990s caused by private autonomous optimism.

Second, policymakers treated deflation as a good idea since they thought it came from a financial system reform and technological progress rather than a deflationary spiral. Third, they were probably waiting for the Pigou effect to come in play. If prices fell enough, expenditure would increase because of rising wealth. The truth is that deflation is coming from falling aggregate demand or IS curve with falling output. And this mistake is closely related to the output gap mismeasurement hypothesis proposed by Orphanides (2004). In the 1970s, U.S. monetary policymakers overestimated the negative output gap and thus continued using expansionary monetary policy, which led to high volatility of inflation and output. In the 1990s, Japan underestimated the output gap and thus continued using passive/contractionary monetary policy, which then led to deflation as shown in Figure 1.8.

1.4.3.6 Fiscal Policy

Based on the Ricardian equivalence argument, the aging population and huge rise in public debt in Japan more or less limited the effectiveness of fiscal policy. The surveys shows discretionary fiscal policy still has the effects on Japan such as tax cuts and government spending increases (Kuttner and Posen 2002). With a growth recovery in 1996, the recession seemed to be over, and Ministry of Finance (MOF) decided that it was time to clean up the budget deficit, which reached 4% of GDP with the aging population in prospect. Therefore MOF implemented so-called expansionary fiscal contractions by raising the value-added tax in April 1997, with rising government spending at the same time. This ill-timed tax increases drove Japanese economy down into an even deeper recession. As shown in Table 1.5, evidence shows the structural breaks in volatility toward destabilization which occurred in 1997:2 for both government spending and nonresidential investment. More research is needed to find the association between Japanese recent fiscal policy and rising volatility in the past decade. It will be interesting to see how much of the Japanese output volatility is attributed to the monetary policy by removing fiscal effects.

1.5 Conclusion

This chapter employs several approaches to identify an unknown structural break and regime switching of postwar Japanese real GDP growth. This chapter has found two breaks: the first break occurred in 1974:1 toward stabilization and the second break in 1994:4 toward destabilization for the aggregate GDP growth and many disaggregate components of GDP as well. Furthermore, we find three regimes as follows, the first regime: high growth and high volatility regime – 1955:3 to 1973:2; the second regime: medium growth and low volatility regime – 1975:2 to 1992:4; and the third regime: low growth and high volatility regime – 1993:1 to 2001:1 by three-state Markov-switching model.

The fixed exchange rate mechanisms were the main reason for the high output volatility in the Japanese first regime. This conclusion supports Obstfeld and Rogoff (1995) and CGG (1998). In the second regime, the monetary policy which follows inflation targeting (raise or lower nominal interest rate sufficiently when expected inflation moves from its long-run target) with little weight on output stabilization was the main reason for the low output volatility. This finding is consistent with CGG (1998, 2000) and supports the view that central bank is undesirable to respond strongly to the output gap. Furthermore, the empirical finding supports the theory (Bernanke and Gertler 1999) that central bank should not respond to asset price fluctuations unless they affect central bank's inflation expectation.

In the open-economy framework, the flexible exchange-rate-targeting (negative nominal interest rate response to the real exchange rate appreciation) instead of Taylor rule or inflation targeting would be a more appropriate explanation for successfully stabilizing monetary policy in the second regime in Japan. This result suggests that a monetary policy rule that reacts directly to the exchange rate gap would not be harmful to the inflation and output fluctuations[16]. This evidence favors empirical result in Andrade and Divino (2005), and

[16] Taylor (2001) argued that reacting to the exchange rate (not exchange rate gap/deviation) might not

theoretical models in Ball (1999) and Svensson (2000) over CGG (1998) and Taylor (2001).

Aside from the inconsistent fiscal policy in Japan, the passive monetary policy caused by asset bubble bursts, especially positive nominal interest rate response to the real exchange rate appreciation was the main reason for the rising output volatility in the third regime. Even though BOJ can not lower the interest rate when the nominal interest rate are bounded at zero, Japan still can let their currency depreciate as suggested in Svensson (2003) to reach the negative coefficient (ψ_3) as that in the second stable regime.

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improve the macroeconomic performance.

Table 1.1 Sample Standard Deviations, by Decade, of Annual Growth Rates or Changes of Major Japan Macroeconomic Time Series

Series	Standard Deviation	Standard Deviation, relative to Whole Period			
	1955-2001	1955-1969	1970-1979	1980-1989	1990-2001
GDP	0.038	1.25	0.82	0.49	1.13
Consumption	0.034	1.22	0.83	0.64	1.09
Investment	0.120	1.37	0.90	0.48	0.89
Fixed investment	0.100	1.30	0.90	0.49	1.00
Nonresidential	0.117	1.38	0.86	0.42	0.92
Residential	0.118	1.02	0.91	0.87	1.15
Δ Inventory/GDP	0.006	1.06	1.35	0.61	0.82
Exports	0.076	1.09	1.12	0.97	0.78
Imports	0.110	1.26	0.93	0.92	0.73
Government Spending	0.051	0.95	1.16	0.79	1.08
Inflation rate	3.753	1.07	1.61	0.50	0.30
Real exchange rate	12.597	-	0.88	1.01	1.05
Short interest rate	2.199	0.96	1.26	1.09	0.62
10-year bond rate	0.842	-	1.07	0.80	1.13

1. Most series are annual growth rates, which are the first difference of the logarithm of the original series, except for the change in inventories as a fraction of GDP, which is the level of series; inflation rate, real exchange rate, short term interest rate, and long term interest rate (10 year government bond yield) are the first difference of the series.
2. All growth rates are four-quarter growth rate, which is $100 \times \ln(Y_t \ / \ Y_{t-4})$. And standard deviation is the absolute value of the deviation of each series from its mean.
3. Inflation rate is the four-quarter change in the annual inflation rate measured from GDP deflator.
4. Most of the data are from Japan ESRI, website: http://www.esri.cao.go.jp/en/sna/qe011-68/gdemenue68.html.
5. Real exchange rate is the index of weighted average of the yen's real exchange rates versus 15major currencies (26 countries) which are calculated from exchange rates and price indexes of the respective countries. The data are available since1973: 1 from Bank of Japan, website: http://www2.boj.or.jp/en/dlong/stat/stat2.htm#03 "ehrate.csv" file.
6. Short-term interest rate is call rate (Collateralized overnight interest rate), which is available since 1960: 1. Short term interest rate data are from Bank of Japan, website: http://www.boj.or.jp/en/stat/stat_f.htm "cdab0720.csv"file.
7. 10-years government bond yield data is available since 1972: 1. Short-term interest rate data are from Bank of Japan, website: http://www.boj.or.jp/en/stat/stat_f.htm "cdab0740.csv" file.

Table 1.2 Unit Root Test Statistics of Japan Major Macroeconomic Time Series 1955:3 to 2001:1

		ADF				Phillips-Perron				DF-GLS			KPSS		
Variables	equation	Test stat	Lag lenth	P-value	Result	Test stat	Band width	P-value	Result	Test stat	Lag lenth	Result	Test stat	Band width	Result
Real GDP	Intercept +trend	-0.48	0	0.98	I(1)	-0.55	7	0.98	I(1)	-0.21	4	I(1)	0.42	10	I(1)
Consumption	Intercept +trend	-0.47	1	0.98	I(1)	-0.63	1	0.98	I(1)	0.26	3	I(1)	0.43	10	I(1)
Investment	Intercept +trend	-2.26	3	0.45	I(1)	-2.46	6	0.35	I(1)	-0.71	3	I(1)	0.36	10	I(1)
Export	Intercept +trend	-0.58	1	0.98	I(1)	-0.49	8	0.98	I(1)	0.01	1	I(1)	0.44	10	I(1)
Import	Intercept +trend	-2.33	2	0.41	I(1)	-2.38	4	0.39	I(1)	-0.99	2	I(1)	0.37	10	I(1)
Government Spending	Intercept +trend	0.53	1	0.99	I(1)	0.45	4	0.99	I(1)	0.10	0	I(1)	0.42	10	I(1)
Call rate	Intercept	-2.20	1	0.21	I(1)	-2.02	4	0.28	I(1)	-1.66	1	I(1)	1.08	10	I(1)
Real exchange rate	Intercept	-1.55	0	0.51	I(1)	-1.79	4	0.39	I(1)	-1.24	0	I(1)	0.93	9	I(1)
Inflation rate	Intercept	-3.08	3	0.03	I(0)	-3.54	4	0.01	I(0)	-2.56	3	I(0)	0.94	10	I(1)

1. ADF is the augmented Dickey-Fuller test of a unit root against no unit root by Dickey and Fuller (1979). Lag length is automatic based on SIC, the maximum lag is 13. Test critical value is -3.43 at 5% significant level. P-value is from Mackinnon (1996).
2. For Phillips –Perron test, Bandwith is based on Newey-West using Bartlett kernel.
3. DF-GLS is a Dickey-Fuller test based on GLS-detrended series by Elliott, Rothenberg, and Stock. (1996).
4. KPSS test is based on the null hypothesis of stationary process proposed by Kwiatkowski, Phillips, Schmidt, and Shin (1992).

Table 1.3 Nyblom's L Test for Stability of Japan Real GDP Growth 1955:3 to 2001:1

Specification: $y_t = \mu + \phi y_{t-1} + \varepsilon_t,\ E(\varepsilon_t^2) = \sigma^2$			
	Estimate	L_c	CV (5 percent)
μ	0.94 (0.15)	3.02	0.48
ϕ	0.26 (0.09)	0.48	0.48
σ^2	1.67 (0.28)	0.67	0.48
Joint L_c		3.64	1.01

Notes: Nyblom's L test from Hansen (1992). y is real GDP growth. Standard errors are in parentheses. L_c is the test statistic for a break point in each of the coefficients in the first column. CV (5 percent) is the 5 – percent critical value for the null hypothesis of no break from Hansen.

Table 1.4 Benchmark Structural Break Tests for Japanese Macroeconomic Variables 1955:3 to 2001:1

	Conditional Mean			Conditional Variance: Break Only			Conditional Variance: Trend and Break		
Series	p-value	Break date	Confidence interval	p-value	Break date	confidence interval	p-value trend	p-value break	Break date
Real GDP	0.00	1973:1	1972:1-1973:3	0.01	**1974:1**	1973:2-1977:3	0.00	0.00	1994:2
Consumption	0.00	1973:4	1973:2-1974:2	0.26	-	-	0.39	0.13	-
Investment	0.00	1970:1	1969:3-1970:3	0.00	**1966:2**	1965:4-1967:2	0.23	0.00	1963:1
Fixed investment	0.01	1990:4	1990:2-1991:2	0.00	**1969:3**	1968:4-1971:2	0.00	0.08	-
Nonresidential	0.60	-	-	0.00	**1969:2**	1968:4-1970:4	0.83	0.00	1969:2
Residential	0.00	1973:4	1973:2-1974:2	0.62	-	-	0.20	0.32	-
Inventory/GDP	0.00	1974:3	1974:1-1975:1	0.00	**1975:2**	1975:1-1977:3	0.64	0.00	1975:2
Exports	0.00	1978:1	1977:3-1978:3	0.01	**1978:3**	1977:4-1982:3	0.97	0.60	-
Imports	0.00	1972:1	1971:3-1972:3	0.01	**1973:1**	1971:4-1976:3	0.02	0.67	-
Government Spending	0.00	1973:3	1973:1-1974:1	0.30	-	-	0.07	0.02	1978:2
Inflation rate	0.00	1969:3	1969:1-1970:1	0.00	**1963:3**	1963:2-1964:3	0.05	0.20	-
Real exchange rate	0.37	-	-	0.03	**1992:4**	1987:2-1994:2	0.99	0.64	-
Nominal exchange rate	0.00	1986:3	1986:1-1987:1	0.00	**1995:1**	1991:4-1995:3	0.35	0.19	-
Short interest rate	0.49	-	-	0.00	**1982:2**	1982:1-1984:4	0.00	0.00	1973:2
10-year bond rate	0.02	1990:4	1990:2-1991:2	0.25	-	-	0.08	0.04	1995:3
Monetary base	0.01	1996:2	1995:4-1996:4	0.31	-	-	0.82	0.38	-
M2+CDs	0.00	1990:2	1989:4-1990:4	0.03	**1980:3**	1980:1-1983:2	0.00	0.22	-

Table 1.5 Benchmark Structural Break Tests for Japanese Macroeconomic Variables 1975:2 to 2001:1

	Conditional Mean			Conditional Variance: Break Only			Conditional Variance: Trend and Break		
Series	p-value	Break date	Confidence interval	p-value	Break date	confidence interval	p-value trend	p-value break	Break date
Real GDP	0.00	1991:1	1990:3-1991:3	0.00	**1994:4**	1992:2-1995:3	0.96	0.25	-
Consumption	0.00	1997:1	1996:3-1997:3	0.05	**1994:4**	1989:4-1996:1	0.95	0.89	-
Investment	0.00	1995:4	1995:2-1996:2	0.99	-	-	0.62	0.82	-
Fixed investment	0.00	1990:4	1990:2-1991:2	0.43	-	-	0.33	0.53	-
Nonresidential	0.02	1997:1	1996:3-1997:3	0.00	**1997:2**	1995:4-1998:1	0.87	0.26	-
Residential	0.04	1979:3	1979:1-1980:1	0.47	-	-	0.86	0.75	-
Inventory/GDP	0.00	1997:2	1996:4-1997:4	0.05	**1993:3**	1992:3-1996:1	0.23	0.01	1993:3
Exports	0.69	-	-	0.80	-	-	0.85	0.83	-
Imports	0.01	1980:2	1979:4-1980:4	0.20	-	-	0.27	0.06	-
Government Spending	0.00	1996:2	1995:4-1996:4	0.01	**1997:2**	1994:3-1998:1	0.00	0.04	1988:2
Inflation rate	0.35	-	-	0.13	-	-	0.98	0.67	-
Real exchange rate	0.39	-	-	0.05	**1992:4**	1987:1-1994:2	0.97	0.61	-
Nominal exchange rate	0.00	1986:3	1986:1-1987:1	0.00	**1995:1**	1990:1-1995:3	0.63	0.72	-
Short interest rate	0.17	-	-	0.00	**1993:4**	1993:3-1995:2	0.00	0.44	-
10-year bond rate	0.02	1990:4	1990:2-1991:2	0.25	-	-	0.08	0.04	1995:3
Monetary base	0.00	1997:2	1996:4-1997:4	0.03	**1997:2**	1987:1-1997:3	0.99	0.31	-
M2+CDs	0.00	1990:2	1989:4-1990:4	0.51	-	-	0.11	0.29	-

Table 1.6 McConnell and Perez-Quiros' Tests for Structural Change on Variances

1955:3-2001:1	1975:2 -2001:1
Sup W_T	Sup W_T
15.20	19.65
Estimated break date	Estimated break date
1974:1	**1994:4**

Table 1.7 Bai and Perron's Tests for Multiple Structural Changes on Means
1955:3 to 2001:1

Sup F_T (1)	Sup F_T (2)	Sup F_T (3)	Sup F_T (4)	Sup F_T (5)
94.66*	53.75*	36.17*	26.01*	22.32*
Sup F_T (2|1)	Sup F_T (3|2)	Sup F_T (4|3)		
11.6*	4.08	0.53		

Number of Breaks Selected	Estimates with Two Breaks	
2	$\hat{T}_1$	$\hat{T}_2$
	1973:1	**1991:2**
	(1972:1-1974:1)	(1983:3-1994:2)

1. All tests allow for heteroskedasticity and autocorrelation in the disturbances, AR(1) prewhitening, and 15 percent of sample trimmed.
2. * represents significance at the 5% level.
3. We use a 5% size for the sequential test sup F (n+1|n).
4. In parentheses are the 95% confidence intervals for $\hat{T}_i$.

Table 1.8 Bai, Lumsdaine and Stock's VAR Structural Change Test on Variances

1955:3-2001:1	1975:2 -2001:1
QLR p-value **0.00**	QLR p-value **0.00**
Estimated break date	Estimated break date
1975:2	**1994:3**
67% confidence interval	67% confidence interval
1974:1 – 1976:3	**1993:3 – 1995:3**

Table 1.9 Bayesian Gibbs-Sampling Approach to a Three-State Markov-Switching Mean-Variance Model of Quarterly Real GDP Growth 1955:3 to 2001:1

parameter	Posterior Mean	Standard deviation	median
ϕ_1	-0.0669	0.1021	-0.0670
ϕ_2	0.1126	0.1002	0.1093
σ_1^2 (1995:1-2001:1)	1.8978	0.8126	1.7146
σ_2^2 (1975:2-1994:4)	0.4228	0.0904	0.4092
σ_3^2 (1955:3-1974:1)	1.7689	0.3505	1.7137
μ_1 (1995:1-2001:1)	0.1037	0.2642	0.1479
μ_2 (1975:2-1994:4)	0.9526	0.1035	0.9585
μ_3 (1955:3-1974:1)	2.1963	0.1956	2.2026

Table 1.10 Estimates for Japanese Closed Economy Monetary Policy Rule

	ψ_1	ψ_2	α	ρ
$R_t = \rho R_{t-1} + (1-\rho)(\alpha + \psi_1 E[\pi_{t+4}] + \psi_2 E[x_{t+1}]) + \varepsilon_t$				
Quarterly Data 1961:1 – 2001:1 Output: Real GDP, Inflation: GDP deflator				
1961:1- 1975:1	-0.85	0.67	11.85*	1.16*
	(0.46)	(0.50)	(2.96)	(0.06)
1975:2- 1992:4	**2.08***	-0.14	1.34*	0.82*
	(0.55)	(0.60)	(1.20)	(0.05)
1993:1- 2001:1	**-0.67***	**0.38***	-0.01	0.97*
	(0.27)	**(0.18)**	(0.27)	(0.01)
$R_t = \rho R_{t-1} + (1-\rho)(\alpha + \psi_1 E[\pi_{t+12}] + \psi_2 E[x_t]) + \varepsilon_t$				
Monthly Data 1978:1 – 2001:12 Output: Industrial Production, Inflation: CPI				
1979:1- 1992:12	**2.04***	0.83	3.88*	0.98*
	(0.98)	(0.53)	(1.53)	(0.01)
1993:1- 2001:12	**0.32***	0.02	0.18*	0.99*
	(0.07)	(0.03)	(0.06)	(0.00)

Table 1.11 Estimates for Japanese Open Economy Monetary Policy Rule

	ψ_1	ψ_2	ψ_3	α	ρ
$R_t = \rho R_{t-1} + (1-\rho)(\alpha + \psi_1 E[\pi_{t+4}] + \psi_2 E[x_{t+1}] + \psi_3 E[e_t]) + \varepsilon_t$					
Quarterly Data 1961:1 – 2001:1 Output: Real GDP, Inflation: GDP deflator					
1975:2- 1992:4	0.17	**0.62***	**-0.17***	5.15*	0.77*
	(0.11)	**(0.25)**	**(0.04)**	(0.29)	(0.03)
1993:1- 2001:1	**0.83***	**-0.29***	**0.10***	1.32*	0.92*
	(0.11)	**(0.06)**	**(0.02)**	(0.10)	(0.02)
$R_t = \rho R_{t-1} + (1-\rho)(\alpha + \psi_1 E[\pi_{t+12}] + \psi_2 E[x_t] + \psi_3 E[e_t]) + \varepsilon_t$					
Monthly Data 1978:1 – 2001:12 Output: Industrial Production, Inflation: CPI					
1979:1- 1992:12	**0.54***	0.13	**-0.31***	4.63*	0.94*
	(0.14)	(0.14)	**(0.06)**	(0.46)	(0.01)
1993:1- 2001:12	**0.70***	-0.02	**0.09***	0.07	0.99*
	(0.16)	(0.04)	**(0.03)**	(0.13)	(0.00)

1. For the quarterly data model, we all can not reject the null hypothesis for test of overidentifying restrictions (the validity of instruments). The instruments are 1, lagged value (t-1, t-2, t-3, t-4) of the call rate, inflation, the output gap, the difference of exchange rate, and the commodity price inflation (Japanese wholesale price index).
2. For the monthly data model, we all can not reject the null hypothesis for test of overidentifying restrictions (the validity of instruments). The instruments are 1, lagged value (t-1, t-2, t-3, t-4, t-5, t-6, t-9, t-12) of the call rate, inflation, the output gap, the difference of exchange rate, and the commodity price inflation (Japanese wholesale price index).
3. The numbers in the parentheses mean standard errors.

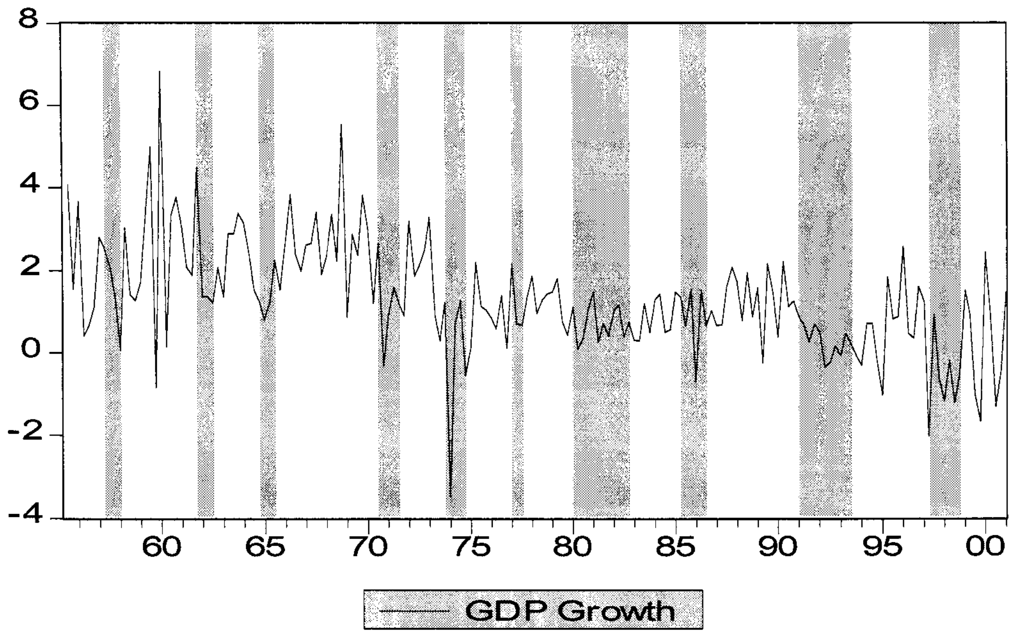

Figure 1.1.A Quarter–To–Quarter Growth Rates in Japan Real GDP from 1955:3 to 2001:1.

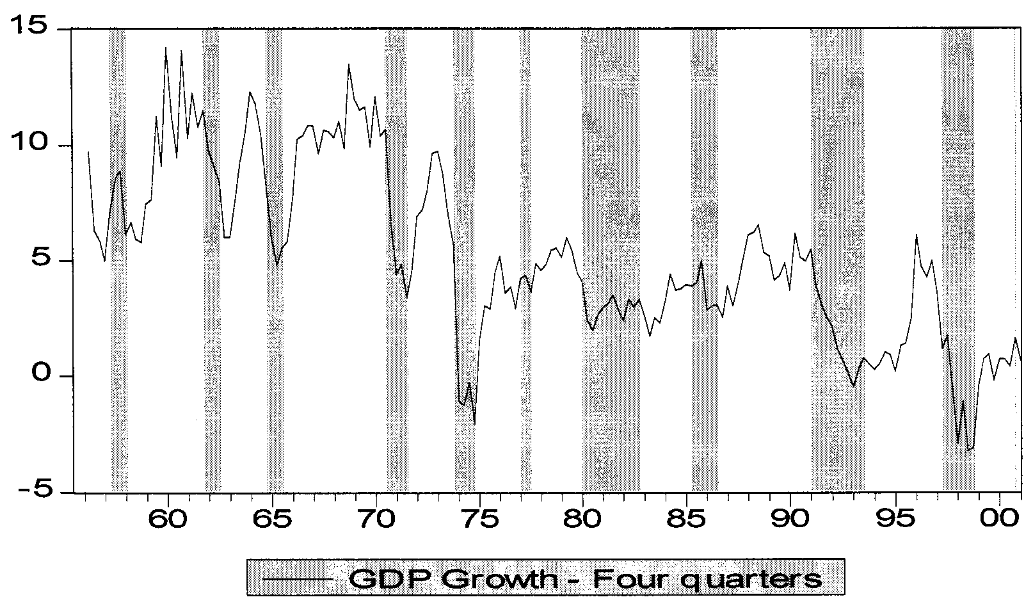

Figure 1.1.B Four–Quarter Growth Rates in Japan Real GDP from 1955:3 to 2001:1

Notes: Shaded area represents recessions (from peak to through of business cycle) in Japan. Reference dates are from ESRI (Official report for Japan business cycle), website: http://www.esri.cao.go.jp/en/stat/di/041112rdates.html.

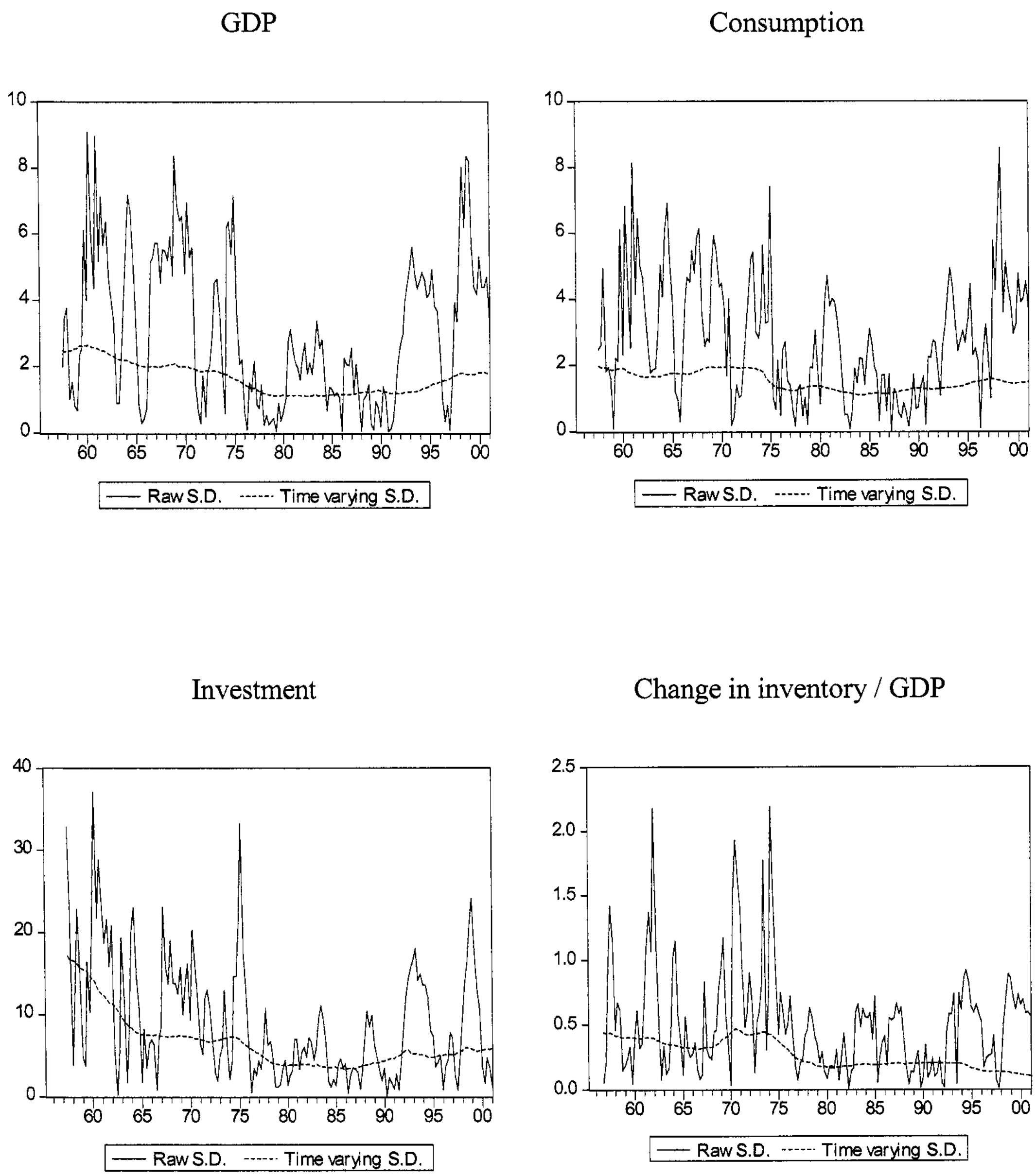

Figure 1.2.A   Time Varying Standard Deviations

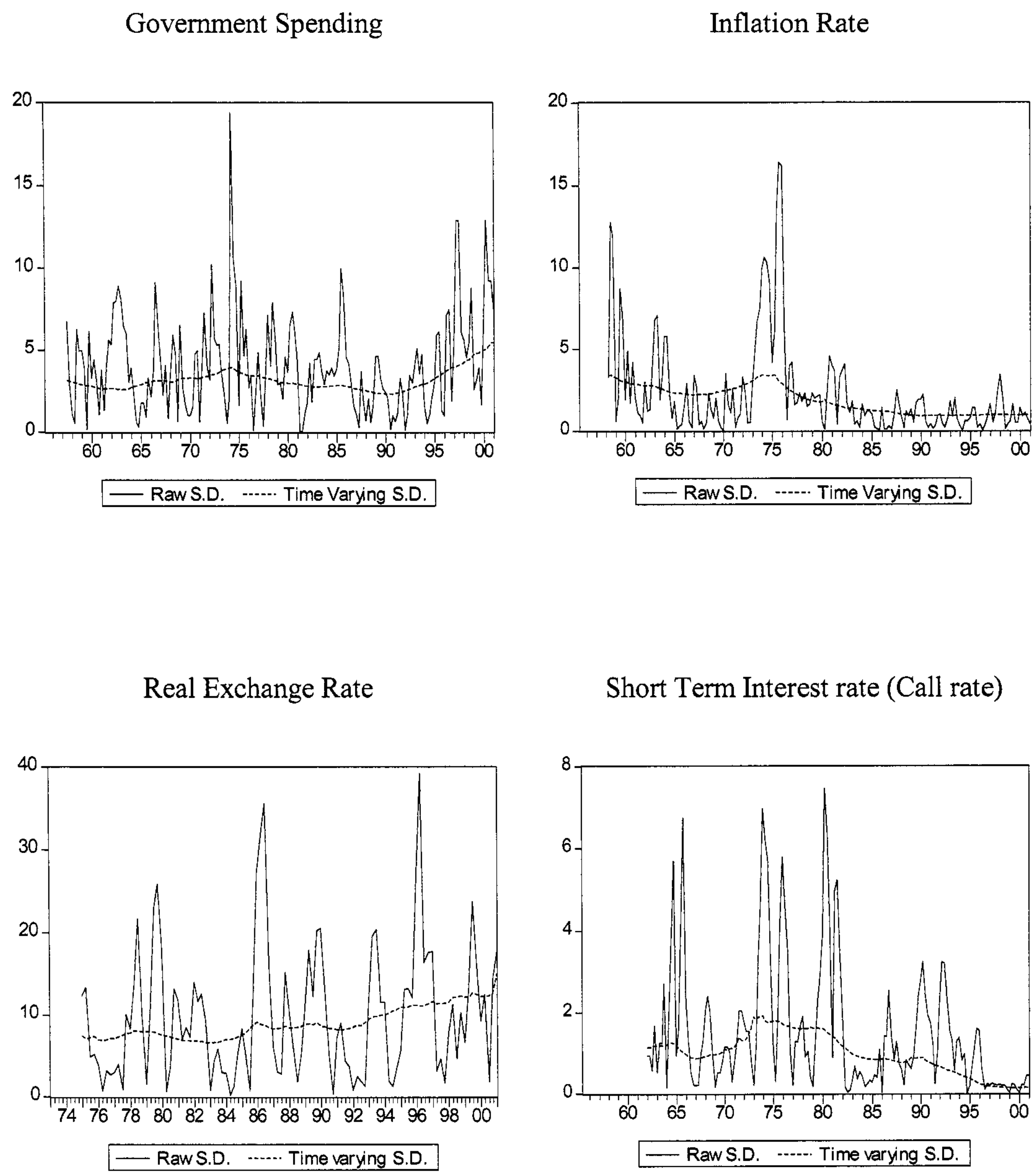

Figure 1.2.B Time Varying Standard Deviations

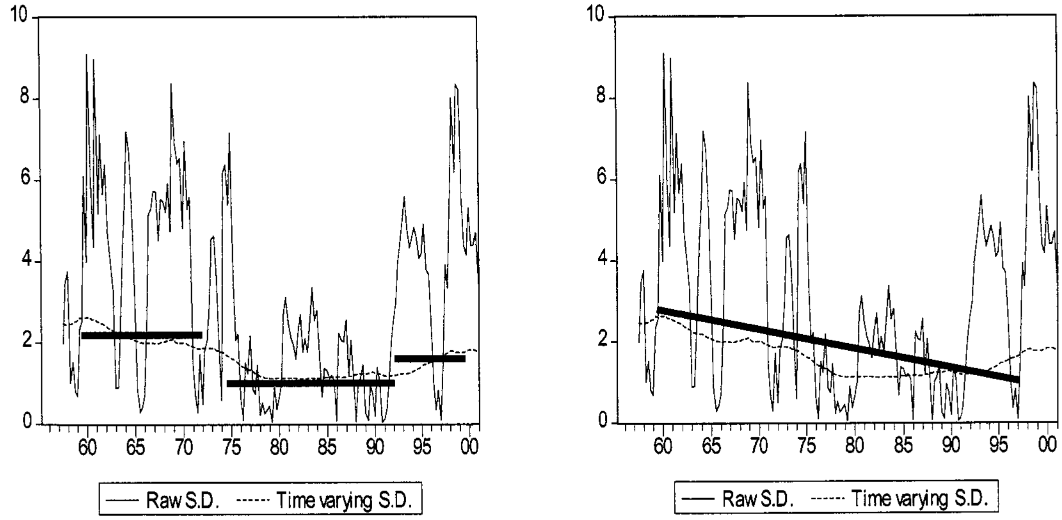

Figure 1.3.A Conditional Variance: Trend and Break Test

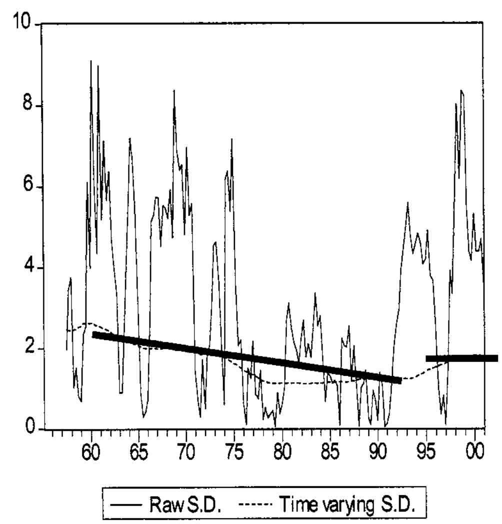

Figure 1.3.B Conditional Variance: Trend and Break Test
Japan Real GDP 1955:3 to 2001:1

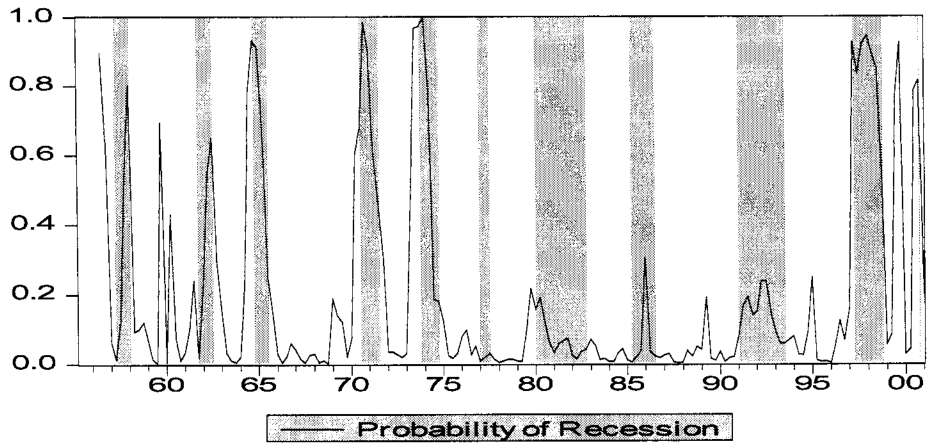

Figure 1.4.A Hamilton's Two-State Markov-Switching Mean Model Probability of Recession

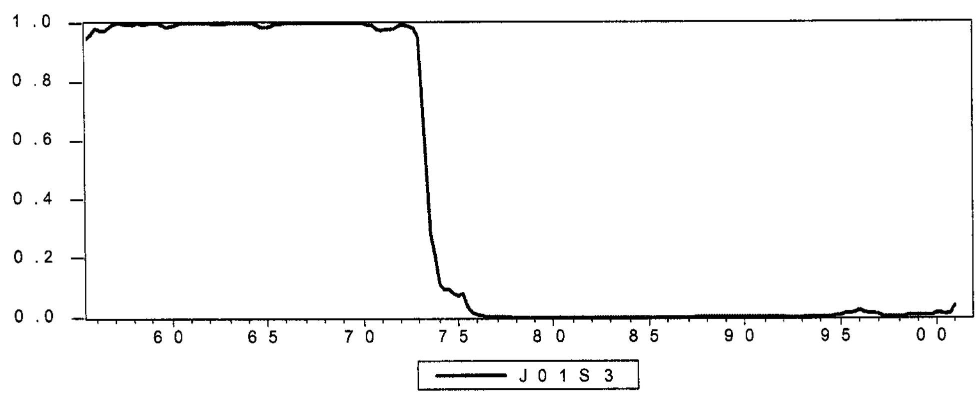

Figure 1.4.B Three-State Markov-Switching Mean-Variance Model -Probability of High Growth - High Volatility Regime

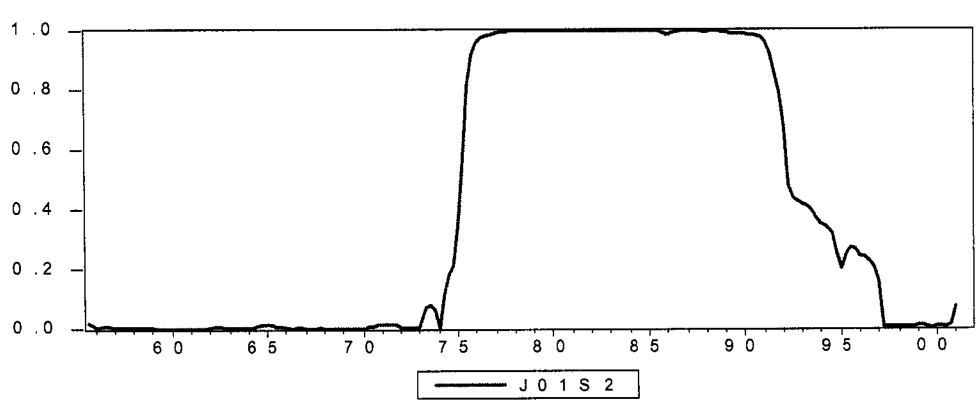

Figure 1.4.C Three-State Markov-Switching Mean-Variance Model - Probability of Medium Growth - Low Volatility Regime

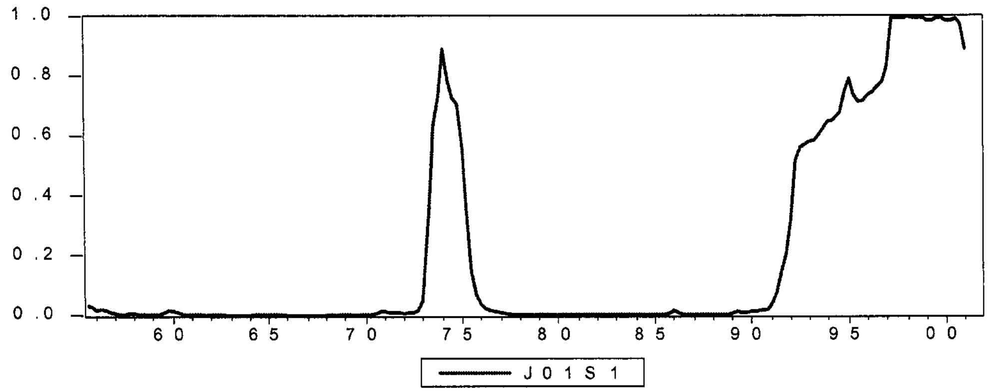

Figure 1.4.D Three-State Markov-Switching Mean-Variance Model - Probability of Low Growth - High Volatility Regime

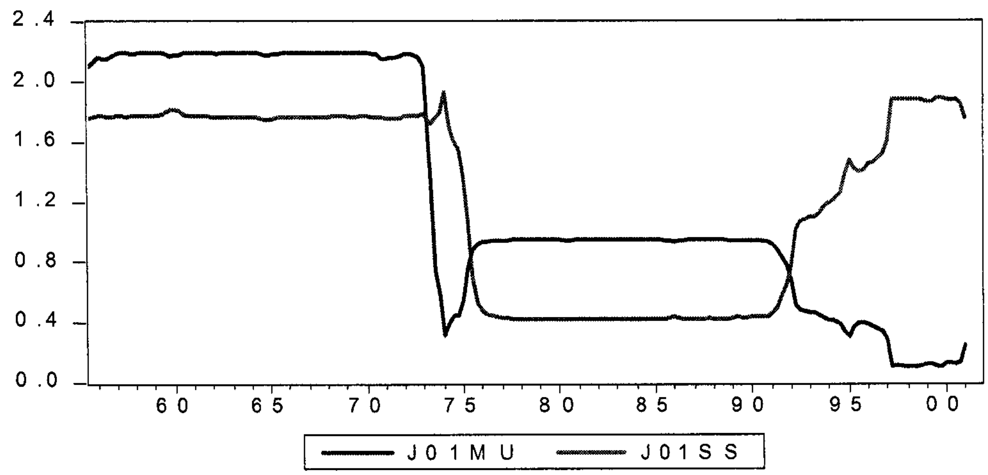

Figure 1.4.E Three-State Markov-Switching Mean-Variance Model - Quarterly GDP Growth Mean and Variance

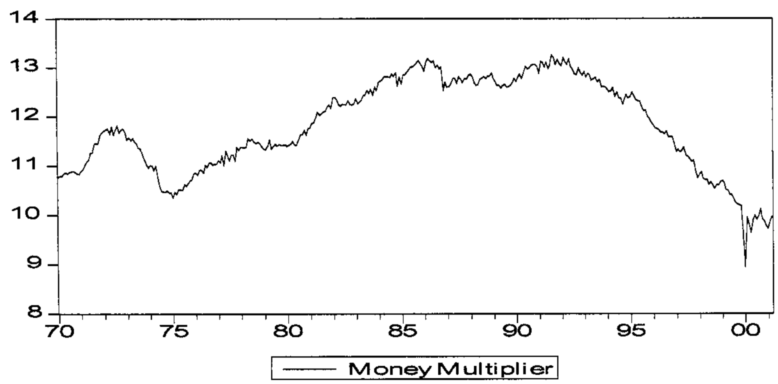

Figure 1.5 M2 Multiplier, 1970 to 2001

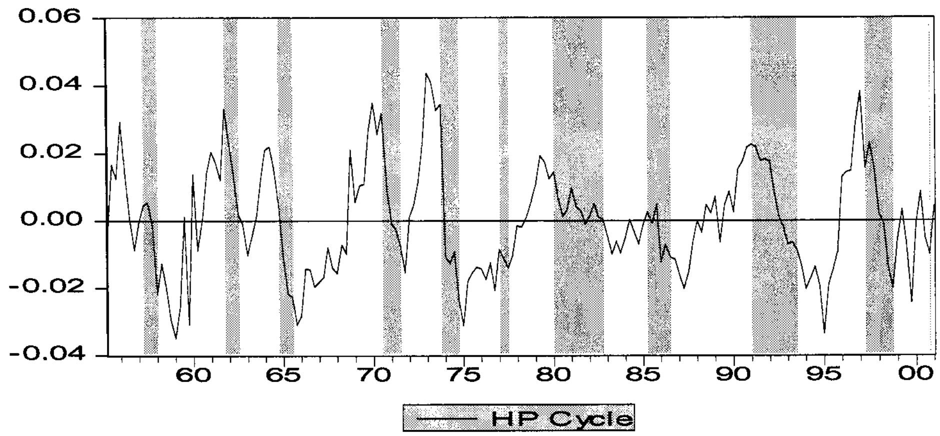

Figure 1.6 Output Gap Computed by HP Filter, 1955 to 2001

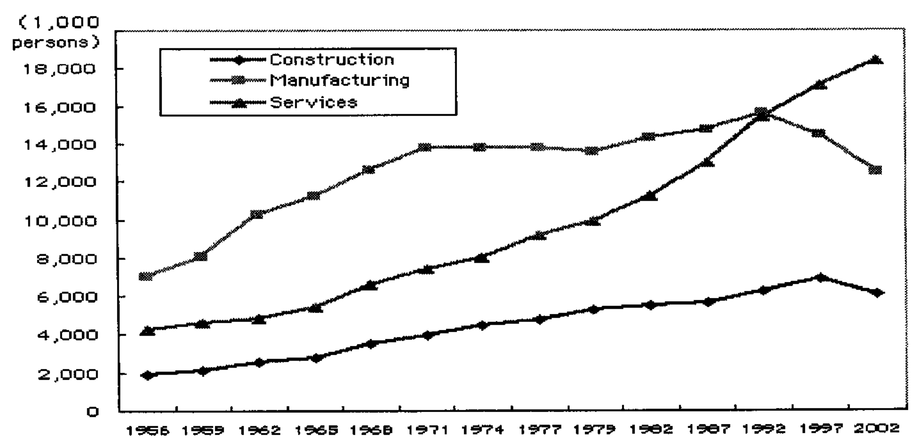

Figure 1.7 Trend of Number of Persons Engaged in Work by Major Industry

Data source: Japan Statistics Bureau -The 2002 Employment Status Survey

http://www.stat.go.jp/english/data/shugyou/2002/kakuhou/youyaku.htm#1

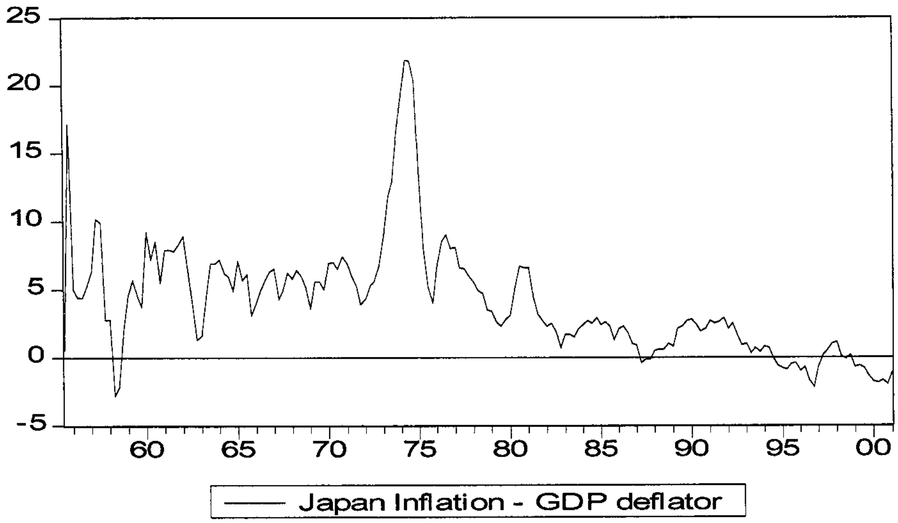

Figure 1.8 Japanese Inflation Rate – GDP Deflator, 1955 to 2001

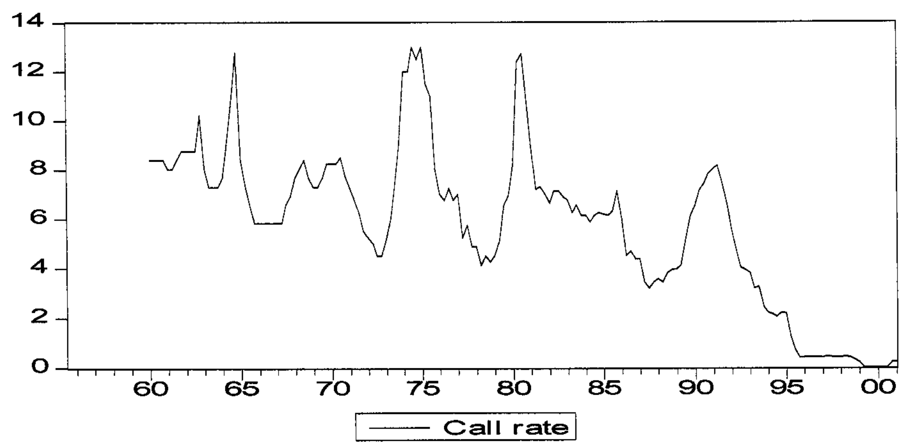

Figure 1.9 Japanese Call Rate, 1960 to 2001

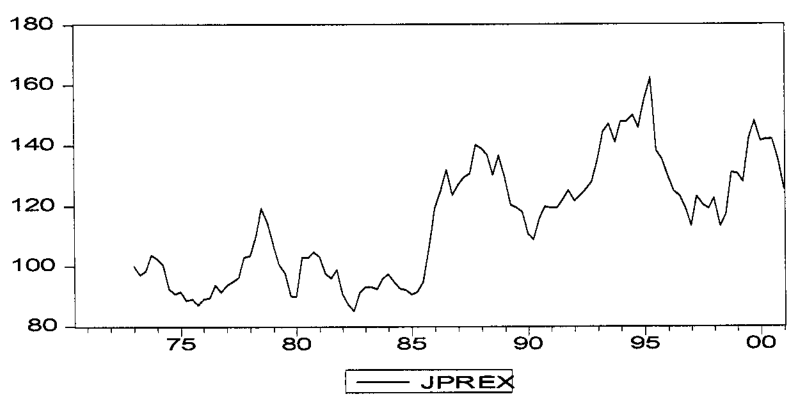

Figure 1.10 Japanese Real Exchange Rate, 1973 to 2001

Chapter 2: Long Memory versus Structural Breaks in Modeling and Forecasting Realized Volatility

2.1 Introduction

Conditional volatility and correlation modeling has been one of the most important areas of research in empirical finance and time series econometrics for the past two decades. Asset return volatility and correlation, henceforth volatility, are especially central to finance, as they are key inputs for asset and derivatives pricing, portfolio allocation, and risk measurement. Although daily financial asset returns are approximately unpredictable, return volatility is time-varying but highly predicable with persistent dynamics.[17] Furthermore, the dynamics of volatility is well modeled as a long memory process. An inherent problem for measuring, modeling and forecasting conditional volatility is that the volatility is unobservable or latent, which implies modeling must be indirect. Typically, measurements of conditional volatility are from parametric methods, such as GARCH models or stochastic volatility models for the underlying returns. However, these parametric volatility models depend on specific distributional assumptions and are subject to misspecification problems.

Given the availability of intraday ultra-high-frequency price and quote data on assets, Andersen, Bollerslev, Diebold, and Labys (2003), henceforth ABDL, and Barndorff-Nielsen and Shephard (2001, 2002, 2004) introduced a consistent nonparametric estimate of the price volatility that has transpired over a given discrete interval, called *realized volatility*. They computed daily Deutschemark/Dollar, Yen/Dollar, and Deutschemark/Yen spot exchange rates realized volatilities simply by summing high-frequency finely sampled intraday squared and cross-products returns. By sampling intraday returns sufficiently frequently, the model-free realized volatility can be made arbitrarily close to underlying integrated volatility, the integral of instantaneous volatility over the interval of interest, which is a natural volatility measure.

ABDL found logarithmic realized volatility could be modeled and accurately forecast using simple parametric fractionally integrated ARFIMA models. Their low-dimensional multivariate realized volatility model provided superior out-of-sample forecasts for both low-

[17] The findings suggest that volatility persistence is highly significant in daily data but will weaken as the data frequency decreases.

frequency and high-frequency movements in the realized volatilities compared to GARCH and related approaches. Many studies, however, have pointed out that observed long memory may not only be generated by linearly fractional integrated process but also by: (1) cross-sectional aggregation of stationary series (Granger and Ding 1996); (2) mixture of numerous heterogeneous short-run information arrivals (Andersen and Bollerslev 1997); (3) non-linear models, such as structural breaks (changes) or regime switches (Granger and Hyung 2004; Choi and Zivot 2006; Diebold and Inoue 2001). In particular, it has been conjectured that persistence of asset return volatility may be overstated with the presence of structural change.

In this chapter, we focus on the possibilities of structural breaks and regime switching in the realized volatility, with the observed long-memory property, for the Deutschemark/Dollar, Yen/Dollar and Yen/Deutschemark spot exchange rate realized volatility from ABDL. First, we test for long memory and estimate long memory models for the realized volatility series. We find strong evidence of long memory property in exchange rate realized volatility. Second, we test for and estimate a multiple mean break model based on Bai and Perron (1998, 2003), and do the same for a Markov switching model based on Hamilton (1989). We find several common structural breaks within the three series. Third, we exam the evidence for long memory in the break adjusted data. We find a substantial reduction of persistence in realized volatility after the removal of breaks. The evidence suggests that part of the long memory may be accounted for by the presence of structural breaks in the exchange rate volatility series.

Fourth, we use Monte Carlo simulation experiments to see how several types of Markov Switching models for volatility can produce long memory behavior. We enlarge the scope of Markov-switching models considered by Diebold and Inoue (2001) by including switching in mean, variance and AR coefficients for different states. Our findings show: (1) transition probabilities close to unity are more likely to generate long memory process, which is consistent with the simple model in Diebold and Inoue (2001); (2) switching in mean (intercept) and AR coefficients can explain long memory process but switching in variance cannot. Our mean-switching result is consistent with Timmermann (2000);[18] this result favors Hamilton and Susmel's (1994) fundamental model over Kim and Kim's (1996) fad model on explaining observed long memory behavior; (3) richer states of regime switching is more likely to generate long memory process.

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[18] Unlike our chapter's focus on long memory behavior from Markov-switching models, Timmermann (2000) focused on higher moments, such as skewness and kurtosis of Markov-switching models.

Finally, we find that our VAR-RV-Break model provides competitive forecasts compared to most of the forecasting models considered by ABDL if future break dates and sizes are known. The VAR-RV-I(d) model, however, is still the best forecasting model even when the true financial volatility series are created by structural breaks and we have little knowledge about break dates and size.

The rest of the chapter is organized as follows. Section 2.2 presents the long memory model and estimations. Section 2.3 presents empirical results using structural breaks model and examines the long memory estimations after adjusted breaks series. In section 2.4, estimations of the Markov-switching model and Monte Carlo simulations are given. Section 2.5 reports the evaluation for forecasting. Section 2.6 concludes.

2.2 Realized Volatility and Long Memory Model

2.2.1 Realized Variance

ABDL utilized an empirical measure of daily return variability called realized volatility, which is easily computed from high-frequent intraday returns. By treating volatility as observed rather than latent, volatility modeling and forecasting using simple ARFIMA model is straightforward.

We assume that an arbitrage-free logarithmic price $p_t = \log(P_t)$ process can be expressed as a continuous-time diffusion process in terms of the following stochastic differential equation without a jump term,

$$dp_t = \mu_t dt + \sigma_t dW_t \tag{2.1}$$

where μ_t is the predictable drift coefficient, σ_t is the instantaneous volatility of the logarithmic price process, and W_t is a standard Brownian motion. We denote the daily continuously compounded return as

$$r_t = p_t - p_{t-1} = \int_{t-1}^{t} \mu_s ds + \int_{t-1}^{t} \sigma_s dW_s \tag{2.2}$$

where $\int_{t-1}^{t} \sigma_s dW_s$ is a local martingale, and we denote the corresponding integrated variance (IV_t) as

$$IV_t = \int_{t-1}^{t} \sigma_s^2 ds \tag{2.3}$$

This natural measure of the inherent return variability, however, is not directly observable. Realized variance (RV_t) is computed by simply summing cross-products of intraday returns,

$$RV_t \equiv \sum_{i=1}^{1/h} r_{t-1+ih}^{(h)} \cdot r_{t-1+ih}^{(h)'} \equiv R'_{t,h} R_{t,h} \approx IV_t \tag{2.4}$$

where $r_t^{(h)} \equiv p_t - p_{t-h}$ is the intraday return, $R'_{t,h} \equiv (r_{t-1+h}^{(h)}, r_{t-1+2h}^{(h)}, \ldots.., r_t^{(h)})$, h is sample frequency[19] and *1/h* is assumed to be an integer. ABDL showed that in the absence of measurement error in high frequency returns, realized variance is consistent for integrated variance as $h \to 0$. In practice, however, there is a lower bound on the sampling frequency because of market microstructure frictions features such as, discrete price, transactions costs, and bid-ask spreads at the very highest frequency.

2.2.2 Data

We use the same data as theirs, which are spot exchange rate for the U.S. dollar, the Deutschemark, and the Japanese yen from December 1, 1986 through June 30, 1999.[20] Following ABDL, we choose equally-spaced thirty-minute[21] return to keep away from microstructure noise.[22] Their realized variance construction process is as follows. We get thirty-minute prices from the linearly interpolated logarithmic average of the bid and ask quotes for the two ticks immediately before and after the thirty-minute time stamps over the global 24-hour trading day. And thirty-minute returns are obtained from the first difference of the logarithmic prices. We exclude all the returns from Friday 21:00 Greenwich Mean Time (GMT) to Sunday 21:00 GMT and certain holiday periods to avoid weekend and holiday effects. We finally get a 3,045-days bivariate series of DM/\$ and Yen/\$ 30-minute returns over the sample period. The returns is $r_t^{(h)}$, where $t = h, 2h, 3h, \ldots.47h, 1, 49h, \ldots.., 3045$, where $h = 1/48 = 0.0208$.

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[19] For example of the 30-minute intraday sample frequency from a 24-hour trading day (1440 minutes), h is 30/1440=1/48. There are 48 intraday returns.

[20] The raw data include all interbank DM/\$ and Yen/\$ bid/ask quotes shown on the Reuters FX screen provided by Olsen & Associates. These three currencies were the most actively traded in the foreign exchange market during the sample period.

[21] Bandi and Russell (2003) suggested that sample horizon range from 5-minute to 30 minute interval is optimal as the minimization of the conditional mean-squared error of the realized volatility estimator.

[22] The findings suggest that volatility measured at an interval shorter than 5-minute are cursed by spurious serial correlation due to nonsynchronous trading, discrete price observations, intraday periodic volatility pattern, and bid-ask spread.

As in equation (2.4), realized volatility for DM/\$ and Yen/\$ will be the diagonal elements of $R_{t,h}^{'}R_{t,h}$. By absence of triangular arbitrage, the Yen/DM returns can be calculated directly from the difference between the DM/\$ and Yen/\$. Therefore, we get 3,045 observations of realized variance for three exchange rate series, as shown in Figure 2.1. Figure 2.2 shows the realized volatilities, also called realized standard deviations, which are calculated from the square root of the realized variance. Both series show strong persistence and occasional clustering as well as possible jump patterns.

2.2.3 Realized Volatility Distributions

As shown in Table 2.1 and the left panel of Figure 2.3, the distributions of three realized volatility series are all right-skewed and fat-tailed. The distribution of logarithmic realized volatilities, however, are close to Gaussian as the logarithmic transformation reduces the impact of outliers. The kernel density estimates in the right panel of Figure 2.3 and the Q-Q plots in Figure 2.4 provide strong evidence for the log-normality property for realized volatility. Last, the Ljung-Box statistics indicate strong serial correlation in all of the series.

2.2.4 Long Memory Model

Before conducting further modeling and forecasting, it is very important to determine whether the time series is stationary or not. However, the distinction between I(0) and I(1) for the conditional mean may be far too narrow. Long memory model that allows fractional orders of integration, I(d), provides more flexibility. For an I(0) process, shocks decay at an exponential rate; for an I(1) process, shocks have permanent effect; for an I(d) process, shocks dissipate at a slow hyperbolic rate. Long memory behavior in volatility has been well established, see for example, Ding, Granger, and Engle (1993), Baillie, Bollerslev and Mikkelsen (1996), and Andersen and Bollerslev (1997).

A time series process, y_t, with autocorrelation function ρ_k at lag k, is a long memory process when

$$\lim_{n\to\infty}\sum_{k=-n}^{n}|\rho_k|\to\infty \tag{2.5}$$

The spectral density $f(\omega)$ tends to infinity at zero frequencies. In contrast, for a stationary process with short memory, the autocorrelation function is geometrically bounded, i.e.

$|\rho_k| \leq cm^{-k}$ with $0 < m < 1$. Granger and Joyeux (1980) and Hosking (1981) show that a long memory process for y_t can be modeled parametrically as a fractionally integrated process I(d), if

$$(1-L)^d (y_t - \mu) = \varepsilon_t \tag{2.6}$$

where L denotes the lag operator, d is fractional difference parameter, μ is the unconditional mean of y_t, and ε_t is independent and identically distributed with zero mean and finite variance. The fractional difference filter $(1-L)^d$ is defined as the binominal expansion

$$(1-L)^d = 1 - dL + \frac{d(d-1)}{2!}L^2 - \frac{d(d-1)(d-2)}{3!}L^3 + \ldots = \sum_{k=0}^{\infty} \frac{\Gamma(k-d)L^k}{\Gamma(k+1)\Gamma(-d)} \tag{2.7}$$

where $\Gamma(k+1)$ is the Gamma function. A more flexible process called the ARFIMA (p, d, q) model[23] allows $(1-L)^d (y_t - \mu)$ to be autocorrelated:

$$\phi(L)(1-L)^d (y_t - \mu) = \theta(L)\varepsilon_t \tag{2.8}$$

where $\phi(L)$ and $\theta(L)$ are autoregressive and moving average polynominals, respectively, with roots lie outside the unit circle. An ARFIMA process is non-stationary when $|d| > 0.5$ and stationary when $|d| < 0.5$. When $0 < d < 0.5$, y_t is called stationary long memory. When $-0.5 < d < 0$, y_t is called intermediate memory and antipersistent.

2.2.5 SEMIFAR Model

To allow for the data-driven distinction of long memory, short memory, stochastic trends, and deterministic trends without any prior knowledge, Beran and Ocker (2001) proposed a semiparametric fractional autoregressive (SEMIFAR) model

$$\phi(L)(1-L)^\delta ((1-L)^m y_t - g(i_t)) = \varepsilon_t \tag{2.9}$$

where δ is the long memory parameter, and $g(i_t)$ is a smooth trend function on [0,1] with $i_t = t/T$. y_t must be differenced to achieve stationarity by parameter $d = \delta + m$. m determines whether the trend should be estimated from the original data (when m = 0) or the

[23] To obtain a stationary process, y_t must be differenced d times. The parameter d determines the long-term behavior, whereas p and q affect the short-term properties.

first difference (when m = 1). When $\delta > 0$, y_t is long memory. When $\delta < 0$, y_t is antipersistent. When $\delta = 0$, y_t has short memory.

2.2.6 Long Memory Estimation

According to the slow decay of autocorrelations in Figure 2.5, it is evident that the logarithmic realized volatility for the exchange rate series appears to have long memory dynamics. In addition to the parametric and semiparametric methods motioned above, we also use the nonparametic method by Geweke and Porter-Hudak (1983), henceforth GPH, based on the simple linear regression of the log periodogram on a deterministic regression

$$\ln[I(\omega_j)] = c - d\ln[4\sin^2(\omega_j/2)] + u_j, \quad j = 1,.....n \tag{2.10}$$

where $I(\omega_j) = (1/2\pi)\left|\sum_{i=1}^{T} y_t \exp(i\omega_j t)\right|^2$ is the periodogram at frequency $\omega_j = 2\pi j/T$. The window size n depends on the sample size T. The least squares estimator d will be asymptotically normal with variance $\pi^2/6n$. There are several other methods of testing long memory time series, and we also use them as a robustness check. For a detailed discussion of long memory testing methods, see Baillie (1996), and Robinson (1995).

The estimates of d for realized volatility are reported in Table 2.2, and the estimates of d for logarithmic realized volatility are reported in Table 2.3. Whether used nonparametric, parametric, or semiparametric methods, all of the estimates of d are in the range between 0.34 and 0.58, which confirms the long memory property in the (logarithmic) realized volatility.

2.3 Structural Break Model

2.3.1 Multiple Structural Break Model

It is well known that structural change and unit roots are easily confused (see Perron 1989; Zivot and Andrews 1992). Recently the confusion between long memory and structural change has been getting more and more attention. Granger and Ding (1996), Granger and Hyung (2004), and Choi and Zivot (2006) suggest that observed long memory property in the asset return volatility may be explained by the presence of structural breaks. To investigate this conjecture for realized volatility, we use the pure multiple mean break method proposed by Bai and Perron (1998, 2003), henceforth BP, to test this hypothesis. The m model (m + 1 regimes) is defined as

$$y_t = c_j + u_t, \quad t = T_{j-1}+1, T_{j-1}+2, ..., T_j \tag{2.11}$$

where $j = 1, 2, \ldots, m+1$, y_t is the logarithmic realized volatility, and c_j is the mean of the logarithmic realized volatility. The break points $(T_1, T_2, ..., T_m)$ are treated as unknown. The error term u_t may be serial correlated and heteroskedastic. The estimation is based on the least-squares principle. The estimated break points $(\hat{T}_1, \hat{T}_2, ..., \hat{T}_m)$ are obtained by solving $\underset{T_1,...,T_m}{\arg\min}\, S_T(T_1, T_2, ..., T_m)$ where

$$S_T(T_1, T_2, ..., T_m) = \sum_{j=1}^{m+1} \sum_{t=T_{i-1}+1}^{Ti} (y_t - c_j)^2 \tag{2.12}$$

Given the estimated break points, the corresponding estimates $\hat{c}_j(\hat{T}_1, \hat{T}_2, ..., \hat{T}_m)$ are obtained for each regime. We used several tests for structural change proposed in BP. Let $\sup F_T(l)$ denote the F statistic for the null of no structural breaks versus an alternative hypothesis containing an arbitrary number of breaks and let M denote the maximum number of breaks allowed. We set M = 5. Define the double maximum statistic, $UD_{\max} = \max_{1 \le l \le M} \sup F_T(l)$, and the weighted double max statistic $WD_{\max} = \max_{1 \le l \le M} w_l \sup F_T(l)$, where the marginal p-values are equal across values of l. The null hypothesis of both tests is no structural breaks against the alternative of an unknown number of breaks given some specific upper bound *M*. Sequential $\sup F_T(l+1 | l)$ tests the null of l breaks versus the alternative $l+1$ breaks. To determine the number of breaks, we first use the $UD_{\max}$ and $WD_{\max}$ to determine if at least one break occurred. If there is evidence for structural change, we select the number of structural breaks using the $\sup F_T(l+1 | l)$. To allow for a penalty factor for the increased dimension of a model, the above procedure may be complemented by selecting the number of breaks by minimizing a Bayesian Information Criterion (BIC) and a modified Schwarz Criterion (LWZ).

2.3.2 Multiple Structural Break Estimation

Table 2.4 displays the values of all the tests used to determine the number of breaks for the logarithmic realized volatility series. The *UD*max and *WD*max tests point to the presence of multiple breaks for all series. The $\sup F_T(l)$ tests reject the null hypothesis of no breaks versus the alternative of an unknown number of breaks for the all series. For DM/$, the

$\sup F_T(l+1\,|\,l)$ is significant at 1% level when $l = 4$, which suggests 5 breaks. BIC suggests 5 breaks as well while LWZ suggests 2 breaks. Therefore, we choose 5 breaks for DM/\$. For Yen/\$, $\sup F_T(l+1\,|\,l)$ is significant when $l = 3$ but not significant when $l = 4$, which suggest 4 breaks. We follow BIC to choose the 5 breaks for Yen/\$. For Yen/DM, $\sup F_T(l+1\,|\,l)$ suggest 4 breaks as well as BIC. Hence 4 breaks should be chosen for Yen/DM.

In Table 2.4 we also report the estimates of the break dates with their respective 90% confidence intervals. The break dates estimated for DM/\$ and Yen/\$ are very similar, which suggests common break dates for the process: May 1989, March – May 1991, March 1993, June – August 1995, and May – July 1997. The estimations of the mean parameters ($\hat{c}_j$) for regimes (m + 1) are also provided on the bottom of Table 2.4. Figure 2.6 presents the graphs for the logarithmic realized volatility and the estimated $\hat{c}$ value. The mean breaks are coincided with country specific or worldwide economics or financial crisis, i.e. Asian financial crisis occurred in July 1997.

2.3.3 Long Memory Estimation After Adjusting for Structural Breaks

The sixth column in Table 2.3 shows the long memory parameter estimates for the three series after adjustment for the estimated structural breaks. The parameter d is estimated using the residual series $y_t - \hat{c}_j$. All estimates of d are lower than estimation using non-adjusted series. Although d is not reduced significantly by the Whittle, ARFIMA, and SEMIFAR methods, d has dropped substantially by the GPH method. In addition, the test statistics (DM/\$: 1.467, Yen/\$: 1.472, and Yen/DM: 1.434) from the rescaled range (R/S) test show that we can not reject the null hypothesis for the absence of long memory. Figure 2.7 displays the autocorrelation function for the adjusted volatility series. Compared to Figure 2.5 for the autocorrelation before adjustment for breaks, it is evident that the persistence of volatility has been reduced after removing the estimated breaks.

Furthermore, from Figure 2.2, there might be an upward trend in the volatility series, especially in Yen/DM series. We use the ARFIMA model with flexible trend by Beran and Ocker (2001) mentioned in Section 2.2.5 to test this possibility. The results for the estimated trend are shown in Figure 2.8. We see that the trend is not statistically significant. It is worth noting that Beran and Ocker' (BO) method is an alternative to the BP model. The BP model gives abrupt change whereas the BO model admits a smoother flexible trend. Our results show that the realized volatility series fit the BP model better than the BO model.

2.3.4 Monte Carlo Simulation for Long Memory Process

We discussed previously that structural change is easily confused with long memory. Granger and Hyung (2004) pointed out that there exists another perplexity: a long memory model without breaks may cause breaks to be detected spuriously by standard estimation methods. To illustrate this phenomenon, we generated six long memory series with d = 0.1, 0.2, 0.3, 0.35, 0.4, 0.45, respectively, with mean: -0.5, standard deviation: 0.4, and sample size: 3,045. These series, which are similar to our sample logarithmic realized volatility, are shown in Figure 2.9. Table 2.5 shows results for the structural break tests of BP for the different DGPs. The results suggest a positive relationship between the number of breaks and the value of d as found in Granger and Hyung (2004). This reveals the fact that a long memory/fractionally integrated process itself contains some portion of a permanent shock, which often appears as a break in some situations.[24] The above Monte Carlo evidence shows that long memory could provide a good and simple mimic of in-sample fit for the true structural-break DGP when we have little knowledge for the past break dates and size.[25]

Next, as mentioned in Section 2.3.3, we notice that the Whittle, ARFIMA, and SEMIFAR methods gave very different estimates of d than the GPH method in the break adjusted data. We estimate the long memory parameters from the simulated data: ARFIMA (0, 0.45, 0), ARFIMA (1, 0.45, 1) with AR coefficient 0.3 and MA coefficient 0.5, and ARFIMA (1, 0.45, 0) with AR coefficient -0.1. The coefficients are selected based on the estimation result in Table 2.3. These DGPs are also graphed on the bottom of Figure 2.9. From Table 2.6, we find the estimates, in particular, for ARFIMA (1, 0.45, 1) are distorted using the Whittle, ARFIMA and SEMIFA methods. The above simulation result presents the biased problems of these methods when the DGP includes moving average process and explains the reason for inconsistent estimates of d in Section 2.3.3.

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[24] Currently there is no formal test available for multiple structural changes in the I(d) process with unknown number of breaks. It will be interesting for the future research.

[25] This property, which is trivial here, will become much more important when we discuss the long memory and structural breaks for out-of-sample forecasting in Section 5.

2.4 Markov Switching Model

2.4.1 The Model

Hamilton and Susmel (1994) have found that stock market volatility can be explained by regime switching model triggered by fundamental factors, i.e. general business cycle, while Kim and Kim (1996) argued that the presence of volatility regime switching is due to the fad factor. Which regime switching model explains observed long-memory realized volatility better? Meanwhile, as the relationship between long memory and structural breaks, Diebold and Inoue (2001) argue that long memory and regime switching are closely related. The difference between the structural break model in the previous section and the Markov-switching model is that in the former breaks are viewed as nonrecurrent and permanent and in the latter they are viewed as recurrent. In this section, we consider the possibility of Markov-switching behavior in log realized volatility by estimating the Hamilton (1989) model. Furthermore, we evaluate tests for long memory in data generated by Markov-switching models using a comprehensive Monte Carlo simulation up to three states and switching parameters on mean, variance, and AR coefficients, while Diebold and Inoue (2001) only discuss two states and switching parameters on mean and variance.

2.4.2 The Estimation

For simplicity, we use two-state AR(4) model based on the partial autocorrelation function in Figure 2.10. The model is

$$y_t - \mu_{St} = \phi_1(y_{t-1} - \mu_{St-1}) + \phi_2(y_{t-2} - \mu_{St-2}) + \phi_3(y_{t-3} - \mu_{St-3}) + \phi_4(y_{t-4} - \mu_{St-4}) + e_t \tag{2.13}$$

where y_t is logarithmic realized volatility, with roots of $\phi(L)$ lie outside the unit circle, $e_t \sim i.i.d.N(0,\sigma^2)$, $\mu_{St} = \mu_0(1-S_t) + \mu_1 S_t$. When $S_t = 0$ and $\mu_{St} = \mu_0$, it is the low mean state. When $S_t = 1$ and $\mu_{St} = \mu_0$, it is the high mean state. The log-likelihood function can be written as

$$\ln L = \sum_{t=5}^{3045} \ln[\sum_{St=0}^{1} f(y_t \mid S_t, \psi_{t-1}) \Pr(S_t \mid \psi_{t-1})] \tag{2.14}$$

where ψ_{t-1} denotes all the information available at time *t-1* and $\Pr(S_t \mid \psi_{t-1})$ can be predicted using

$$\Pr(S_t = j \mid \psi_{t-1}) = \Pr(S_t = j \mid S_{t-1} = i) \Pr(S_{t-1} = i \mid \psi_{t-1}) \tag{2.15}$$

where $\Pr(S_t = j \mid S_{t-1} = i), i = 0,1, j = 0,1$, are the transition probabilities such that $\Pr(S_t = 1 \mid S_{t-1} = 1) = p$ and $\Pr(S_t = 0 \mid S_{t-1} = 0) = q$. Once y_t is observed, we can update the state probability using

$$\begin{aligned}\Pr(S_t = j \mid \psi_t) &= \Pr(S_t = j \mid \psi_{t-1}, y_t) = \frac{f(S_t = j, y_t \mid \psi_{t-1})}{f(y_t \mid \psi_{t-1})} \\ &= \frac{f(y_t \mid S_t = j, \psi_{t-1}) \Pr(S_t = j \mid \psi_{t-1})}{\sum_{j=0}^{1} f(y_t \mid S_t = j, \psi_{t-1}) \Pr(S_t = j \mid \psi_{t-1})}\end{aligned} \tag{2.16}$$

The estimation of (2.13) is based on Kim's smoothing algorithm (Kim and Nelson 1999b) using all the information in the sample and the results are provided in Table 2.7. Figure 2.11 depicts the smoothed probabilities for the low mean (log realized volatility). Interestingly, Markov-switching model for the exchange rate realized volatility predicts many more short-life regime switches than the result of BP model. Nevertheless, this implies that we might need richer states model to fit the data, we investigate the relationship between regime switches and long memory using Monte Carlo experiment instead of the estimation.

2.4.3 Monte Carlo Evidence

For the Monte Carlo experiment, we use the general autoregressive Markov-switching model

$$\begin{aligned} & y_t = \mu_{St} + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \phi_3 y_{t-3} + \ldots\ldots + \phi_p y_{t-p} + e_t \\ & e_t \sim N(0, \sigma_{St}^2) \\ & \mu_{St} = \mu_1 S_{1t} + \ldots. + \mu_j S_{jt} \\ & \sigma_{St}^2 = \sigma_1^2 S_{1t} + \ldots. + \sigma_j^2 S_{jt} \\ & \phi_{1..p} = \phi_{1..p} S_{1t} + \ldots. + \phi_{1..p} S_{jt} \end{aligned} \tag{2.17}$$

where $S_{jt} = 1 \text{ if } S_t = j \text{ and } S_{jt} = 0 \text{ otherwise}$. We consider 16 different DGPs: 12 DGPs are 2-state Markov-switching, and 4 are 3-state Markov-switching models. In addition to regime-switching occurring in mean (intercept), we also investigate regime-switching in AR coefficient (ϕ), and error term (e_t). The values we use are similar to the estimates we got in the previous section. Simulations from the different DGPs are plotted in Figure 2.12. Using the simulated series, we estimate the long memory parameter d by the GPH method.

The results from the Monte Carlo experiment are reported in Table 2.8. There are 5 models which indicate the presence of long memory out of the 16 models. First, from Models

C and D, the results suggest that when transition probabilities are closer to unity, it is more likely to find evidence for long memory. Second, processes with switching in mean (intercept) and AR coefficients are more likely to explain long memory dynamics than switching in variance; i.e., Models E, F, and G. This suggests that a break model is more capable of producing long memory than an extreme value (jump) model. This result favors Hamilton and Susmel (1994) model over Kim and Kim (1996) model on explaining observed long memory behavior. Third, from Models O and P, we see that richer states of regime switching are more likely to generate long memory behavior.

The above Monte Carlo experiment sheds light on the closed relationship between long memory and some forms of Markov-switching models. When out-of-sample forecasting ability of Markov-switching model is still problematic and/or the model parameters are unknown or hard to decide (like Section 2.4.2), long memory model could provide an easy alternative for forecasting the true Markov-switching DGP. We explore the forecast evaluation in more details in Section 2.5.

2.5 Forecast Evaluation and Simulation

2.5.1 Forecast evaluation and comparison

Many models have been provided for modeling and forecasting asset return volatility and the success of a volatility model lies in its out-of-sample forecasting power. For example, ABDL propose a trivariate VAR-RV-I(d) (fractionally integrated Gaussian vector autoregressive-realized volatility),

$$\Phi(L)(1-L)^d (Y_t - \mu) = \varepsilon_t \tag{2.18}$$

where Y_t is (3×1) vector of logarithmic realized exchange rate volatilities; μ is unconditional mean and ε_t is a vector white noise process. They fix the value of d for each series at 0.401, which is also close to our long memory estimates in Table 2.3. They choose the orders of 5 for the lag polynomials in $\Phi(L)$ to being equal to five days, or one week. They compare with the volatility forecasts from several popular models, and they find that their VAR-RV-I(d) model produces superior out-of-sample forecasts.

Here we assess the forecasting performance from our VAR-RV-Break model,

$$\Phi(L)(Y_t^* - \mu) = \varepsilon_t \tag{2.19}$$

where Y_t^* is the vector of logarithmic realized exchange rate volatilities after mean break adjustment. Although the Bayesian information criteria select a fourth-order VAR, we use a fifth-order model to compare our result to those in ABDL.[26] Forecasts are obtained by estimating rolling models. We estimate initially over the first 2449 observations, December 2, 1986 to December 1, 1996, and using the in-sample parameter estimates,[27] one-day-ahead forecasts are made for the next day, say day 2450. The process is then rolled forward 1 day, deleting the first observation and adding on the 2450 observation, the model is re-estimated and the second forecast is made for 2451. The rolling method is repeated until 3045, the end of the out-of-sample forecast period. We get 596 one-step-ahead predictions in the out-of-sample period, which is from December 2, 1996 to June 30, 1999. After getting the forecasts, we adjust them back based on the given mean breaks.

In Figure 2.13, we plot the DM/\$, Yen/\$, and DM/Yen realized volatility along with the corresponding one-day-ahead VAR-RV-Break forecasts. It appears that our forecasts capture movement of the realized volatilities well. Next, to determine which model provides more information about the future value, we use the encompassing regression[28] by Mincer and Zarnowitz (1969),

$$\mathrm{vol}_{t+1,i} = \beta_0 + \beta_1 \mathrm{vol}_{t+1|t,i}^{VAR-RV-Break} + \beta_2 \mathrm{vol}_{t+1|t,i}^{Model} + \varepsilon_t \tag{2.20}$$

where we denote our benchmark VAR-RV-Break model prediction of future volatility by $\mathrm{vol}_{t+1|t}^{VAR-RV-Break}$ and future volatility prediction from other candidate methods by $\mathrm{vol}_{t+1|t}^{Model}$. The alternative models are all selected by ABDL and described as follows. First, the VAR-RV-I(d) model (2.18) is the main model proposed by ABDL. Second, the VAR-ABS model is fractionally integrated vector autoregressive using daily absolute returns instead of realized volatility. Third, the GARCH model pioneered by Engle (1982) and Bollerslev (1986) describes short-memory conditional volatility via maximum likelihood procedure as a linear function of past squared forecast errors. Based on 2,449 daily in-sample returns, we get the GARCH (1,1) estimates with AR polynomial for DM/\$, Yen/\$, and DM/Yen being 0.986, 0.968, and 0.99, respectively. Fourth, the RiskMetrics model from J. P. Morgan is widely used

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[26] We also evaluate model by VAR(4). The results are similar to VAR(5).

[27] We choose this in-sample period to compare our result to those in ABDL.

[28] This is a regression-based method where the prediction is unbiased only if β_0=0 and β_1=1. When there are more than one forecasting models, additional forecasts are added to the right-hand-side to check for incremental explanatory power. The first forecast is said to subsume information in other forecasts if these additional forecasts do not significantly increase the R^2.

by practitioners. We get the RiskMetrics daily variances and covariances using exponentially weighted moving averages of the cross products of daily returns by a smoothing factor λ=0.94.[29] Fifth, the fractionally integrated exponential GARCH (FIEGARCH)[30] (1,d,0) by Bollerslev and Mikkelsen (1996) is a variant of FIGARCH model by Baillie, Bollerslev, and Mikkelsen (1996). The last one is the high-frequency FIEGARCH model using the "deseasonalized"[31] and "filtered"[32] 30-minutes returns.

For the robustness check, we also present the popular out-of-sample forecast evaluation, relative mean squared error (MSE),

$$\frac{\sum (vol_{t+1} - vol_{t+1|t}^{Model})^2}{\sum (vol_{t+1} - vol_{t+1|t}^{Break})^2} \tag{2.21}$$

where the denominator is the benchmark model mean squared forecast error and the numerator is the candidate methods mean squared forecast error. If the relative MSE is less than one, the candidate model forecast is determined to have performed better than the benchmark. The results are presented in Table 2.9. Our VAR-RV-Break model out-of-sample forecasts perform as well as ABDL's VAR-RV-I(d) model and outperform most of the rest of the models.

First, the regression R^2 from VAR-RV-Break model is similar to that from VAR-RV-I(d) model and is higher than most of the rest models. Second, we can not reject the hypothesis that $\beta_0 = 0$ and $\beta_1 = 1$ in the VAR-RV-Break model using t tests while we reject the hypothesis that $\beta_0 = 0$ and/or $\beta_2 = 1$ for all the other models except the VAR-RV-I(d) model. Third, in the encompassing regression that includes both the break model and an alternative forecast, the estimates for β_1 are closer to unity and the estimates for β_2 are closer to zero. Fourth, including an alternative forecast method has little contribution to

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[29] RiskMetrics is a special form of integrated GARCH (IGARCH) in which the intercept is fixed at zero and the coefficient for the squared returns (λ) is 0.94. λ could be interpreted as a persistence parameter. When λ is closer to one, more weight is put on the previous period's estimate relative to the current period's observation, which means it is more persistent.

[30] FIEGARCH has volatility persistence shorter than IGARCH but longer than GARCH. Bollerslev and Mikkelsen (1996) found that FIGARCH outperforms GARCH and IGARCH and FIEGARCH is better than FIGARCH for S&P 500 returns.

[31] The deseasonalization is from the fact that the intraday volatility has obvious "seasonal" components related to the opening and closing hours of exchange worldwide. This intraday patterns damage the estimation of traditional volatility models from the raw high-frequency returns. Following ABDL, we get the seasonal factor by averaging the individual squared returns in the various intra-day intervals. And then we can construct the seasonal adjusted high frequency returns.

[32] To decrease the impact of the serial correlation in high frequency asset returns from different market microstructure frictions, following ABDL, we use simple first order AR "filter" to the high-frequency returns before estimating FIEGARCH model.

increasing R^2. Finally, most of the relative MSEs are bigger than one, which means that VAR-RV-Break model has the smaller MSE than that in other forecasts.

The results in Table 2.9 show the superior forecasting ability for the VAR-RV-Break model in which the future break dates and sizes are known in the out-of-sample period. This result is consistent with Hyung, Poon and Granger (2006). Without the additional information in detecting out-of-sample breaks, the prediction ability of the VAR-RV-Break would be lessened and its performance depends on the numbers and sizes of the out-of-sample breaks as shown in Table 2.10. For the DM/$ series, the VAR-RV-Break model still outperforms all the models except the VAR-RV-I(*d*) model because the out-of-sample break is not large as shown in Figure 2.6. But for Yen/$ and Yen/DM, which show larger breaks, the VAR-RV-Break model's prediction ability becomes inferior to the other models (except VAR-ABS). In this case, the VAR-RV-I(*d*) would be the best forecasting model.

2.5.2 Forecast simulation for break and long memory models

For the robustness check about the comparison of the VAR-RV-Break and the VAR-RV-I(*d*) out-of-sample forecasts, we simulate a DGP for an AR(1) process with 3000 observations, AR(1) coefficient: 0.41, unconditional variance: 0.16 and six periods divided by four ad hoc breaks shown in Figure 2.14.A. Each period's range and mean are as follows: P1[1:700; 0.5], P2[701:1500; -1.3], P3[1501:2000; -0.5], P4[2001:2300; -0.5], P5[2301:2700; -1.2], and P6[2701:3000, 0.7] where P1 to P3 are in-sample period and P4 to P6 are out-of-sample period.

For the AR-Break model, we perform one step ahead forecasts simply based on the true DGP with AR(1) coefficient: 0.41. When the out-of-sample breaks are known, we adjust the mean for the forecast evaluation. For the AR-I(*d*) model, we use in-sample data (Figure 2.14.A P1 to P3) to estimate the long memory parameter and the AR(1) coefficient. We get d = 0.2697 and AR(1) = 0.2137. We perform one-step-ahead forecasts from the ARFIMA model. Figure 2.14.B shows the result for period 4 in which the out-of-sample break has not occurred. Whether breaks are known or not, the break model performs a little bid better than I(*d*) model. The relative MSE is 1.02. Surprisingly, in period 5 and 6 after breaks occurred, the I(*d*) model still accurately predicts while the break model deteriorates substantially when the breaks are unknown.

Note that even though the DGP is pure mean break series without any long memory, we still can get very good out-of-sample forecast performance using simple AR-I(d). This result shows that long memory/fractional integrated model will still be the best forecasting model when the true financial volatility series are created by structural breaks and we have little knowledge about break dates and size.

2.6 Conclusions

In this chapter, we explore the existence and of structural changes in realized volatility for the DM/$, Yen/$ and Yen/ DM spot exchange rate realized volatility. First, our analysis has found strong evidence of long memory behavior in exchange rate realized volatility. Second, we test for and estimate a multiple mean breaks model and a Markov-switching model. We find several common structural breaks within the three series. Third, after adjusting the realized volatility series for the estimated breaks, we find a substantial reduction of persistence in the realized volatility. The evidence suggests that long memory may be caused by the presence of structural breaks.

Fourth, Monte Carlo simulation results for different Markov Switching models suggest the findings: (1) when transition probabilities are closer to unity, it is more likely to generate long memory process; (2) processes with switching in mean (intercept) and AR coefficients are more likely to explain long memory process than switching in variance; (3) Richer states of regime switching is more likely to generate long memory process. Finally, VAR-RV-Break model is superior among most of the current forecasting methods if the future break dates and sizes are known. The VAR-RV-I(d) model, however, is still the best forecasting model even when the true financial volatility series are created by structural breaks and we have little knowledge about break dates and size.

Table 2.1 Daily Realized Volatility Distributions

	Mean	S.D.	Skewness	Kurtosis	Q(20)
		Volatility			
DM/$	0.616	0.269	2.111	11.55	6095.6
Yen/$	0.661	0.331	3.323	33.72	6523.2
Yen/DM	0.618	0.279	2.985	32.56	12443.9
		Logarithmic Volatility			
DM/$	-0.562	0.386	0.308	3.49	8627.2
Yen/$	-0.51	0.43	0.217	3.65	9150.1
Yen/DM	-0.565	0.406	0.101	3.38	18402.3

1. The sample is from Dec 1, 1986 to June 30, 1999.
2. The top panel is the distribution of realized standard deviation, $(\text{realized variance})^{1/2}$.
3. The bottom panel is the distribution of logarithmic realized standard deviation.
4. Ljung-Box test statistics for twentieth order serial correlation, Q(20).

Table 2.2 Realized Volatility Long Memory Parameters before Adjustment

Tests	Series	d	AR(1)	MA(1)
GPH	DM/$	0.3958	N/A	N/A
	Yen/$	0.3812	N/A	N/A
	Yen/DM	0.5426	N/A	N/A
Whittle	DM/$	0.3489	N/A	N/A
	Yen/$	0.3931	N/A	N/A
	Yen/DM	0.4160	N/A	N/A
ARFIMA (p,d,q)	DM/$	0.3489	0	0
	Yen/$	0.39	0	0
	Yen/DM	0.4143	0	0
SEMIFAR $(p,d,0)$	DM/$	0.3444	0	0
	Yen/$	0.3859	0	0
	Yen/DM	0.4096	0	N/A

1. GPH test is based on Geweke and Porter-Hudak (1983).
2. Whittle's method is based on a frequency domain maximum likelihood estimation of a process i.e. equation (2.6).
3. ARFIMA model is based on Beran (1995). $\phi(L)(1-L)^{\delta}[(1-L)^{m} y_t - \mu] = \theta(L)\varepsilon_t$ where $-0.5 < d < 0.5$. The integer m is the number of times that y must be differenced to achieve stationarity, and the long memory parameter is given by $d = \delta + m$. The method uses BIC to choose the short memory parameters p and q. When $m = 0$, μ is the expectation of y_t; when $m = 1$, μ is the slope of linear trend component in y_t.
4. SEMIFAR (Semiparametric Fractional Autoregressive) model is based on Beran and Ocker (2001). $\phi(L)(1-L)^{\delta}[(1-L)^{m} y_t - g(i_t)] = \varepsilon_t$. By using a nonparametric kernel estimate of $g(i_t)$ instead of constant term μ. The method uses BIC to choose the short memory parameter p.

Table 2.3 Estimations for Long and Short Memory Parameters

		Log Realized Volatility Before Adjustment			Log Realized Volatility After Adjustment			
		d	AR(1)	MA(1)	d	AR(1)	MA(1)	Q(20)
GPH	DM/$	0.4239 (0.0975)	N/A	N/A	0.021 (0.0975)	N/A	N/A	5438
	Yen/$	0.3571 (0.0975)	N/A	N/A	0.0823 (0.0975)	N/A	N/A	5309
	Yen/DM	0.5867 (0.0975)	N/A	N/A	0.0576 (0.0975)	N/A	N/A	5610
Whittle	DM/$	0.3816	N/A	N/A	0.3693	N/A	N/A	
	Yen/$	0.4146	N/A	N/A	0.3975	N/A	N/A	
	Yen/DM	0.4229	N/A	N/A	0.3852	N/A	N/A	
ARFIMA (p,d,q)	DM/$	0.3817 (0.0142)	0	0	0.3671 (0.0142)	0	0	
	Yen/$	0.4107 (0.0142)	0	0	0.3945 (0.0142)	0	0	
	Yen/DM	0.5673 (0.0316)	0.28 (0.05)	0.49 (0.02)	0.3839 (0.0142)	0	0	
SEMIFAR $(p,d,0)$	DM/$	0.3778 (0.0142)	0	N/A	0.367 (0.0142)	0	N/A	
	Yen/$	0.4096 (0.0142)	0	N/A	0.3976 (0.0142)	0	N/A	
	Yen/DM	0.4685 (0.0212)	-0.1018 (0.03)	N/A	0.3833 (0.0142)	0	N/A	
R/S Test	DM/$	test stat: 3.4712**	Reject the Null		test stat: 1.4671	Do Not Reject the Null		
	Yen/$	test stat: 2.9046**	Reject the Null		test stat: 1.4718	Do Not Reject the Null		
	Yen/DM	test stat: 4.4041**	Reject the Null		test stat: 1.4337	Do Not Reject the Null		

1. * indicates 5% significance level and ** indicates 1% significance level and the numbers in the parentheses indicate standard errors.
2. GPH, Whittle, ARFIMA, and SEMIFAR models are explained in the detail below the Table 2.2.
3. *R/S* Test is called rescaled range statistic defined as $R_T = \max_{0\le j\le T}[\sum_{j=1}^{T}(y_j - j\bar{y})] - \min_{0\le j\le T}[\sum_{j=1}^{T}(y_j - j\bar{y})]$ and $s_T = [(1/T)\sum(y_t - \bar{y})^2]^{1/2}$ where R is the range, s_T is the sample standard deviation and $\bar{y}$ is the sample mean. We actually use the modified rescaled range statistic $Q_T = R_T / \sigma_T(q)$ where $\sigma_T^2(q) = c_0 + 2\sum_{j=1}^{q} w_j(q)c_j$, c_j is the *j*th-order sample autocovariance and $w_j(q)$ is the Bartlett window weights.

Table 2.4 Multiple Structural Changes Test Results

\Series Statistics	DM/$	Yen/$	Yen/DM
		Tests	
$\sup F_T(1)$	52.58	133.36	305.13
$\sup F_T(2)$	55.64	76.86	246.36
$\sup F_T(3)$	42.37	54.06	188.79
$\sup F_T(4)$	36.92	50.74	149.35
$\sup F_T(5)$	33.94	42.29	110.46
$UD\max$	55.64**	133.36**	305.13**
$WD\max$	84.95**	133.36**	323.48**
$\sup F_T(2\mid 1)$	36.23	17.88**	131.56
$\sup F_T(3\mid 2)$	12.83	7.19	71.95
$\sup F_T(4\mid 3)$	16.29	26.37	21.31
$\sup F_T(5\mid 4)$	16.29	8.57	0
		Numbers of Changes Selected	
BIC	**5**	**5**	**4**
LWZ	2	2	2
Sequential	4	2	4
		Multiple Structural Changes Dates Estimation	
$\hat{T}_1$	1989.5.11 [89.2.14-89.11.1]	1989.5.11 [88.12.21-89.9.6]	1989.11.21 [89.11.7-89.12.15]
$\hat{T}_2$	1991.3.18 [90.9.24-91.8.20]	1991.5.16 [91.3.20-91.10.2]	1992.6.10 [92.3.4-92.10.20]
$\hat{T}_3$	1993.3.5 [92.12.7-93.5.14]	1993.3.30 [92.11.25-93.5.21]	1994.5.4 [94.3.24-94.6.1]
$\hat{T}_4$	1995.8.24 [95.6.15-95.11.29]	1995.6.15 [94.8.24-96.6.19]	1997.5.8 [97.4.17-97.5.28]
$\hat{T}_5$	1997.7.10 [97.4.9-89.10.27]	1997.5.7 [97.4.3-97.6.17]	
		Estimations of Mean for Each Regime	
$\hat{c}_1$	-0.662 (0.015)	-0.686 (0.017)	-0.924 (0.012)
$\hat{c}_2$	-0.472 (0.017)	-0.457 (0.018)	-0.5 (0.013)
$\hat{c}_3$	-0.334 (0.016)	-0.687 (0.017)	-0.342 (0.015)
$\hat{c}_4$	-0.553 (0.015)	-0.446 (0.017)	-0.659 (0.012)
$\hat{c}_5$	-0.770 (0.017)	-0.580 (0.018)	-0.205 (0.014)
$\hat{c}_6$	-0.585 (0.017)	-0.205 (0.018)	

1. * indicates 5% significance level
2. ** indicates 1% significance level
3. In bracket are the 90% confidence intervals
4. In parentheses are standard errors
5. Number of Changes Selected From Sequential Method is based on 1% level

Table 2.5 Estimated Spurious Breaks for Long Memory Simulation

	Breaks exist or not		Number of Breaks Selected			
d	*Ud*max	*Wd*max	$\sup F_T(l+1\mid l)$	BIC	LWZ	Sequential
0.1	No	No	0	0	0	0
0.2	Yes	Yes	0	2	0	1
0.3	Yes	Yes	3	4	2	3
0.35	Yes	Yes	3	3	3	3
0.4	Yes	Yes	2	4	2	2
0.45	Yes	Yes	3	4	3	3

1. Six different long memory parameters DGP based on Monte Carlo Simulation for 3045 observations.
2. Structural breaks tests are based on Bai and Perron (1998, 2003).
3. The tests are based on 1% significance level.

Table 2.6 Long Memory Tests for Long Memory Simulation

d=0.45	GPH	Whittle	ARFIMA	SEMIFA	R/S Test
ARMA (0,0)	0.4061 (0.0975)	0.4604	0.4580 (0.0142)	0.4581 (0.0142)	3.3255**
ARMA (1,1)	0.4019 (0.0975)	0.2756	0.3593 (0.0206)	0.3270 (0.021)	2.9011**
AR: 0.3, MA: 0.5			MA: 0.1419 (0.026)	AR: -0.1104 (0.0267)	
ARMA (1,0)	0.6022 (0.0975)	0.4107	0.4698 (0.0210)	0.4613 (0.0211)	3.6268**
AR: -0.1			AR: -0.113 (0.0266)	AR: -0.1060 (0.0268)	

1. Long Memory Test based on long memory DGP with d = 0.45.
2. In parentheses are standard errors.
3. R/S Test results show the test statistics. **meaning significant at 1% level.

Table 2.7 Maximum Likelihood Estimates of the Markov-Switching Model

	DM/$		Yen/$		Yen/DM	
Parameter	Estimates	Standard Errors	Estimates	Standard Errors	Estimates	Standard Errors
p	0.61623	(0.04304)	0.18793	(0.06629)	0.19741	(0.06709)
q	0.96506	(0.00582)	0.96931	(0.00845)	0.95315	(0.01165)
ϕ_1	0.40935	(0.02041)	0.45653	(0.02176)	0.43008	(0.02348)
ϕ_2	0.02105	(0.01599)	0.15473	(0.02393)	0.18510	(0.02380)
ϕ_3	0.68091	(0.01708)	0.06439	(0.02321)	0.10331	(0.02498)
ϕ_4	-0.27695	(0.02128)	0.14751	(0.02064)	0.17449	(0.02211)
σ^2	0.24521	(0.00435)	0.28339	(0.00558)	0.22879	(0.00470)
μ_0	-0.70610	(0.02716)	-0.53491	(0.02953)	-0.59283	(0.03924)
μ_1	-0.05591	(0.04156)	0.21056	(0.07187)	-0.06934	(0.05917)
Log likelihood	-483.97		-769.21		-182.56	

Note: The model is as follows.

$$y_t - \mu_{St} = \phi_1(y_{t-1} - \mu_{St-1}) + \phi_2(y_{t-2} - \mu_{St-2}) + \phi_3(y_{t-3} - \mu_{St-3}) + \phi_4(y_{t-4} - \mu_{St-4}) + e_t$$

Table 2.8 Monte Carlo Simulation Results for Markov-Switching Models

Model	AR	Regime Switching Factors	Transition Probability p, q	Intercept coefficients	AR coefficients	Sigma coefficients	*d*	Q(20)
Benchmark	AR(4)	Intercept	0.95,0.6	0, -0.6	0.41,0.02, 0.68, -0.27	0.24	0.0643 (0.6594)	8987
2	AR(1)	Intercept	0.9, 0.8	0, -1	0.3	0.24	-0.0808 (0.8289)	3656
3	AR(1)	Intercept	0.95, 0.9	0, -1	0.3	0.24	0.1481 (1.5195)	7650
4	AR(1)	Intercept	0.99, 0.95	0, -1	0.3	0.24	0.3258 (3.3425)**	16115
5	AR(1)	Sigma	0.95, 0.9	-0.5	0.3	0.18, 0.3	0.128 (1.3128)	255
6	AR(1)	Sigma	0.95, 0.9	-0.5	0.3	0.12, 0.36	-0.0971 (-0.9958)	340
2 Regimes	AR(1)	Sigma	0.99, 0.95	-0.5	0.3	0.18, 0.3	-0.0019 (-0.0199)	293
8	AR(1)	AR	0.95, 0.9	-0.5	0.5, 0.1	0.08	0.066 (0.6769)	2543
9	AR(1)	AR	0.95, 0.9	-0.5	0.5, -0.2	0.08	-0.1666 (-1.7093)	3285
10	AR(1)	AR	0.99, 0.95	-0.5	0.5, 0.1	0.08	0.1885 (1.9342)	3420
11	AR(2)	Intercept	0.99, 0.95	0, -1	0.5, 0.1	0.08	0.2352 (2.4126)*	21685
12	AR(2)	Sigma	0.99, 0.95	-0.5	0.5, 0.1	0.01, 0.25	0.0788 (0.8088)	1939
13	AR(1)	Intercept	0.99, 0.98, 0.95	0, -0.5, -1	0.3	0.08	0.499 (5.1191) **	19632
3 Regimes	AR(1)	Sigma	0.99, 0.98, 0.95	-0.5	0.3	0.01, 0.13, 0.25	0.0927 (0.9509)	317
15	AR(1)	AR	0.99, 0.98, 0.95	-0.5	0.8, 0.5, 0.1	0.08	0.4622 (4.7418)**	28709
16	AR(1)	Intercept, Sigma	0.99, 0.98, 0.95	-0.3,-0.5,-0.7	0.3	0.13, 0.1, 0.16	0.4702 (4.8239)**	6964

1. * indicates 5% significance level
2. ** indicates 1% significance level
3. In parentheses are test statistics.

Table 2.9 Out-of-Sample Forecast Evaluation When Future Breaks Are Known

	β_0	β_1	β_2	R^2	Rel MSE
DM/$					
VAR-RV-Break	0.036 (0.048)	0.978 (0.091)	--	0.246	--
VAR-RV-I(d)	0.021 (0.049)	--	0.987 (0.092)	0.249	--
VAR-ABS	0.439 (0.028)	--	0.450 (0.089)	0.028	--
Daily GARCH	0.051 (0.063)	--	0.854 (0.105)	0.096	--
Daily RiskMetrics	0.219 (0.042)	--	0.618 (0.075)	0.097	--
Daily FIEGARCH	0.305 (0.052)	--	0.436 (0.083)	0.037	--
Intraday FIEGARCH deseason/filter	-0.069 (0.060)	--	1.012 (0.099)	0.266	--
VAR-RV-Break + VAR-RV-I(d)	0.021 (0.049)	0.366 (0.332)	0.628 (0.327)	0.250	0.98
VAR-RV-Break + VAR-ABS	0.037 (0.046)	0.980 (0.102)	-0.009 (0.096)	0.246	3.86
VAR-RV-Break + Daily GARCH	-0.041 (0.060)	0.907 (0.120)	0.189 (0.137)	0.249	1.23
VAR-RV-Break + Daily RiskMetrics	-0.004 (0.047)	0.906 (0.119)	0.139 (0.098)	0.250	1.22
VAR-RV-Break + Daily FIEGARCH	0.046 (0.052)	0.987 (0.109)	-0.024 (0.100)	0.246	1.38
VAR-RV-Break + Intraday FIEGARCH deseason/filter	-0.066 (0.059)	0.369 (0.207)	0.689 (0.217)	0.274	1.08
Yen/$					
VAR-RV-Break	-0.030 (0.106)	1.090 (0.144)	--	0.330	--
VAR-RV-I(d)	-0.006 (0.110)	--	1.085 (0.151)	0.329	--
VAR-ABS	0.349 (0.086)	--	1.256 (0.241)	0.115	--
Daily GARCH	-0.002 (0.147)	--	1.020 (0.187)	0.297	--
Daily RiskMetrics	0.164 (0.108)	--	0.767 (0.131)	0.266	--
Daily FIEGARCH	-0.289 (0.193)	--	1.336 (0.236)	0.373	--
Intraday FIEGARCH deseason/filter	-0.394 (0189)	--	1.647 (0.263)	0.380	--
VAR-RV-Break + VAR-RV-I(d)	-0.024 (0.101)	0.603 (0.564)	0.490 (0.662)	0.331	1.02
VAR-RV-Break + VAR-ABS	-0.058 (0.109)	1.044 (0.148)	0.166 (0.136)	0.331	3.01
VAR-RV-Break + Daily GARCH	-0.103 (0.141)	0.734 (0.131)	0.432 (0.263)	0.348	1.03
VAR-RV-Break + Daily RiskMetrics	-0.048 (0.112)	0.842 (0.102)	0.245 (0.134)	0.340	1.13
VAR-RV-Break + Daily FIEGARCH	-0.279 (0.209)	0.384 (0.260)	0.962 (0.484)	0.385	0.95
VAR-RV-Break + Intraday FIEGARCH deseason/filter	-0.395 (0.252)	-0.007 (0.375)	1.656 (0.734)	0.380	1.06
DM/Yen					
VAR-RV-Break	-0.047 (0.096)	1.097 (0.132)	--	0.353	--
VAR-RV-I(d)	-0.047 (0.101)	--	1.146(0.143)	0.355	--
VAR-ABS	0.405 (0.062)	--	1.063 (0.175)	0.119	--
Daily GARCH	0.243 (0.092)	--	0.692 (0.119)	0.300	--
Daily RiskMetrics	0.248 (0.084)	--	0.668 (0.107)	0.286	--
Daily FIEGARCH	0.101 (0.105)	--	0.918 (0.144)	0.263	--
Intraday FIEGARCH deseason/filter	-0.231 (0.150)	--	1.455 (0.217)	0.404	--
VAR-RV-Break + VAR-RV-I(d)	-0.054 (0.099)	0.483 (0.452)	0.650 (0.548)	0.357	1.04
VAR-RV-Break + VAR-ABS	-0.044 (0.094)	1.107 (0.148)	-0.028 (0.140)	0.353	3.60
VAR-RV-Break + Daily GARCH	-0.021 (0.082)	0.816 (0.135)	0.235 (0.167)	0.365	1.16
VAR-RV-Break + Daily RiskMetrics	-0.029 (0.089)	0.860 (0.117)	0.199 (0.121)	0.362	1.21
VAR-RV-Break + Daily FIEGARCH	-0.063 (0.106)	0.978 (0.118)	0.141 (0.143)	0.355	1.01
VAR-RV-Break + Intraday FIEGARCH deseason/filter	-0.228 (0.156)	0.232 (0.294)	1.197 (0.530)	0.407	1.08

Notes: In parentheses are standard errors.

Table 2.10 Out-of-Sample Forecast Evaluation When Future Breaks Are Unknown

	β_0	β_1	β_2	R^2	Rel MSE
DM/$					
VAR-RV-Break	0.057 (0.050)	0.879 (0.088)	--	0.214	--
VAR-RV-I(d)	0.021 (0.049)	--	0.987 (0.092)	0.249	--
VAR-ABS	0.439 (0.028)	--	0.450 (0.089)	0.028	--
Daily GARCH	0.051 (0.063)	--	0.854 (0.105)	0.096	--
Daily RiskMetrics	0.219 (0.042)	--	0.618 (0.075)	0.097	--
Daily FIEGARCH	0.305 (0.052)	--	0.436 (0.083)	0.037	--
Intraday FIEGARCH deseason/filter	-0.069 (0.060)	--	1.012 (0.099)	0.266	--
VAR-RV-Break + VAR-RV-I(d)	0.018 (0.050)	0.057 (0.179)	0.933 (0.196)	0.249	0.95
VAR-RV-Break + VAR-ABS	0.065 (0.047)	0.895 (0.103)	-0.056 (0.104)	0.214	3.73
VAR-RV-Break + Daily GARCH	-0.002 (0.060)	0.814 (0.131)	0.160 (0.161)	0.216	1.19
VAR-RV-Break + Daily RiskMetrics	0.029 (0.046)	0.814 (0.131)	0.115 (0.116)	0.216	1.18
VAR-RV-Break + Daily FIEGARCH	0.069 (0.051)	0.890 (0.111)	-0.029 (0.108)	0.214	1.33
VAR-RV-Break + Intraday FIEGARCH deseason/filter	-0.072 (0.059)	0.140 (0.189)	0.888 (0.210)	0.267	1.05
Yen/$					
VAR-RV-Break	-0.040 (0.127)	1.419 (0.218)	--	0.262	--
VAR-RV-I(d)	-0.006 (0.110)	--	1.085 (0.151)	0.329	--
VAR-ABS	0.349 (0.086)	--	1.256 (0.241)	0.115	--
Daily GARCH	-0.002 (0.147)	--	1.020 (0.187)	0.297	--
Daily RiskMetrics	0.164 (0.108)	--	0.767 (0.131)	0.266	--
Daily FIEGARCH	-0.289 (0.193)	--	1.336 (0.236)	0.373	--
Intraday FIEGARCH deseason/filter	-0.394 (0189)	--	1.647 (0.263)	0.380	--
VAR-RV-Break + VAR-RV-I(d)	-0.000 (0.120)	-0.042 (0.151)	1.111 (0.146)	0.329	0.67
VAR-RV-Break + VAR-ABS	-0.156 (0.137)	1.242 (0.212)	0.577 (0.155)	0.282	1.98
VAR-RV-Break + Daily GARCH	-0.153 (0.147)	0.688 (0.129)	0.686 (0.203)	0.327	0.68
VAR-RV-Break + Daily RiskMetrics	-0.096 (0.132)	0.841 (0.137)	0.471 (0.108)	0.319	0.74
VAR-RV-Break + Daily FIEGARCH	-0.360 (0.185)	0.458 (0.146)	1.084 (0.295)	0.387	0.62
VAR-RV-Break + Intraday FIEGARCH deseason/filter	-0.399 (0.190)	-0.371 (0.260)	1.961 (0.450)	0.384	0.70
DM/Yen					
VAR-RV-Break	-0.052 (0.138)	1.486 (0.248)	--	0.227	--
VAR-RV-I(d)	-0.047 (0.101)	--	1.146(0.143)	0.355	--
VAR-ABS	0.405 (0.062)	--	1.063 (0.175)	0.119	--
Daily GARCH	0.243 (0.092)	--	0.692 (0.119)	0.300	--
Daily RiskMetrics	0.248 (0.084)	--	0.668 (0.107)	0.286	--
Daily FIEGARCH	0.101 (0.105)	--	0.918 (0.144)	0.263	--
Intraday FIEGARCH deseason/filter	-0.231 (0.150)	--	1.455 (0.217)	0.404	--
VAR-RV-Break + VAR-RV-I(d)	-0.030 (0.131)	-0.087 (0.175)	1.190 (0.096)	0.355	0.56
VAR-RV-Break + VAR-ABS	-0.106 (0.142)	1.259 (0.269)	0.484 (0.143)	0.247	1.93
VAR-RV-Break + Daily GARCH	0.004 (0.123)	0.655 (0.162)	0.519 (0.110)	0.325	0.62
VAR-RV-Break + Daily RiskMetrics	-0.041 (0.132)	0.762 (0.177)	0.485 (0.085)	0.324	0.65
VAR-RV-Break + Daily FIEGARCH	-0.140 (0.148)	0.795 (0.194)	0.631 (0.107)	0.303	0.54
VAR-RV-Break + Intraday FIEGARCH deseason/filter	-0.188 (0.133)	-0.261 (0.192)	1.608 (0.295)	0.407	0.58

Notes: In parentheses are standard errors.

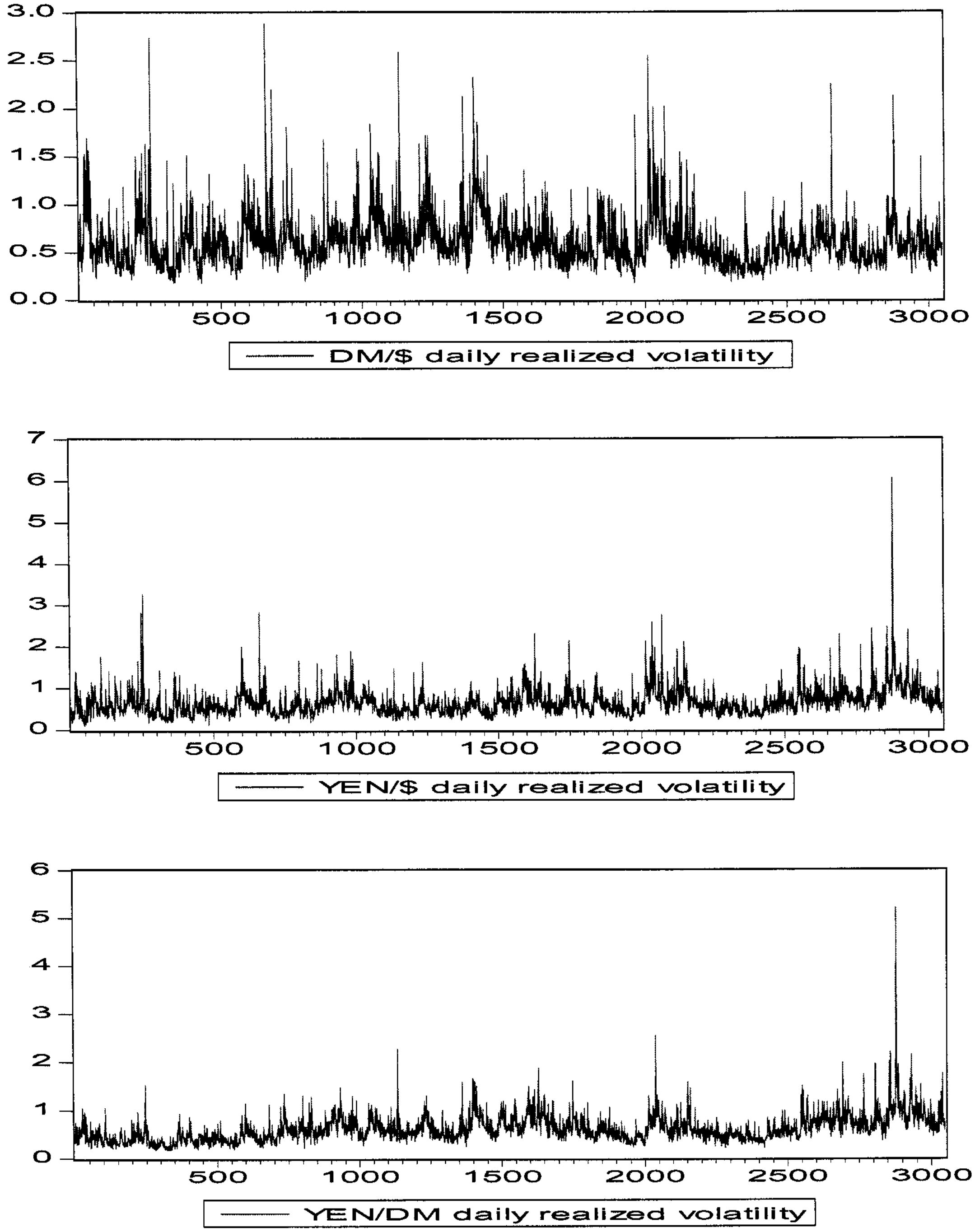
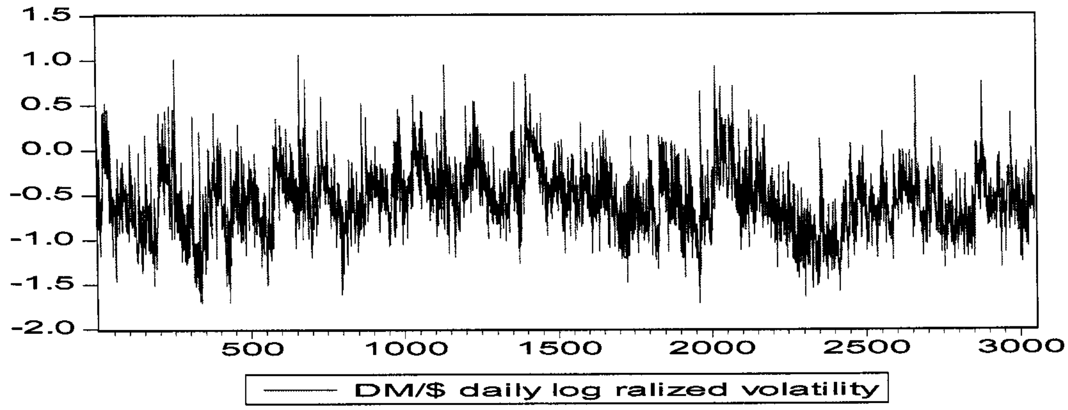
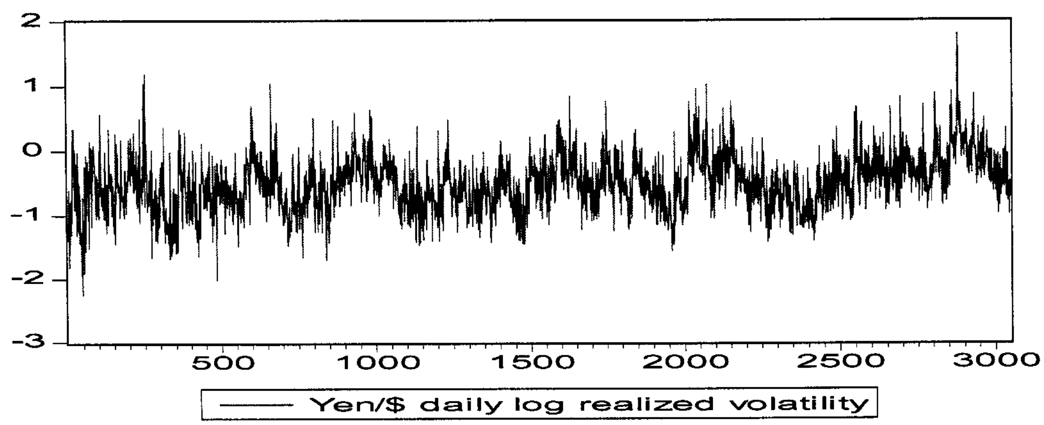


Figure 2.1 Daily Exchange Rate Realized Volatility
(1986.12.2 – 1999.6.30; 3045 observations)





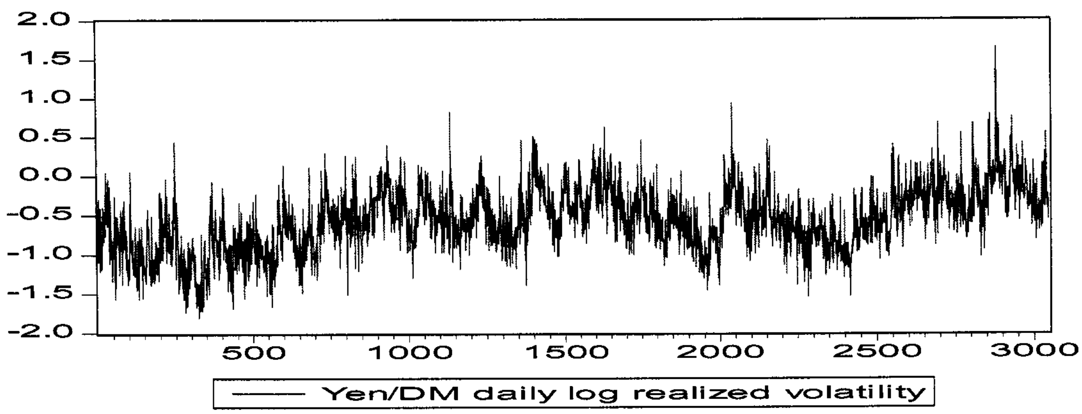


Figure 2.2 Daily Exchange Rate Log Realized Volatility
(1986.12.2 – 1999.6.30)

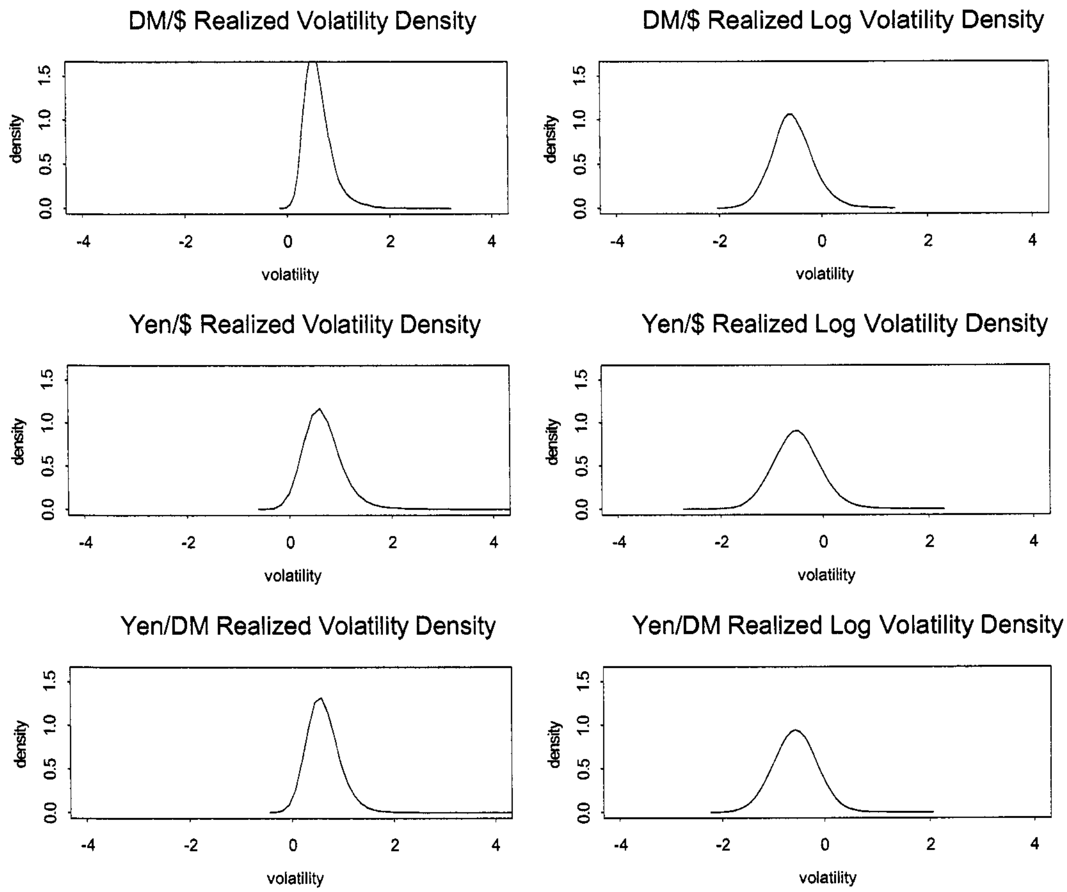


Figure 2.3 Realized Volatility Distributions

Notes: The figure shows kernel estimates of the density of daily DM/$, Yen/$, and Yen/DM realized volatility. The sample extends from December 2, 1986 to June 30, 1999.

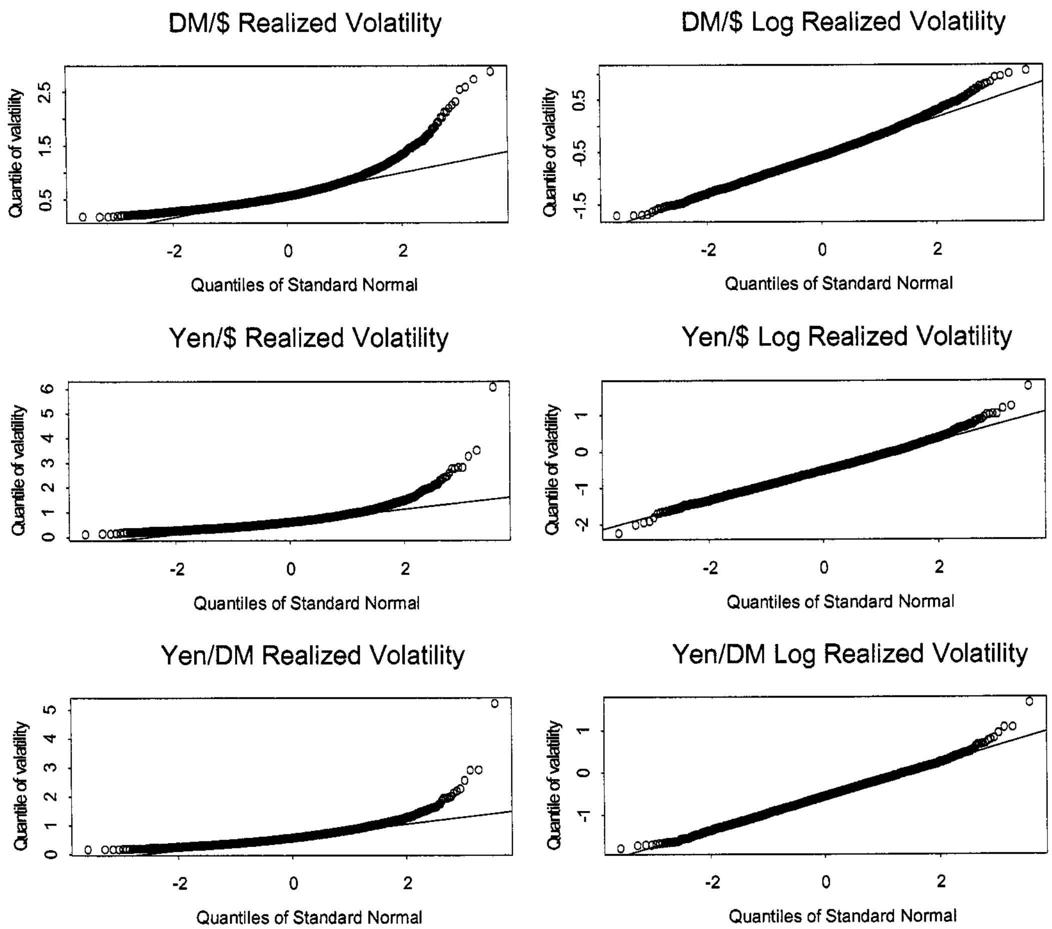


Figure 2.4 QQ Plot for Realized Volatility

Notes: Quantiles of daily realized volatilities and logarithmic realized volatility from extends from December 2, 1986 to June 30, 1999 against the corresponding quantiles from a standard normal distribution..

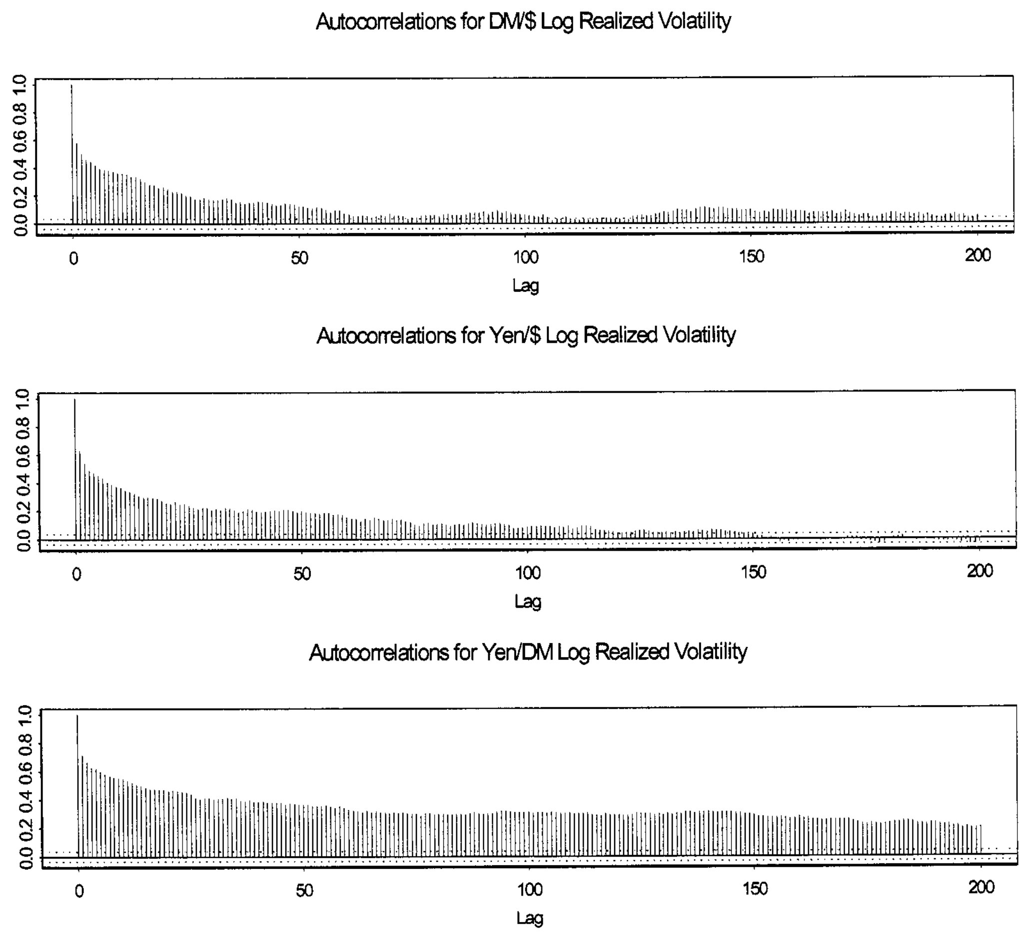


Figure 2.5 Autocorrelations for Log Realized Volatility

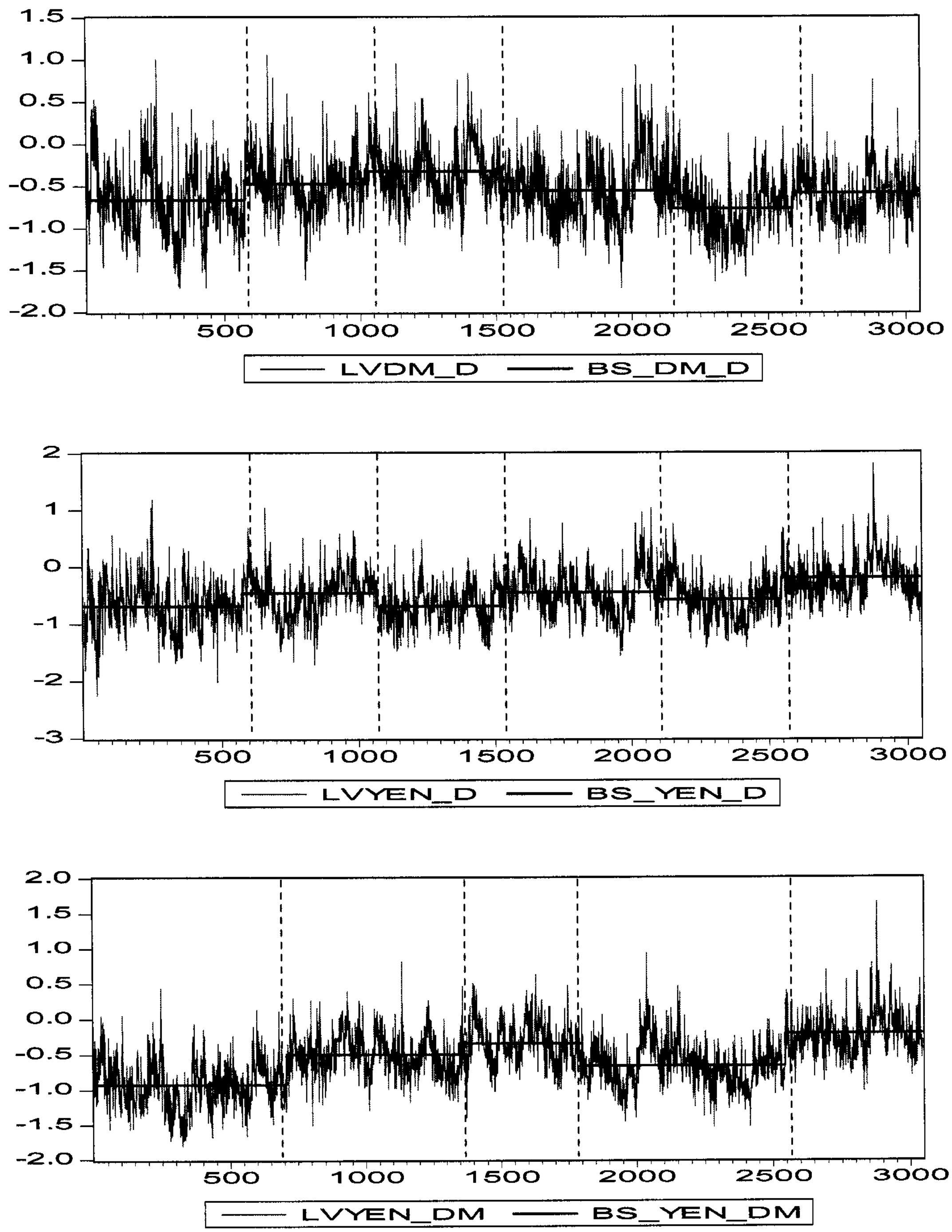


Figure 2.6 Estimated Structural Breaks Means and Dates for Daily Exchange Rate Log Realized Volatility
(1986.12.2 – 1999.6.30)

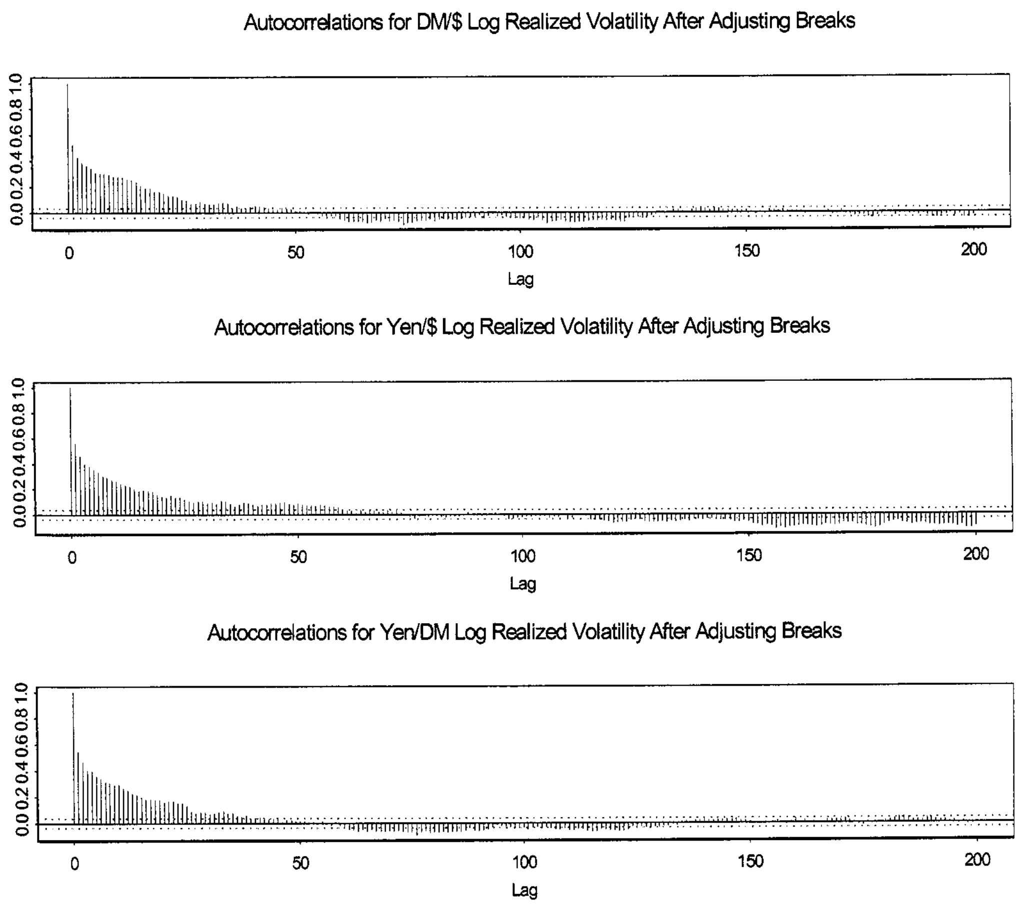


Figure 2.7 Autocorrelations for Log Realized Volatility After Adjusting for Structural Breaks

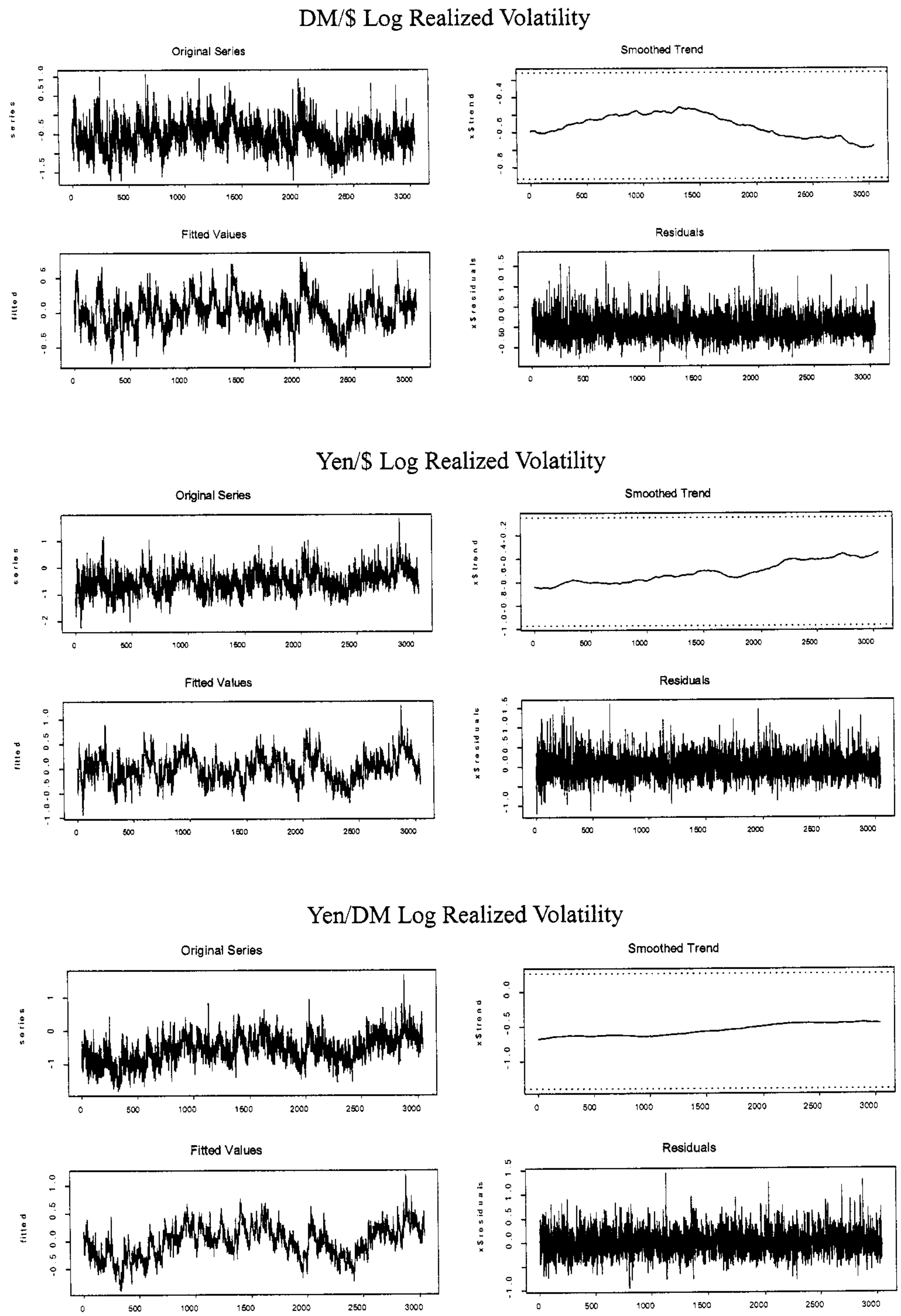


Figure 2.8 Semiparametric Fractional Autoregressive Model Decomposition

Notes: Based on Beran, Feng and Ocker's method (1998)

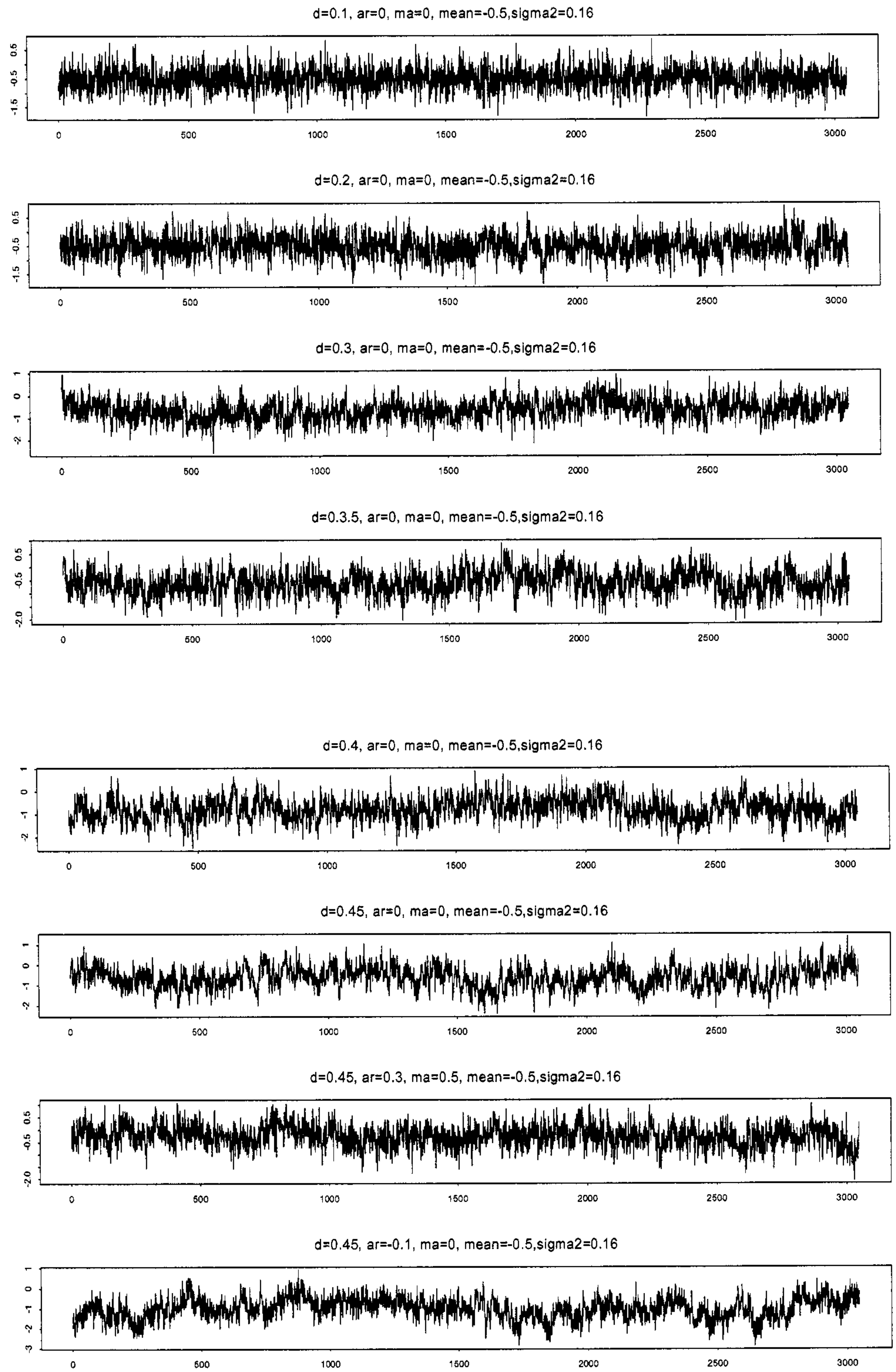


Figure 2.9 Monte Carlo Simulation for Long Memory Processes

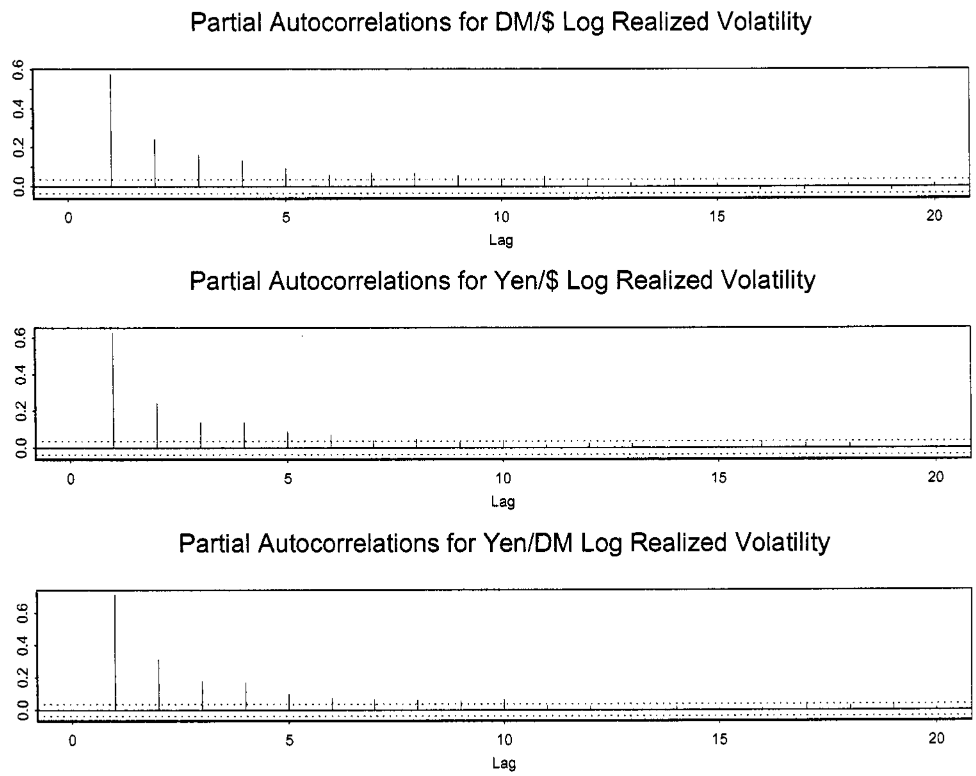


Figure 2.10 Partial Autocorrelation Function for Log Realized Volatility

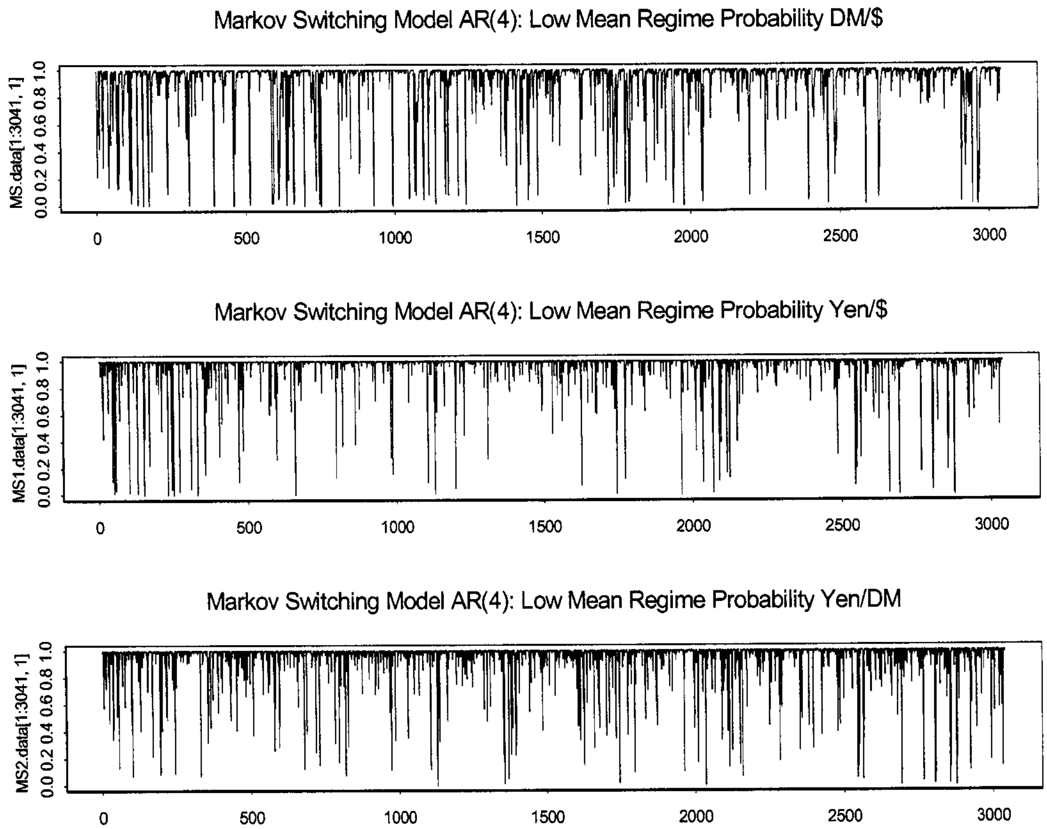
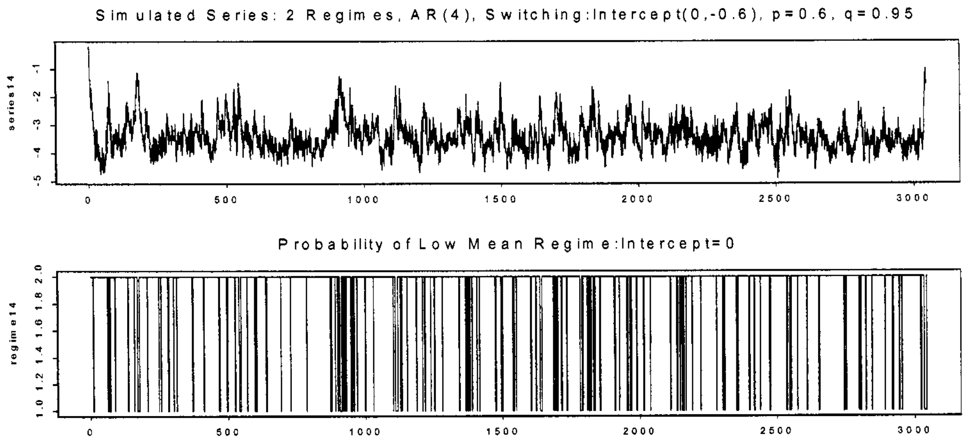


Figure 2.11 Markov-Switching Model – 2 States Switching in Mean

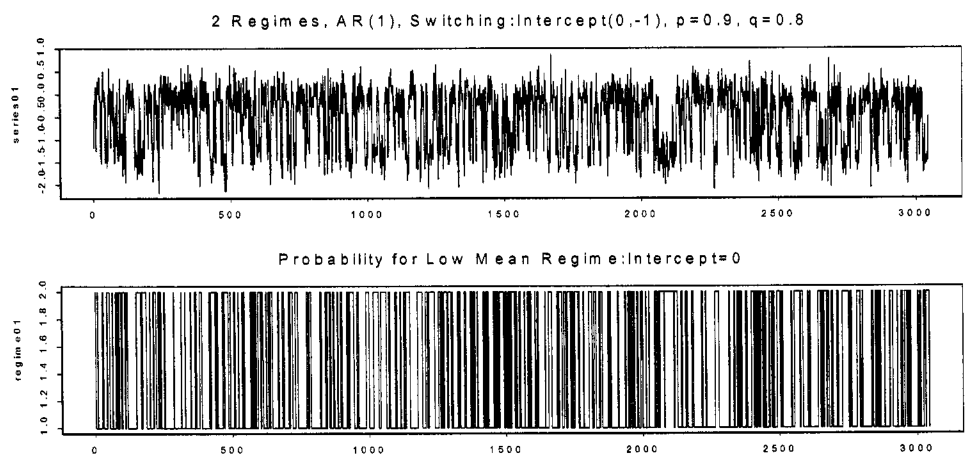
Notes: The model is as follows.

$$y_t - \mu_{St} = \phi_1(y_{t-1} - \mu_{St-1}) + \phi_2(y_{t-2} - \mu_{St-2}) + \phi_3(y_{t-3} - \mu_{St-3}) + \phi_4(y_{t-4} - \mu_{St-4}) + e_t$$

A. Benchmark Simulation



B.



C.

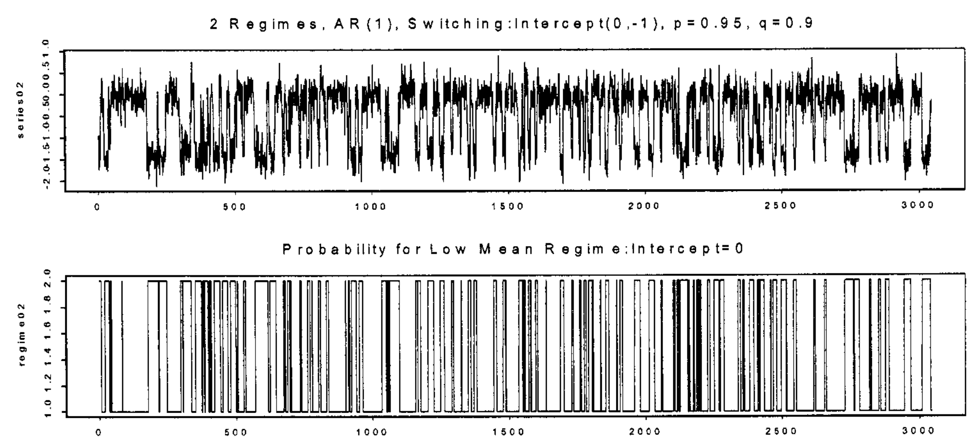
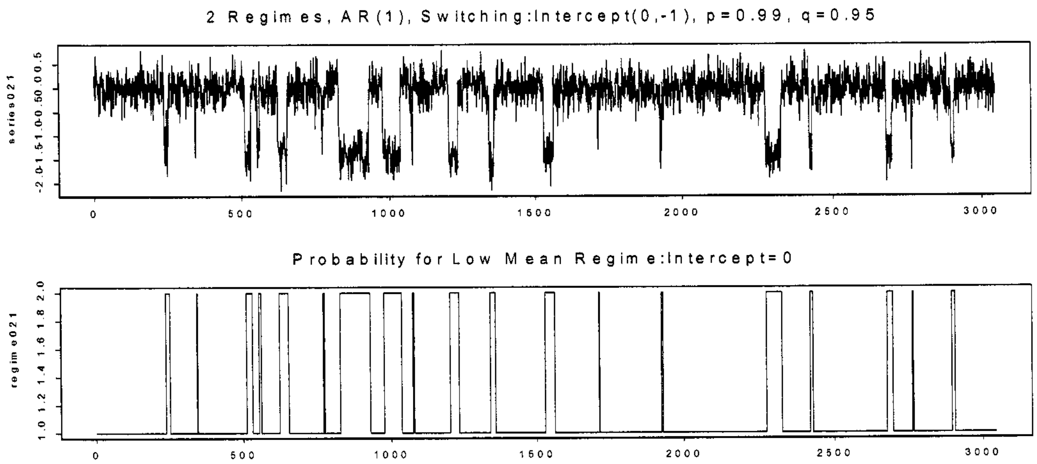
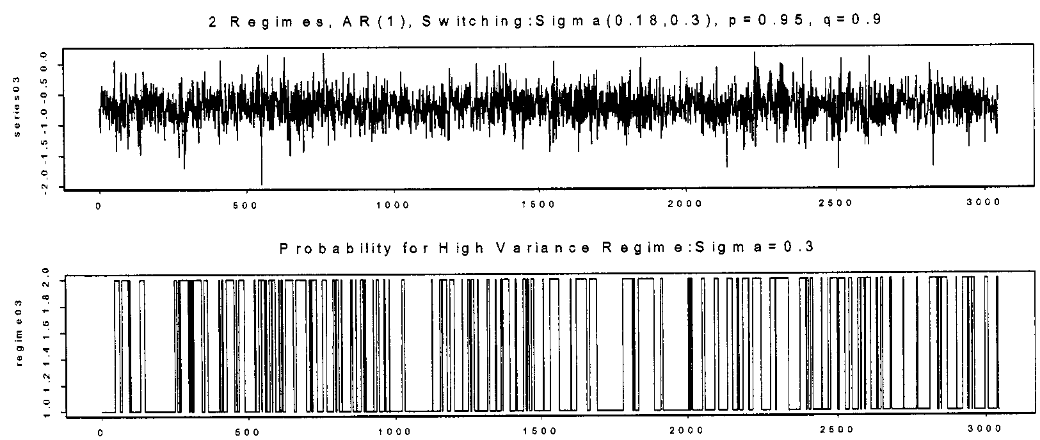


Figure 2.12 Monte Carlo Simulation for Markov-Switching Model

D.



E.



F.

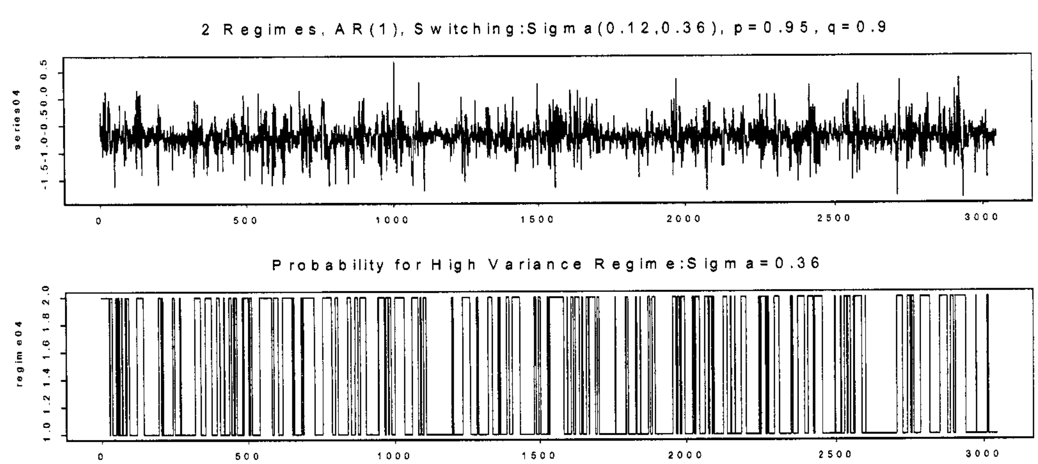
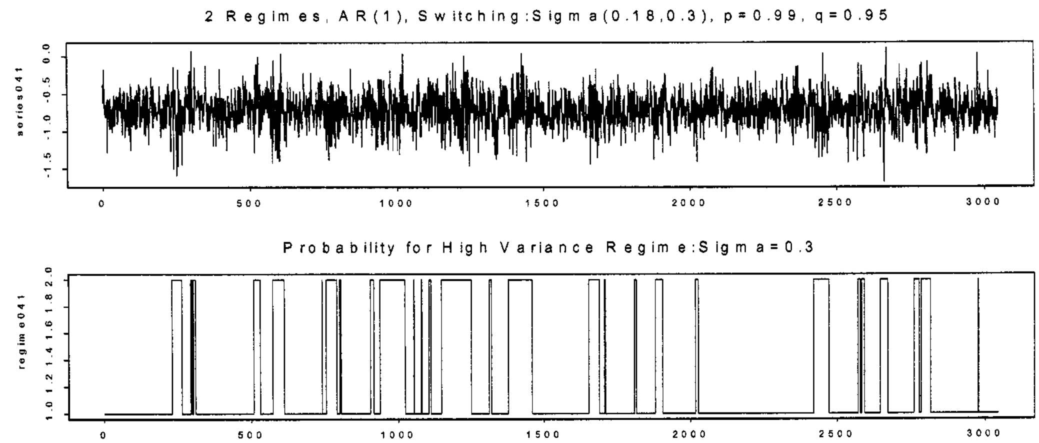
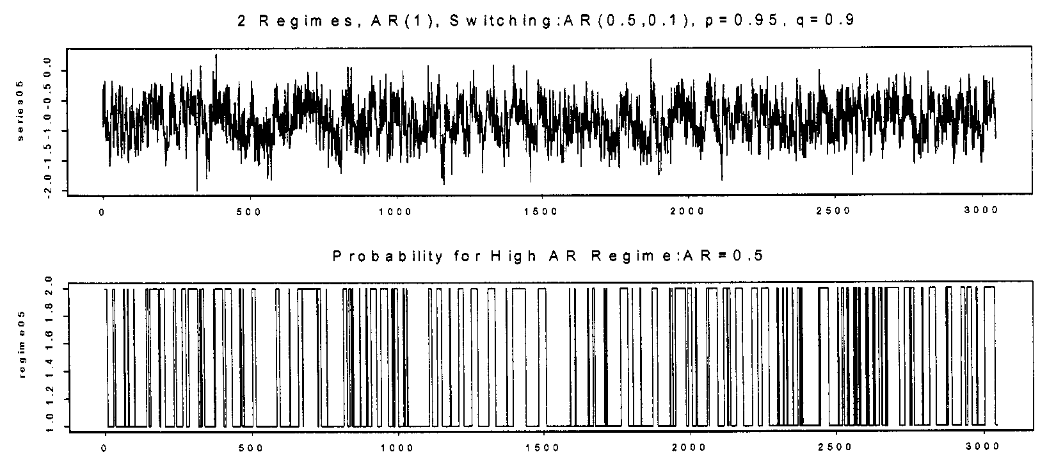


Figure 2.12 (Continued)

G.



H.



I.

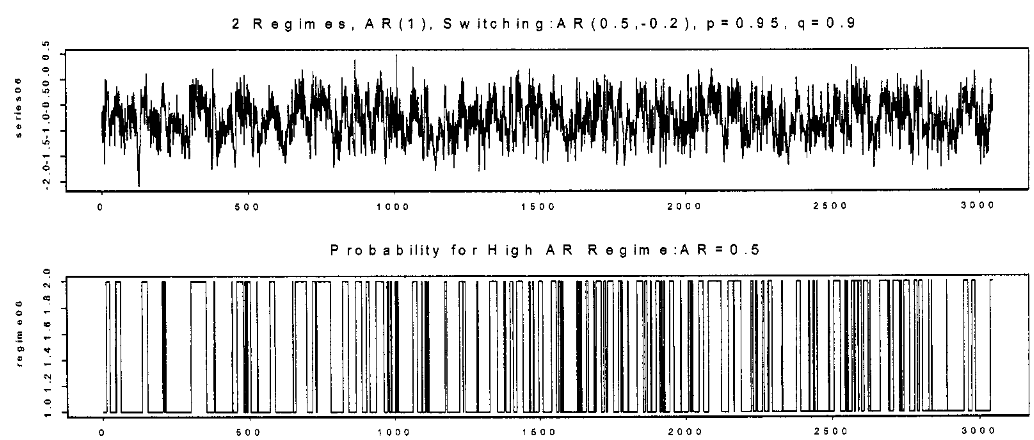
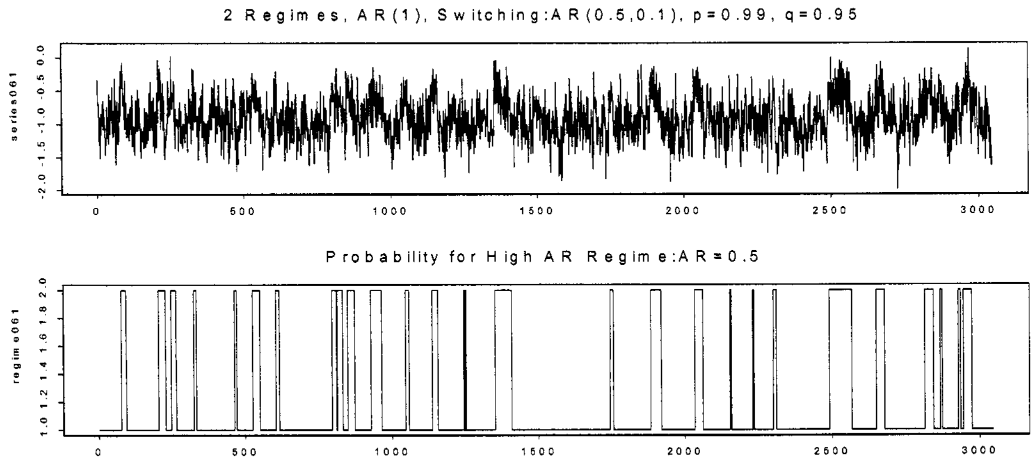
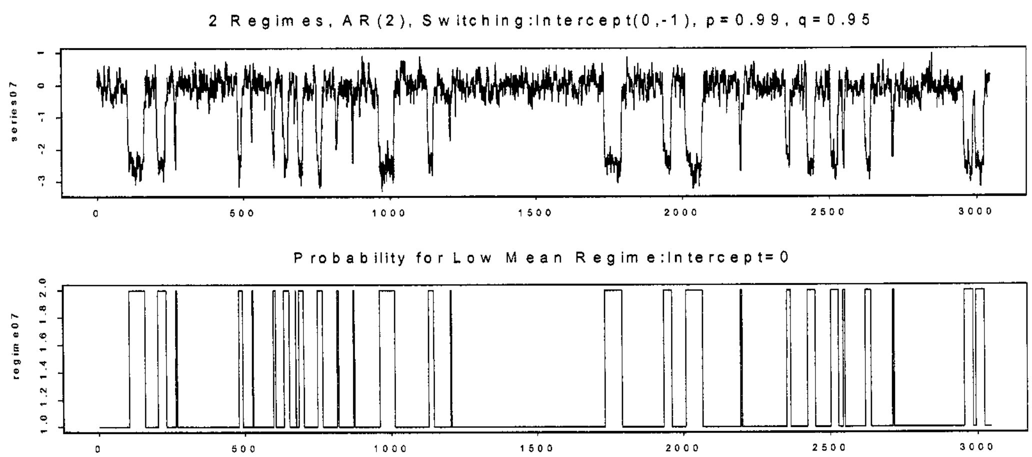


Figure 2.12 (Continued)

J.



K.



L.

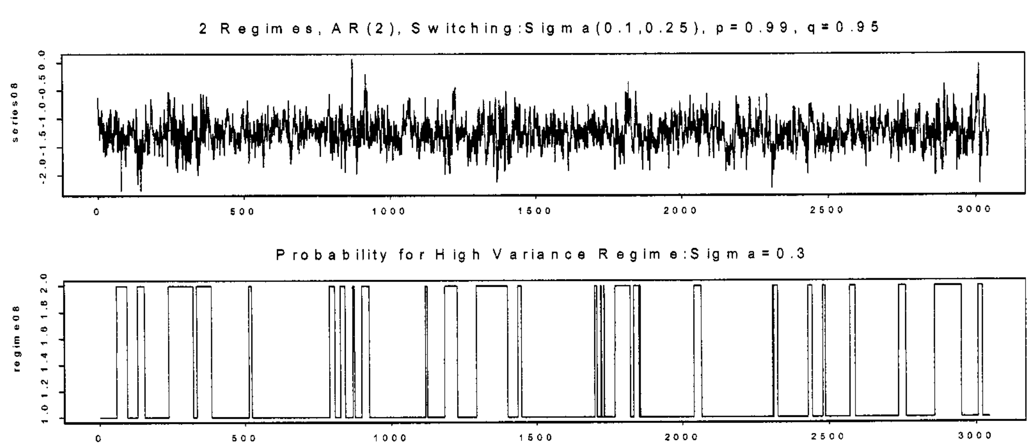
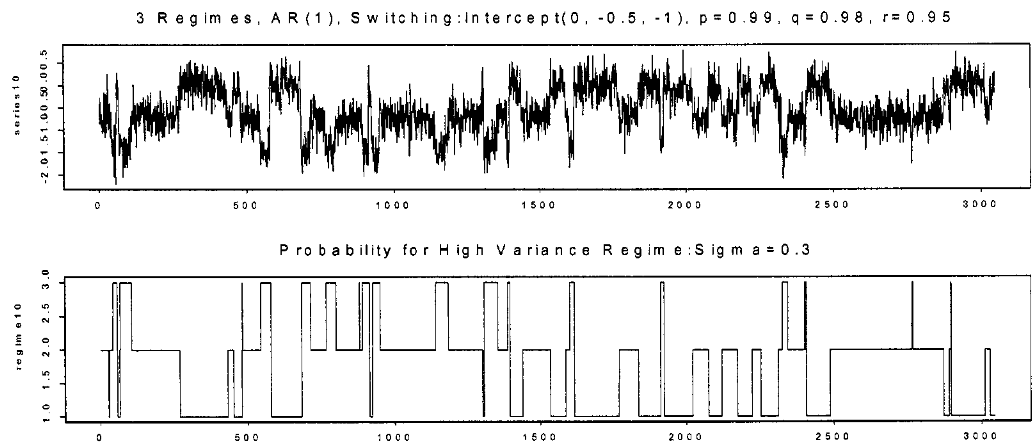
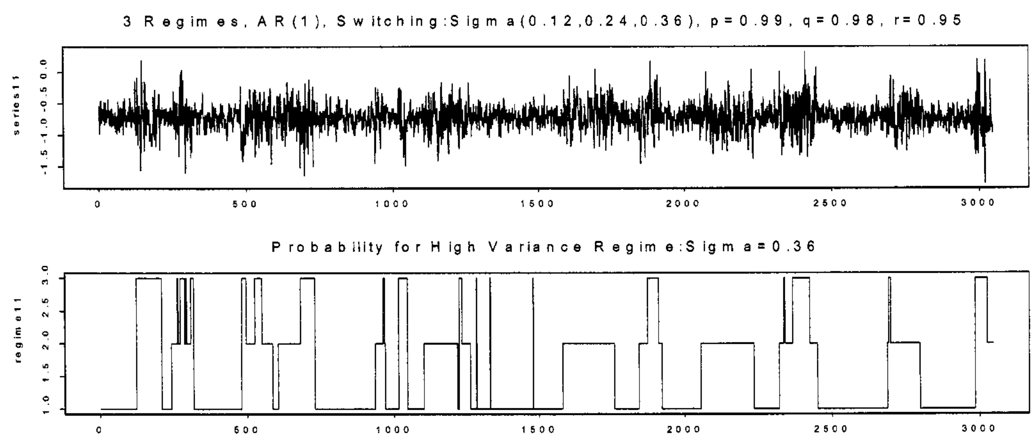


Figure 2.12 (Continued)

M.



N.



O.

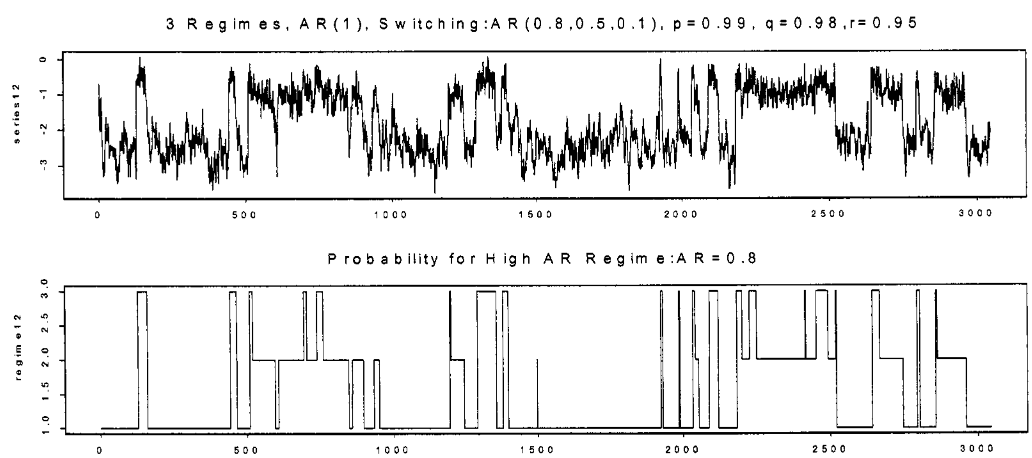


Figure 2.12 (Continued)

P.

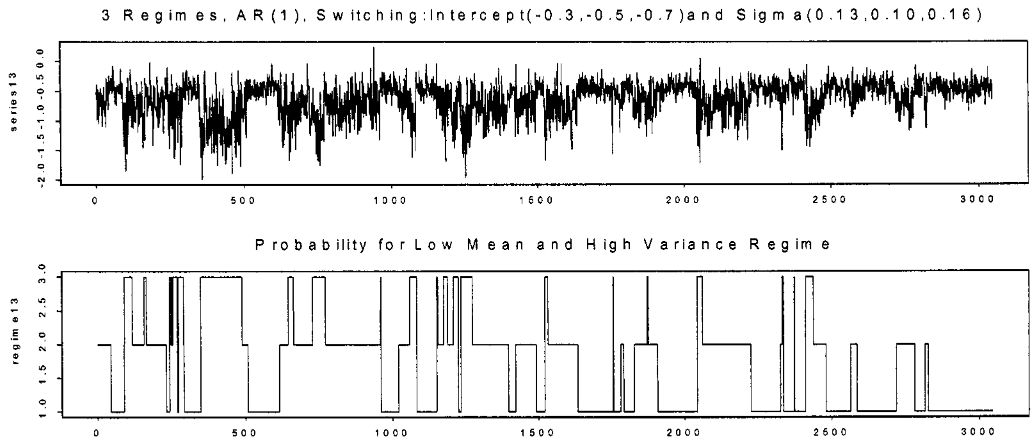


Figure 2.12 (Continued)

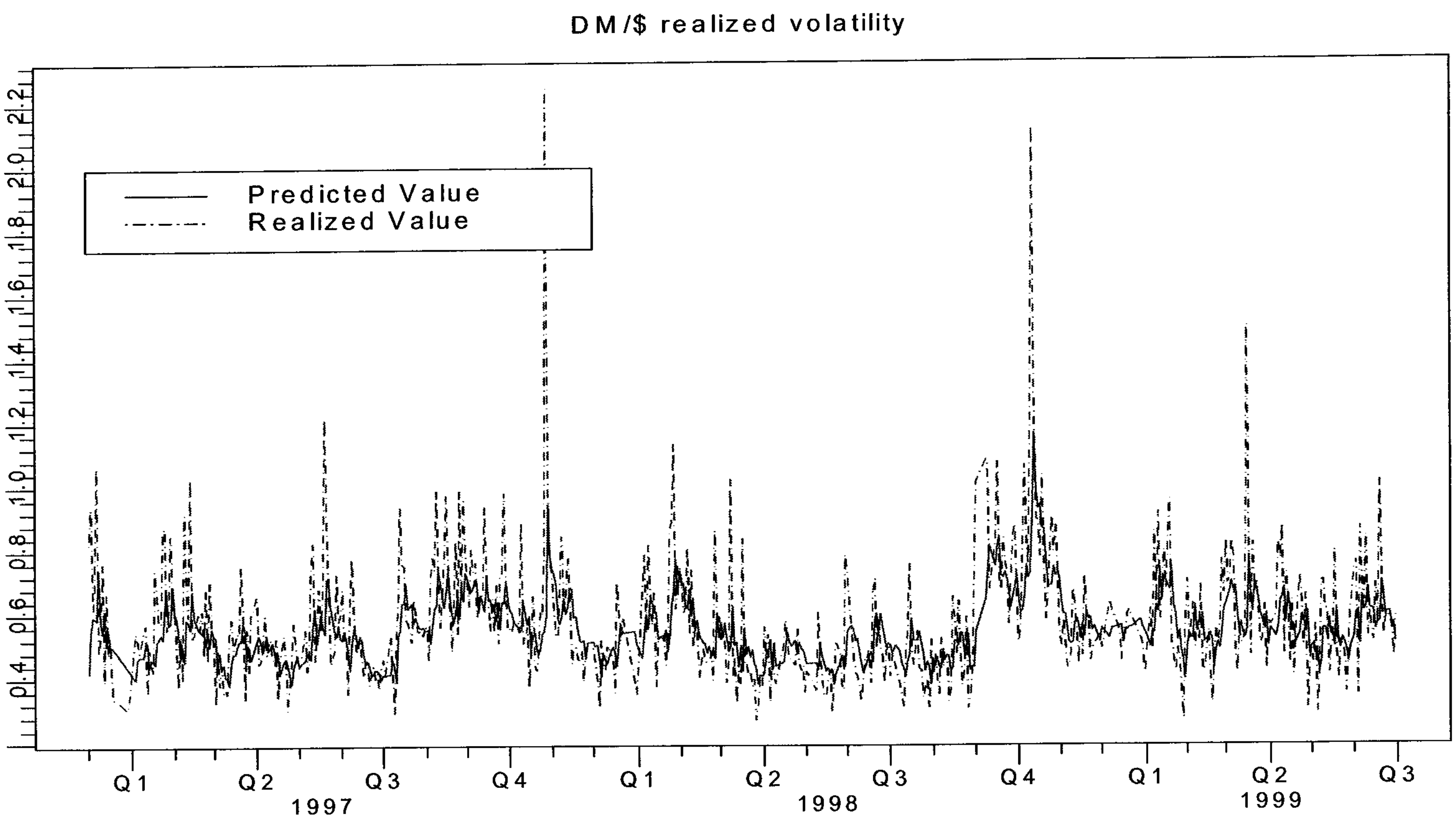


Figure 13.A. Realized Volatility and Out-of-Sample VAR-RV-Break Forecasts

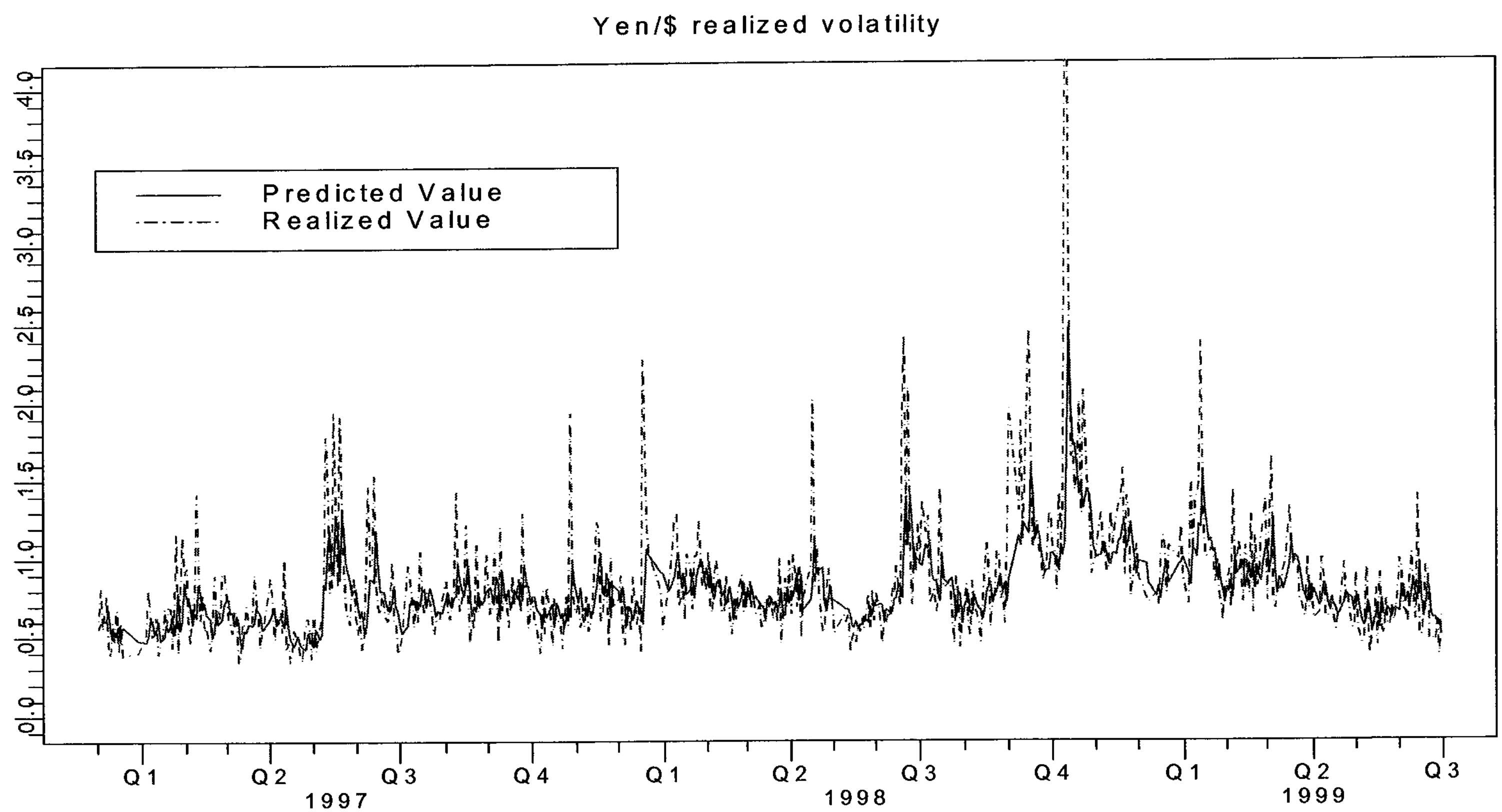


Figure 13.B. (Continued)

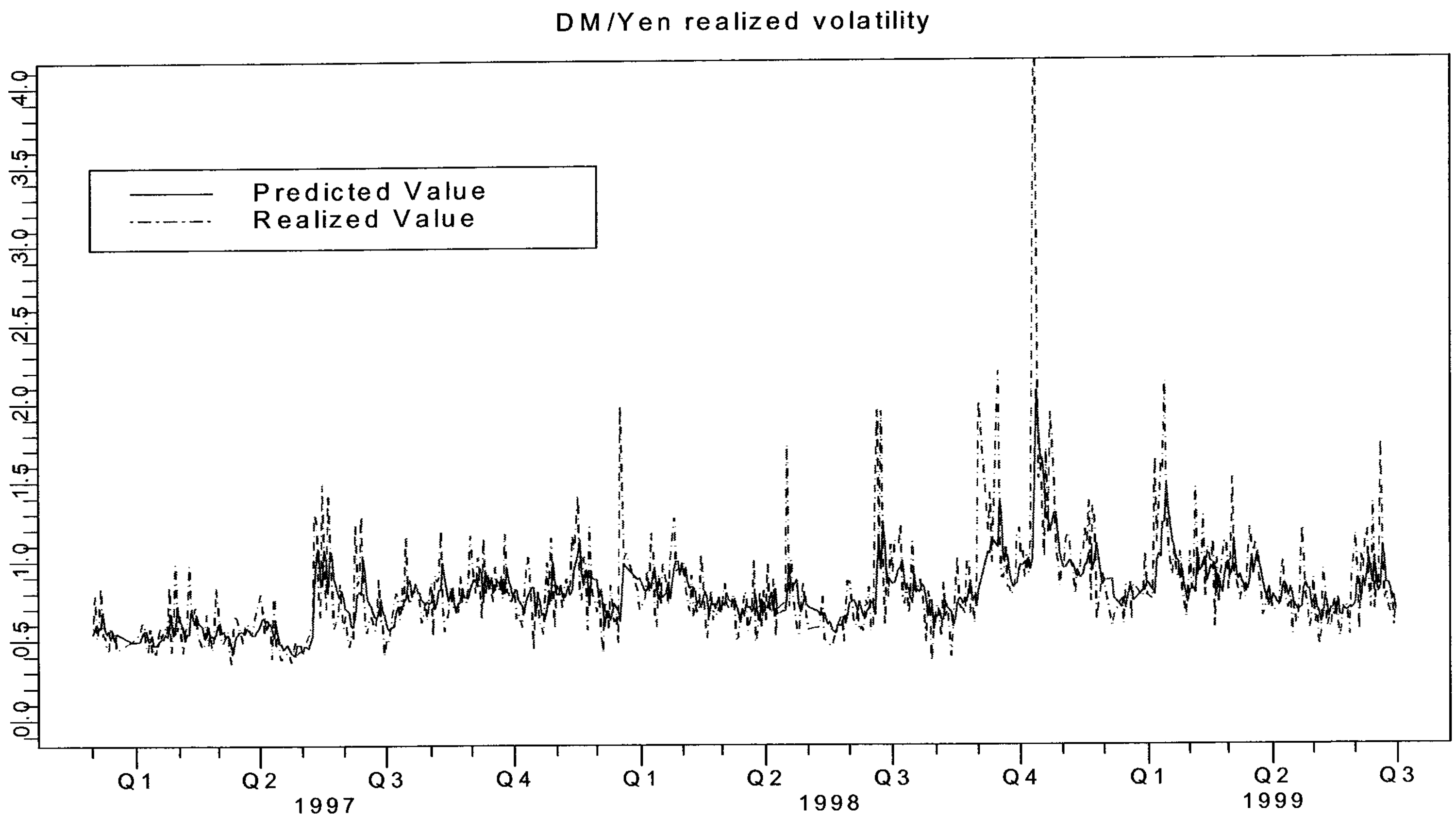
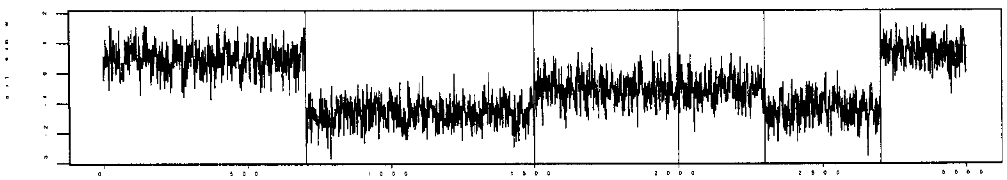
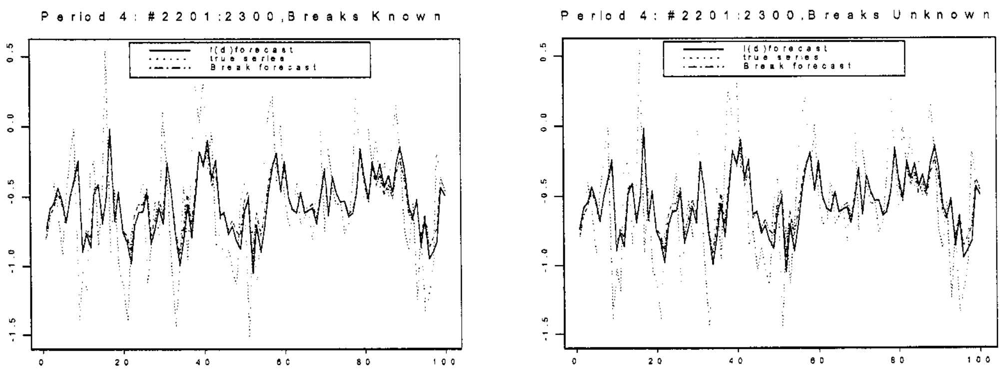


Figure 13.C. (Continued)

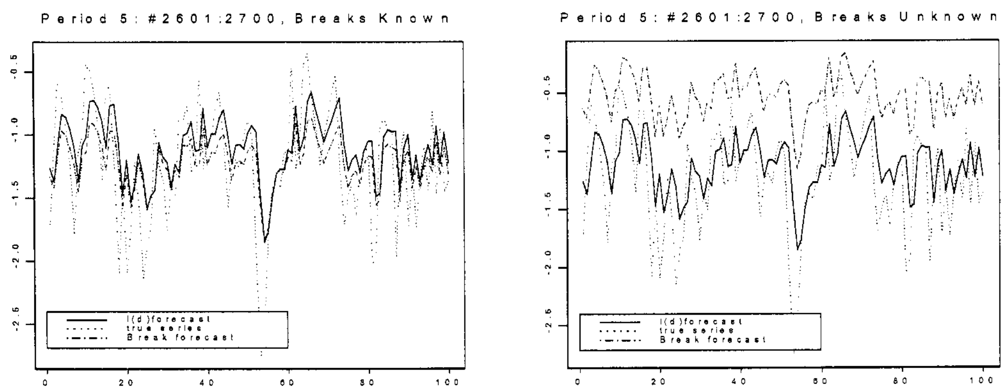
A. Simulated Mean Breaks Series



B.



C.



D.

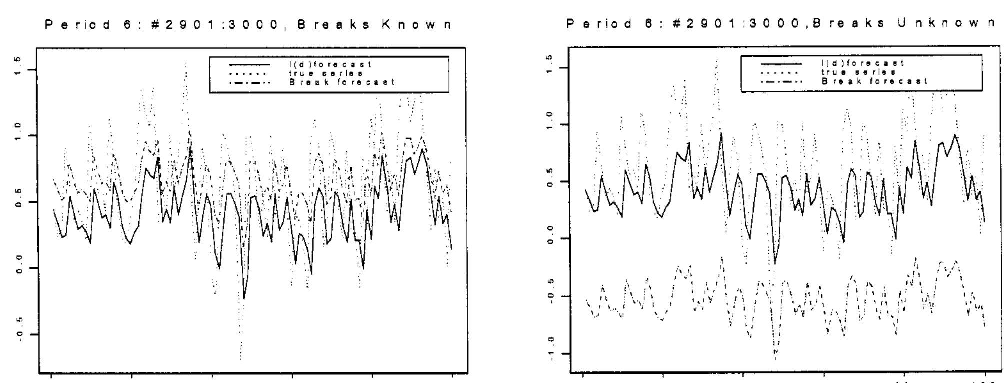


Figure 2.14 Out-of-Sample Forecasts Evaluation from Simulation

Chapter 3: The Relationship between Macroeconomic and Financial Market Volatility: An Empirical Evidence of Factor Model

3.1 Introduction

The Great Moderation, which represents the substantial decline of the volatility of real output and inflation in the U.S. since the mid 1980s, has been well documented (Kim and Nelson 1999a; MaConnell and Perez-Quiros 2000; Stock and Watson 2002a). As yet, there has been no widely accepted explanation for the main cause of these macroeconomic stabilities. Meanwhile, only few studies have been proceeded on the impact of the Great Moderation on, in particular, financial market activities. Are the real economy and financial market fluctuations related? Have less-volatile real activities resulted in the higher valuation and lower variation in the financial markets?

Lattau, Ludvigson, and Wachter (2006) suggested that the Great Moderation contributed to a lower long-run equity premium and lifted the stocks prices in the late 1990s. Campbell (2005) argued that the volatility of investors' forecasts of future earnings, dividends or cash flow has declined substantially. In contrast, the volatility of the discount rate, main force of stock market volatility, did not reduce. Campbell and Cochrane (1999) showed the volatility of investors' risk aversion is independent of macroeconomic volatility based on their habit formation model. Kim and Wright (2005) found that the large decline in long-term yields, distant-horizon forward rates, and term premiums since mid 2004 occurred because of the increased demand of long-term bonds coming from better anchored inflation expectations and a lower real variability.

Using structural break test on mean and volatility for several financial variables, we find no strong evidence in favor of reduced volatilities on these financial indicators in the 1980s and 1990s. This chapter further investigates the volatility of the whole financial markets, including money, stocks, and bonds markets rather than one specific market or financial indicator. We use the factor models based on principal components to analyze a large number of macroeconomic and financial series. The factor models present the idea that the fluctuations and comovements of a lot of economic and financial variables are produced by a handful of observable or unobservable factors, which are driven by the common structural shocks. For example, the observable factors include market return in the capital asset pricing theory (CAPM), aggregate consumption in the consumption-based CCAPM models, common factors in the arbitrage pricing theory (APT), and famous Fama and French's three factors model: the market excess return, small minus big factor, and high minus low factor. The unobservable/latent statistical factors include term structure three factors model: level, slope, and curvature by Nelson and Siegel (1987), dynamic factor models proposed by Sargent and Sims (1977), Geweke (1977), and Forni et al. (2000), static factor models by Chamberlain and Rothschild (1983), Connor and Korajczyk (1986), and Stock and Watson (2002b, 2002c). Furthermore, modern dynamic general equilibrium macroeconomic models often assume that a small set of driving variables is responsible for the dynamics of macro time series.

This chapter finds that there are 12 static factors and 8 dynamic factors using Bai and Ng's (2002, 2005) methods out of 140 macro and financial time series data sets from 1959:1 to 2005:11. The real factors, which explain most of the variation of output, consumption, and employment, have very different dynamics from the financial market factors, which explain the fluctuations of a range of financial variables. In other words, we find that the real economy and financial market fluctuations are not closely related because they per se are driven by different factors.

The rest of the chapter is organized as follows. Section 3.2 presents the structural break tests and time-varying estimation on the volatility of several important financial variables. Section 3.3 applies the static factor model using principal components to examine the factors. Section 3.4 discusses an application to financial forecasting. Section 3.5 concludes. Data resources and description are given in the Appendix B.

3.2 Financial Market Volatility

Figure 3.1.A and 3.1.B show the monthly growth of industrial production and personal consumption expenditures from 1957:3 to 2005:12. The bottom panel of the graph represents the time-varying volatility of the upper series using GARCH (1,1) model. The industrial production seemed to become less volatile since the mid 1980s and the personal consumption expenditures (PCE) became more stable since the late 1980s. Figure 3.2.A and 3.2.B present the monthly growth of core consumer price index (CPI) inflation[33] and core personal

[33] Core CPI is measured for the CPI for all urban consumers, and all items less food and energy, which disposes of highly volatile components in order to get the more informative price trends.

consumption expenditures inflation. The CPI inflation seems to be well contained since the mid 1980s while the volatility of PCE inflation seemed not quite different. Generally speaking, the evidence supports the great moderation on real output and inflation.

Does the reduced volatility of real activity affect the volatility of asset prices? In brief, the evidence of the lower variation in financial markets is mixed. Table 3.1 reports the sample standard deviation of major U.S. financial time series by decade (1957 to 1959 are included in the 1960s; 2001 to 2005 is included in 1990s). Each decade's standard deviation is shown relative to the full-sample standard deviation, so a value more than one means a period of relatively high volatility. Most series were less volatile in the 1960s than the whole sample while more volatile in the 1970s and 1980s than the whole sample. In 1990s, only few series became stable, such as short- term treasury bills returns. Figure 3.3 plots the time-varying volatility by GARCH (1,1) for major financial time series. Unlike the real output volatility, which presents high and low regimes by the structural break in the mid 1980s, financial market volatility, except for long term bonds return (discussed in the following), was relatively low in the 1960s, relatively high in the 1970s, 1980s, lower in the 1990s, and increased in 2000s.

3.2.1 Structural Break Test

Next, we use the following model to test if there is a structural break in the conditional mean and variance. To test a break in the conditional variance, we let $\varepsilon_t(\tau)$ denote the errors in the autoregression in equation (3.1),

$$y_t = \mu_t + \phi(L) y_{t-1} + \varepsilon_t \tag{3.1}$$

and

$$\mu_t + \phi_t(L) = \begin{cases} \mu_1 + \phi_1(L), \ t \le \tau_1 \\ \mu_2 + \phi_2(L), \ t > \tau_1 \end{cases} \text{ and } \mathrm{E}(\varepsilon^2) = \begin{cases} \sigma_1^2, \ t \le \tau_2 \\ \sigma_2^2, \ t > \tau_2 \end{cases} \tag{3.2}$$

where y_t is the monthly time series from 1957 to 2005, $\phi(L)$ denotes a lag polynomial representing persistence parameter, τ_1 is the break date for conditional mean (including constant μ and AR(6) coefficients $\phi(L)$) and τ_2 (innovation variance) is the break date for the conditional variance. Equation (3.2) implies conditional mean and variance might change at different dates. We use supremum of the sequence of Wald test statistics, $W_T(\pi)$, which tests the null hypothesis that the parameters are constant against the alternative that they have a single break at a fraction π through the sample. The break date is treated as an unknown priori so that the tests compute the sequence W_T for $t = t_0 + ..., t_1$ and then compute a supremum of the sequence. This method is called Quandt likelihood ratio (QLR[34]), proposed by Quant (1960) and also referred to sup-Wald statistic proposed by Andrews (1993).

3.2.2 Bond Market

Table 3.2 reports the results for the structural break tests. We find that the following financial variables were stabilized with their break dates: federal funds rate (1985:8), 30-day Treasury bill returns (1991:6), 90-day Treasury bill returns (1988:3), 1-year Treasury bond returns (1989:8), term spreads (1987:1), equal-weighted stocks returns (1991:2), earning price ratio (1991:2), and dividend price ratio (1991:2). For the long-term bonds returns, the breaks occurred in the 1960s and 70s toward destabilization. From Table 3.1 and Figure 3.3. D, E, F, the variability of long-term bonds returns has increased in the recent decades relative to the earlier decades. What is the relationship between the less-volatile short-term rates or bonds returns and increased long-term bonds returns? Watson (1999) provided an explanation: because the persistence of changes in federal funds rate (short-term rates) increased, expectations theories of the term structure imply that such higher persistence will have a large effect on the variability of changes in long-term bonds market but have little effect on the variability of changes in short-term bonds market.

What leads to the increased persistence in federal funds rate? There are two components of federal funds rates: real rate and inflation. Suppose movements of real rate are transitory, more persistent inflation dynamics will result in more persistent federal funds rate. In Table 3.2, we find structural break in 1981:9 on conditional mean (including persistent component) toward less persistent, which is consistent with the result in Kim, Nelson, and Piger (2004). They found CPI inflation persistence parameter was 0.941 before the structural break - 1979:Q2 and was 0.722 after the break. Therefore, the possible explanation would be the central bank's monetary policy rule. Using time-varying Taylor rule reaction function, which responds to expected inflation and real output gap, Kim and Nelson (2004) documented

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[34] We use heteroscedasticity-robust version of the QLR statistics where $W_T(\pi)$ is computed by using White (1980) heteroscedasticity-robust covariance matrix, in which the residuals were computed under the null rather than each of the alternatives for computational convenience.

that the smoothing parameter of Federal Reserve's federal fund rate has increased since the mid 1970s.

3.2.3 Stock Market

For the stock market from 1957:3 to 2005:12, we could not find any evidence of structural break on aggregate stock market except for the equal-weighted stocks returns (1991:2). This result is consistent with the conclusion in Kim, Morley, and Nelson (2005). Using S&P500 monthly realized volatility data from 1962 to 1997, Campbell et al. (2001) argued that there was no increased or decreased trend in stock industry or market volatility while they found there was an upward-sloping trend in idiosyncratic firm-level volatility. This implies that the correlations among individual stock returns have declined for the recent decades. The R–Squares of the market model for a typical stock has also decreased; in other words, the number of stocks needed to obtain portfolio diversification has increased. We get the similar result in Table 3.2: two risk factors (small minus big; high minus low) of Fama and French's three factors model[35] have become more volatile since the late 1990s.

Equity valuation, which was measured by the price earning ratio or price dividend ratio, has been higher in the recent decades than in the earlier decades. Lattau, Ludvigson, and Wachter (2006) suggested that the Great Moderation contributed to a lower long-run equity premium and lifted the stocks prices. We use log earnings price ratio and log dividend price ratio as proxies for equity premiums. Figure 3.4 plots the relationship between equity premiums and macroeconomic volatilities, as measured by GARCH (1,1) volatilities of industrial production, personal consumption expenditures, and Core CPI inflation rate. Indeed, there is a downside comovement for equity premiums and macroeconomic volatilities since 1980s. However, between 1996 and 2003, the magnitude of the equity premium seems not being explained by the declining macro volatilities.

---

[35] The Fama/French factors are constructed using the 6 value-weight portfolios formed on size and book-to-market. SMB (Small Minus Big) is the average return on the three small portfolios minus the average return on the three big portfolios. HML (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios. R_m-R_f, the excess return on the market, is the value-weight return on all NYSE, AMEX, and NASDAQ stocks (from CRSP) minus the one-month Treasury bill rate. See Fama and French, 1993, "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics*, for a complete description of the factor returns. The data are from Kenneth French's website:
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

3.3 Factor Model Analysis

In section 3.2, like most of the literature, we only use a small number of variables to investigate the dynamics and relationship among macroeconomic and financial markets. However, these limited variables are unlikely to span the information sets used by actual market participants and policy makers. For example, Federal Reserve System and other central banks monitor and analyze a wide range of data series from different sources, frequencies, and levels of aggregation in preliminary and revised versions. Recent surveys confirmed that professional forecasters, which use a large number of data may significantly improve forecasts of key macroeconomic variables.

Currently time series models and forecasting methods, however, only use a few series. For example, vector autoregressions (VAR) typically contain fewer than 18 variables. Because some information is not reflected in this VAR analysis, it might not be enough to span the space of structural shocks and the measurement of policy shocks might be contaminated. Famous example is the "price puzzle."[36] Furthermore, in the Philips curve, is the unemployment rate, capacity utilization, or the real GDP the best measurement for the output gap? Is any single real-time data of these variables reliable for forecasting and policy making? Factor model, which determines a few factors by a dimension reduction from pooling the information for all the candidate variables, offers an alternative method for modeling and forecasting. Stock and Watson (2002b, 2002c), which considered forecasting real output and inflation with diffusion indexes constructed from a large number of time series data, showed their forecasting method outperforms many competing methods.

3.3.1 Static Factor Model

Consider the factor representation for a multiple time series data X_{it}, ($i = 1,\ldots N$, $t = 1,\ldots T$)

$$X_{it} = \Lambda F_t + e_{it} \tag{3.3}$$

where Λ $(N \times r)$ is the factor loadings, F $(r \times T)$ is the static factor process, r is the

[36] In low-dimensional VAR analysis, a contractionary monetary policy shock is followed by a rising price level in the impulse response functions instead of decreasing price that theory would suggest. The reason for this price puzzle is that it is the result of imperfectly controlling for information that the central bank may have for future inflation. When the policy response is only partially offset the inflation, the monetary tightening is followed by an increased price in mis-specified VAR. The price puzzle could be solved by including commodity price index as a signal of future inflation for central bank.

number of static factor, and $e\ (N \times T)$ is the idiosyncratic disturbance. The factor loadings, factor process, and idiosyncratic errors are not observable. In the classical model, it is assumed that $T > N$ and the disturbances are assumed to be i.i.d. and normally distributed and are independent of the factor process. Normalizing the covariance matrix of F to be an identity matrix, the factor model covariance matrix is then

$$\Sigma = \Lambda\Lambda' + \Omega \tag{3.4}$$

where Ω is the diagonal covariance matrix of e_{it}. A root-T consistent and asymptotically normal estimator, $\hat{\Sigma} = (1/T)\sum_{t=1}^{T}(X_t - \bar{X})(X_t - \bar{X})'$ can be obtained. But the diagonal Ω assumption is unlikely to be appropriate in the macroeconomic model, because the variables are serially correlated and possibly cross-correlated. Following the approximate factor structure proposed by Chamberlain and Rothschild (1983) and Connor and Korajczyk (1986, 1988, 1993), we assume that e_{it} could be serial correlated. With large N, factors could be consistently estimated by asymptotic principal components technique.

Bai and Ng (2002) developed asymptotic results for consistent estimation of the number of factors when N and T are large. They started with an arbitrary number k ($k <$ min$\{N,T\}$). The number of static factors (r) is estimated by the information criteria (IC)

$$\hat{r} = \arg\min \ln(\hat{\sigma}_k^2) + k\left(\frac{N+T}{NT}\right)\ln(\min\{N,T\}) \tag{3.5}$$

where $\hat{\sigma}_k^2 = 1/NT\sum_i\sum_t(X_{it} - \hat{\Lambda}^k\hat{F}^k)^2$, $\hat{F}^k$ is $k \times T$.

3.3.2 Dynamic Factor Model

The static factor model considers the static relationship between X_{it} and F_t but r static factors could be dynamically related. The dynamic factor model is

$$X_{it} = \lambda(L)f_t + e_{it} \tag{3.6}$$

where $\lambda(L)$ with order s is a $N \times q$ matrix lag polynomial, called dynamic factor loadings. q is the number of dynamic factor, which also represents the number of primitive shocks. Dynamic factor model could be written as static factor form. In (3.6), we assume that $\lambda_i(L)$ $= \lambda_{i0} + \lambda_{i1}L + \ldots + \lambda_{is}L^s$ and put it in the Λ of (3.3) where Λ_i is $[\lambda_{i0}, \lambda_{i1}, \ldots, \lambda_{is}]$ and Λ_i = $[f_t, f_{t-1}, \ldots, f_{t-s}]'$. The dimension of F_t is $r = q(s+1)$. If $s = 0$, then $r = q$, which means there is no difference between static and dynamic factor. Although in the forecasting, little would be gained from a distinction between the static and dynamic factors as long as N and $T \to \infty$ (Stock and Watson 2002c), it is important to understand the primitive shocks from dynamic factor model.

Bai and Ng (2005) proposed an approach to estimate the number of dynamic factor. Given the known $\hat{r}$ estimated from (3.3) determined from the IC, we get $\hat{F}_t^r$ by using principal component method. Let $\hat{u}_t$ be the residuals from estimating a VAR (p) in $\hat{F}_t^r$ where p is the lead and lag of the VAR process and let $\hat{\Sigma}_u = 1/T\sum_{t=1}^{T}\hat{u}_t\hat{u}_t$. The number of dynamic factor could be determined from a spectral decomposition of $\hat{\Sigma}_u$ given T is large.

3.3.3 Data

The whole dataset to estimate the factors contains 140 monthly time series for the U.S. from 1959:1 to 2005:11. Following Stock and Watson (2002b, 2002c, 2005b), the series were selected to represent broad categories of macroeconomic and financial time series : real output, income and consumption; employment and hours; construction, inventories, and orders; money markets, interest rates and bond market, stock market, and exchange rate market; and price indexes. The detail description, sources and transformation of complete list of series are given in the Appendix B. Similar to Stock and Watson (2005b), we have updated data with a little more weight on financial market indicators. We assume that X_{it} is I(0) so the series are subjected to some stationary transformation: taking logarithms, first differencing, second differencing, or a combination of the above after preliminary data analysis and inspection. Basically, logarithms were taken for all nonnegative series that were not in percentage units. Most series were first differenced. Then the transformed data were further standardized to have zero mean and unit sample standard deviation.

3.3.4 Factors Interpretation

Using principal component method (3.3) and following IC criteria (3.5) from Bai and Ng (2002), we get 12 static factors. Based on Bai and Ng (2005) criteria for dynamic factors, we get 8 dynamic factors.[37] Table 3.3 presents the summary statistics for 12 estimated factors

[37] Using different methods and similar range of data, Stock and Watson (2005) found 9 static factors and 7 dynamic factors. Using the same method but different range of data (1960:1-1998:12), Bai and Ng (2005) found 10 static factors and 7 dynamic factors.

$\hat{F}_t$. From accumulated R^2, the first 6 factors could explain 42 percent of the variation in the whole series and 12 factors could explain 56 percent of the variation. From marginal R^2, the first, second, third, fourth, and fifth factor explain 14.2, 7.8, 6, 4.9, and 4.6 percent of the variation respectively. To understand the persistence of the estimated static factors, we also calculate the AR(1) coefficient for each factor. All of the factors have a persistence parameter smaller than 0.77 but with widespread coefficients from 0.77 to -0.29.

Figure 3.5 shows the R^2 of the regressions of the 140 individual time series against each of the 12 factors. These R^2 are plotted as bar charts with one chart for each factor. The 140 series are grouped by category and ordered numerically based on the ordering in the Appendix B. In general, factor 1 loads heavily on output, consumption, employment, construction, and orders but not correlated with price variables. This is a *real factor*, which is also the most important factor and accounting for 14.2 percent of the whole series. Factor 6, 7, and 10 also explain part of the variation of output, income, consumption, and construction, inventories, and orders. They are also included in real factor. Accordingly we could see them as one dynamic factor. Figure 3.6 illustrates the correlation of the moving average of both industrial production growth and factor 1. The graph confirms that the real factor explains most of the medium-run variation in industrial production.

Figure 3.7 plots the factors series and their time-varying volatility by GARCH(1,1). It is worth noting that factor 6 which only contains the variation of output, construction and orders without accounting for any nominal movements might be referred as the natural (potential) output fluctuated by the productivity shocks. In Figure 3.7.F, there is a downside slump of natural output from 1974 to 1977 and there is an upside trend since the early 1990s. Factor 2 accounts for most of the short-term, long term, term spread financial, bond market variation, and partial stock market variation so we refer it as *interest rate factor.* Factor 3 describes the most volatility in bond market, so it is called *bond market factor*. Factor 4 accounts for most of the fluctuations of the commodity, producer and consumer price indexes, and we refer it as *price factor*. Factor 5 loads primarily on stock market and we call it as *stock market factor*. Factor 8 explains mostly money market variation, it is named as *money market factor*. Factor 9 is foreign exchange market since it captures mostly exchange rate market variation. Factor 11 and 12 are called *wage factors* because they load mainly wage movements.

From Figure 3.7.A, it is shown that factor 1: real factor became stabilized since 1984 and we can see the similar pattern in factor 2: interest rate factor from Figure 3.7.B. Therefore, the volatility of aggregate financial market did get reduced because of Great Moderation. However, bond market factor in Figure 3.7.C and stock market factor in Figure 3.7.E didn't become less volatile for the past two decades. Foreign exchange factor in Figure 3.7.I has become destabilized since the mid 1990s. It is surprising that price factor composed of consumer, producer, and commodity prices indexes has become more volatile since the late 1990s. If we assume the price factor as cost-push shocks and factor 6 as productivity shocks, without becoming smaller or less frequent in the past two decades, the "good luck" hypothesis as the main explanation for Great Moderation suggested by Stock and Watson (2002a) might be more likely rejected.

3.4 Conclusions

In this chapter, we provide three empirical findings. First, using unknown structural break test on mean and variance, we find mixed evidence on volatility destabilization for the financial market. In other words, unlike the real activity or inflation being substantially less volatile since the mid 1980s, financial market indicators present diverse fluctuations and dynamics depending on their category, size, and maturity. In general, we could not find evidence of smaller variance on long-term bond market and stock market especially in the small-size and high book-to-market value stocks. We do find breaks toward smaller and less volatile for term premium and equity premium. However the unusual low equity premium in the late 1990s remains unexplained.

Second, exploring 140 monthly macroeconomic and financial variables and applying principal component method, we find 12 static factors and 8 dynamic factors from 1959 to 2005. Based on their properties, they are categorized and ordered according to their explanatory power as real factor, interest rate factor, bond market factor, price factor, stock market factor, money market factor, foreign exchange factor, and wage factor. Third, we find real factor and interest rate factor become less volatile since the mid 1980s; price factor and foreign exchange factor, on the contrary, become more volatile since the last decade; the rest of factors have no obvious pattern. In addition, the evidence from this chapter sheds some light on the weakness of the "good luck" hypothesis as an explanation for the Great Moderation.

Table 3.1 Sample Standard Deviations, by Decade of U.S. Macroeconomic and Financial Time Series

Series	Standard Deviation	Standard Deviation, relative to Whole Period			
	1957:3-2005:12	1957:3-1969:12	1970:1-1979:12	1980:1-1989:12	1990:1-2005:12
Industrial Production Growth	0.009	1.33	1.08	0.90	0.62
Personal Consumer Expenditures	0.006	1.09	1.02	1.20	0.76
CPI Inflation Rate	0.003	0.83	1.34	1.11	0.84
Core CPI Inflation Rate	0.003	0.94	1.30	1.21	0.60
Federal Fund Rate	0.006	0.54	0.95	1.85	0.34
30-day Treasury Bill Return	0.002	0.79	0.78	1.59	0.78
90-day Treasury Bill Return	0.003	0.74	0.74	1.65	0.75
1-year Treasury Bond Return	0.005	0.61	0.98	1.70	0.58
10-year Treasury Bond Return	0.022	0.77	0.91	1.42	0.89
20-year Treasury Bond Return	0.028	0.69	0.87	1.49	0.91
30-year Treasury Bond Return	0.029	0.67	0.82	1.41	1.01
Term Spreads	0.017	0.60	1.26	1.25	0.88
Default Spreads	0.004	0.83	0.85	1.62	0.62
Equal-Weighted Stock Return	0.049	0.87	1.33	1.04	0.81
Value-Weighted Stock Return	0.041	0.84	1.16	1.14	0.91
S&P 500 Stock Return	0.042	0.81	1.10	1.13	0.98
Excess Market Stock Return	0.043	0.81	1.13	1.12	0.97
Small Minus Big	0.031	0.77	1.10	0.76	1.21
High Minus Low	0.028	0.68	0.98	0.99	1.21
Earnings Price Ratio	0.028	0.50	1.06	1.45	0.92
Dividend Price Ratio	0.012	0.39	1.17	1.18	1.10

Table 3.2 Structural Break Tests for US Macroeconomic and Financial Variables

	Conditional Mean			Conditional Variance:		
Series	p-value	Break date	confidence interval	p-value	Break date	confidence interval
Industrial Production Growth	0.00	1982:1	1981:10-1982:3	0.00	1965:3	1964:7-1966:4
Personal Consumer Expenditures	0.12	-	-	0.00	1991:3	1989:10-1994:11
CPI Inflation Rate	0.00	1981:9	1981:7-1981:11	0.01	1984:2	1975:8-1992:4
Core CPI Inflation Rate	0.00	1990:8	1990:6-1990:10	0.00	1984:2	1983:5-1985:10
Federal Fund Rate	0.00	1987:11	1987:9-1988:1	0.00	1985:8	1985:6-1989:2
30-day Treasury Bill Return	0.02	1980:5	1980:3-1980:7	0.00	1991:6	1991:1-1995:8
90-day Treasury Bill Return	0.08	-	-	0.00	1988:3	1987:12-1991:9
1-year Treasury Bond Return	0.01	1980:4	1980:2-1980:6	0.00	1989:8	1989:2-1993:10
10-year Treasury Bond Return	0.11	-	-	0.00	1966:7	1961:12-1968:6
20-year Treasury Bond Return	0.05	1981:10	1981:8-1981:12	0.00	1966:9	1960:3-1967:11
30-year Treasury Bond Return	0.22	-	-	0.00	1979:9	1975:3-1986:2
Term Spreads	0.03	1980:6	1980:4-1980:8	0.00	1987:1	1986:8-1992:9
Default Spreads	0.14	-	-	0.00	1970:1	1957:9-1971:5
Equal-Weighted Stock Return	0.48	-	-	0.00	1991:2	1988:10-1997:1
Value-Weighted Stock Return	0.67	-	-	0.25	-	-
S&P 500 Stock Return	0.85	-	-	0.12	-	-
Excess Market Stock Return	0.79	-	-	0.06	-	-
Small Minus Big	0.71	-	-	0.00	1996:3	1988:9-1998:7
High Minus Low	0.14	-	-	0.00	1998:4	1991:11-1999:9
Earnings Price Ratio	0.30	-	-	0.00	1991:2	1990:11-1993:5
Dividend Price Ratio	0.04	1975:1	1974:11-1975:3	0.00	1991:2	1990:11-1993:3

Table 3.3 Summary Statistics for Static Factors

Factor $\hat{F}_t$	Accumulated R^2	Marginal R^2	AR(1) coefficient	Description
1	0.142	0.142	0.774 (0.027)	Real factor
2	0.220	0.078	0.611 (0.033)	Interest rate factor
3	0.280	0.060	0.574 (0.035)	Bond market factor
4	0.329	0.049	-0.295 (0.040)	Price factor
5	0.375	0.046	0.418 (0.038)	Stock market factor
6	0.416	0.041	0.553 (0.035)	Real factor
7	0.447	0.031	0.584 (0.034)	Real factor
8	0.477	0.030	-0.080 (0.042)	Money market factor
9	0.500	0.023	0.282 (0.041)	Foreign exchange factor
10	0.523	0.023	0.140 (0.042)	Real factor
11	0.544	0.021	0.006 (0.042)	Wage factor
12	0.564	0.020	0.069 (0.042)	Wage factor

A. Industrial Production

B. Personal Consumer Expenditure

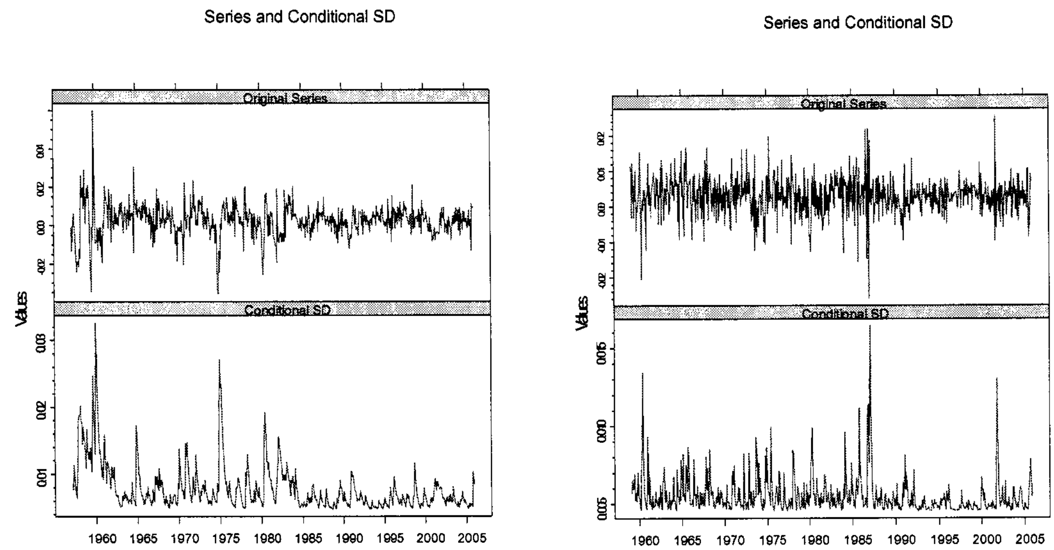


Figure 3.1 Real Output and Consumption Growth Series and GARCH Volatility

A. Core CPI Inflation Rate

B. Core PCE Inflation Rate

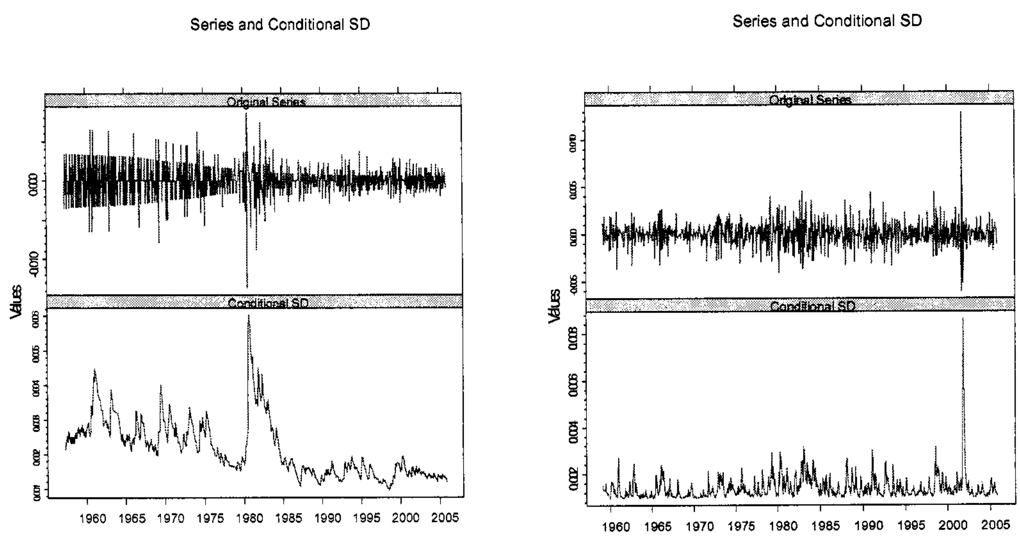
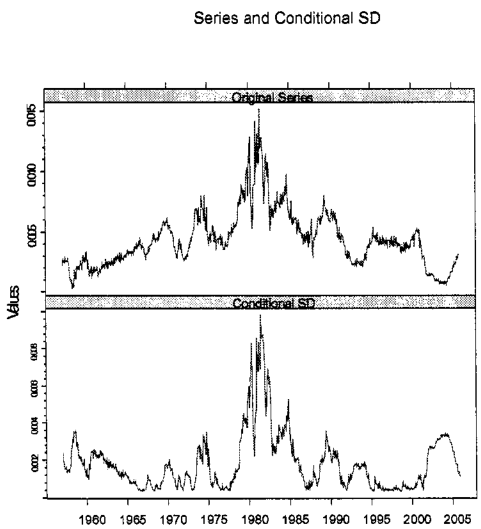
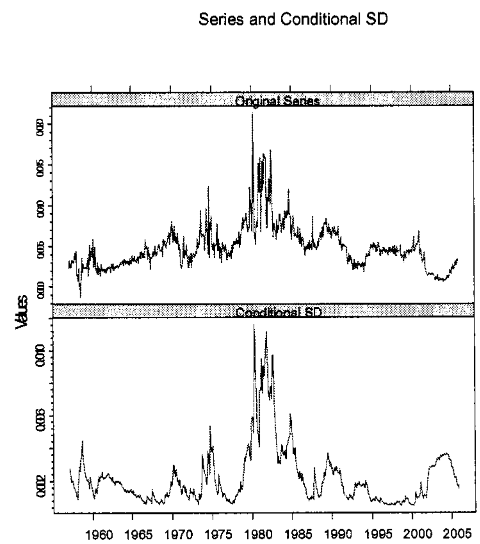


Figure 3.2 Inflation Rate Growth Series and GARCH Volatility

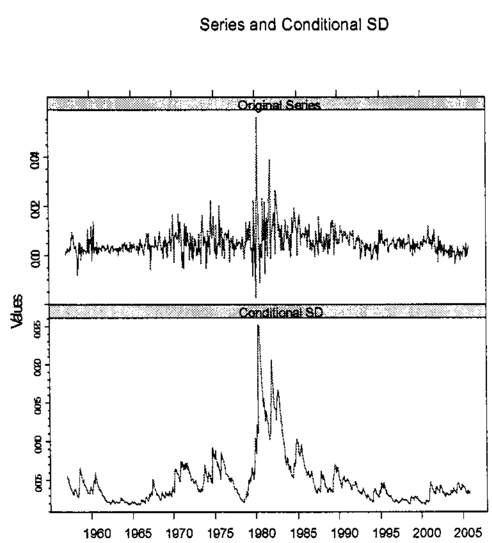
A. 30-day Treasury Bill Return



B. 90-day Treasury Bill Return



C. 1-Year Treasury Bond Return



D. 10-Year Treasury Bond Return

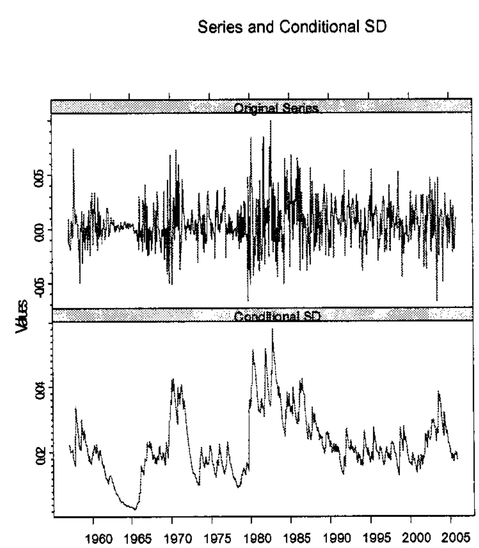
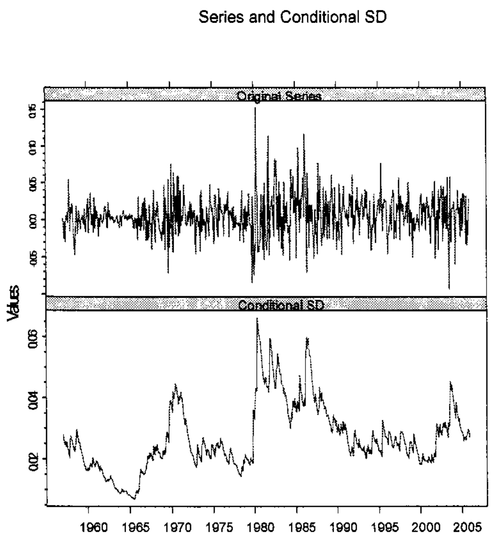
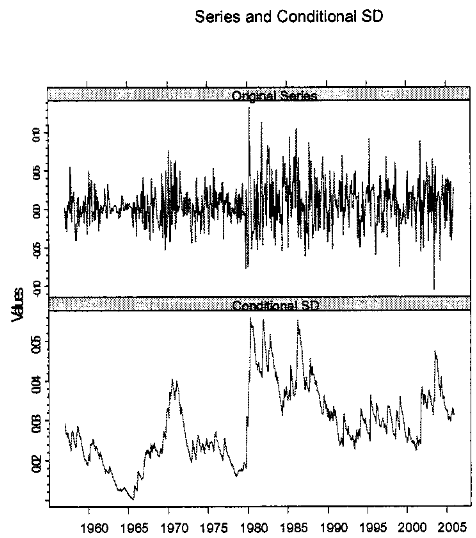


Figure 3.3 Financial Variables Series and GARCH Volatility

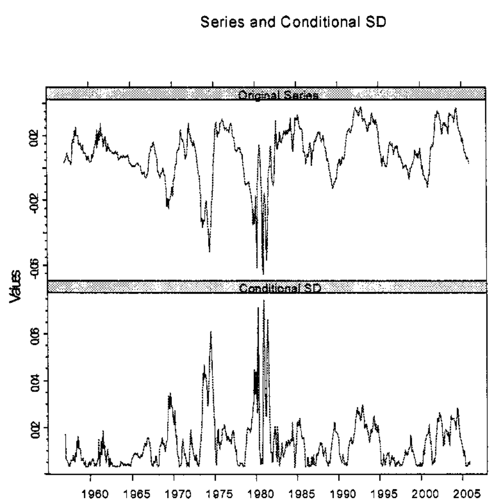
E. 20-Year Treasury Bond Return



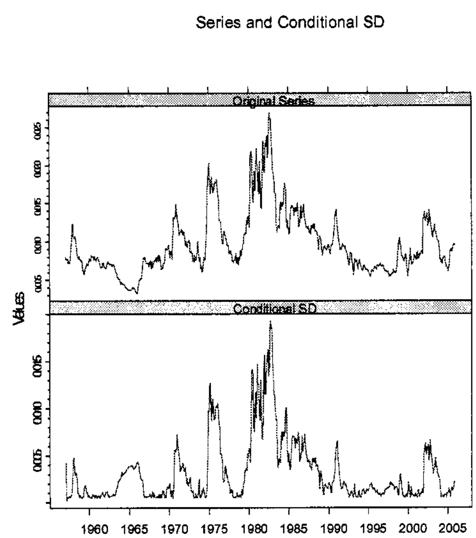
F. 30-Year Treasury Bond Return



G. Term Spread



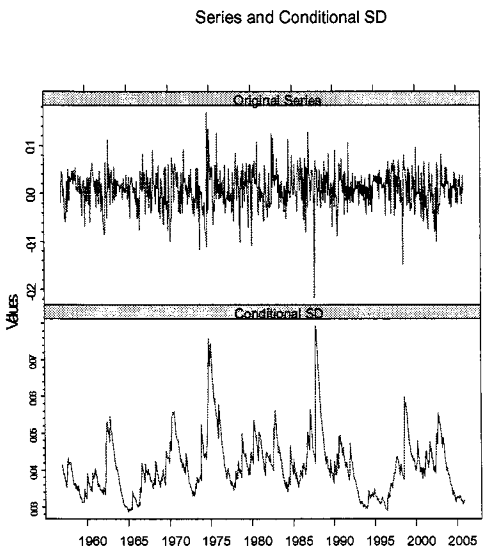
H. Default Spread



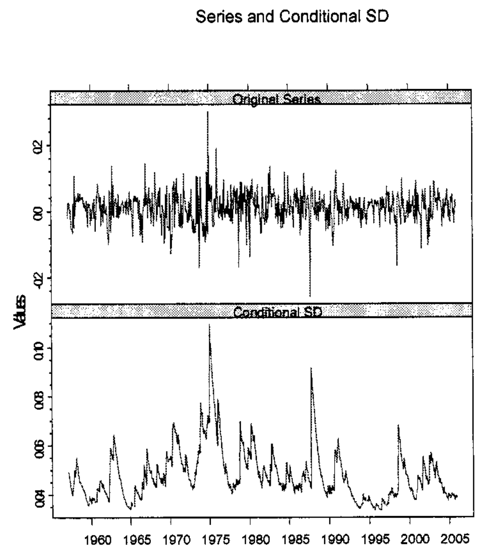
1. Term Spread is 10 year Treasury Bond Rate Minus Federal Fun Rate.
2. Default Spread is Moody's Aaa Bond Rate Minus Baa Bond Rate.

Figure 3.3 (Continued)

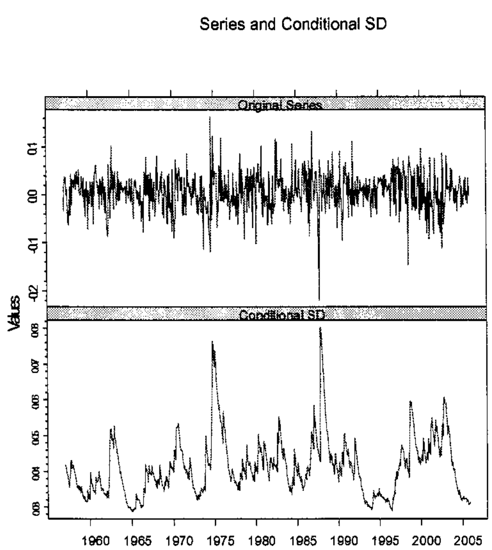
I. Value-Weighted Stocks Return



J. Equal-Weighted Stocks Return



K. S&P 500 Stocks Return



L. S&P 500 Excess Stocks Return

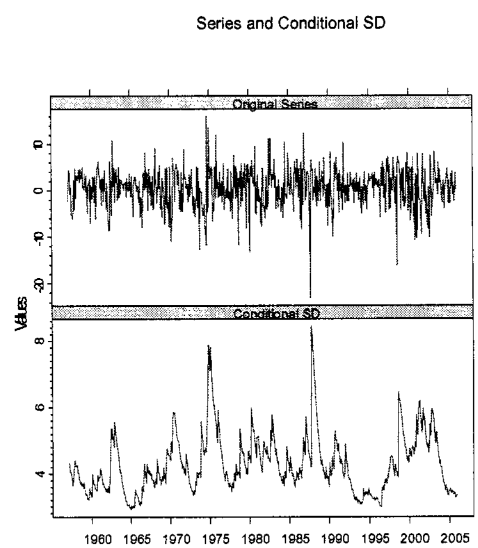
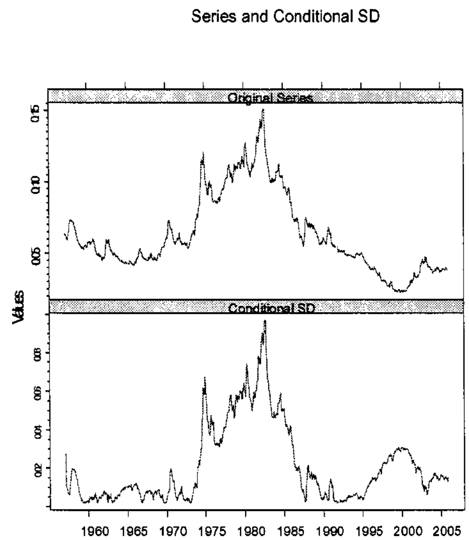
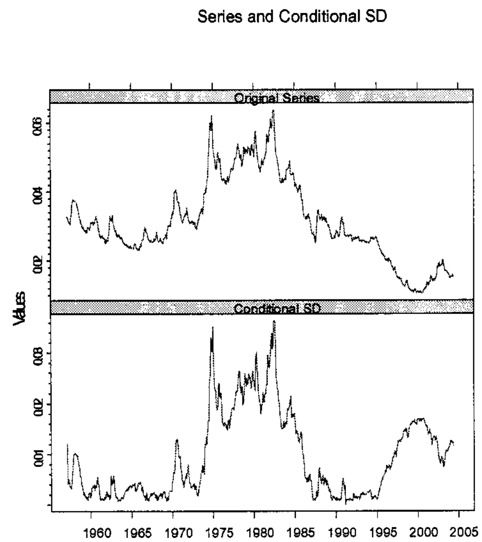


Figure 3.3 (Continued)

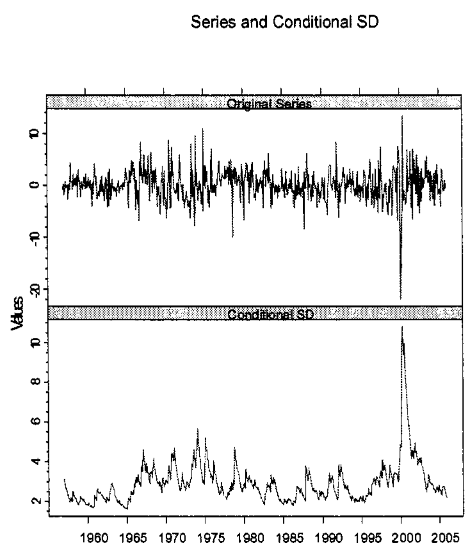
M. Earnings Price Ratio



N. Dividend Price Ratio



O. Small Minus Big



P. High Minus Low

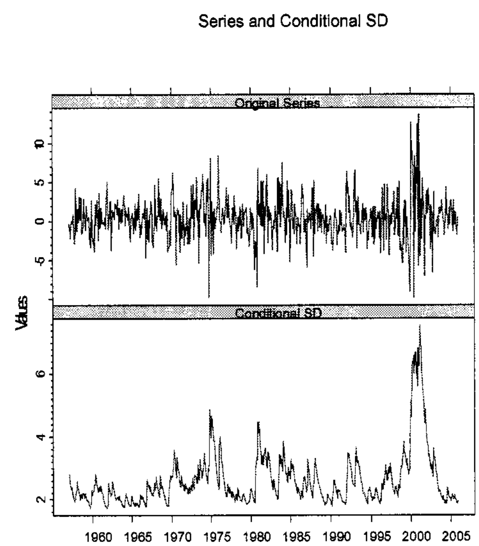
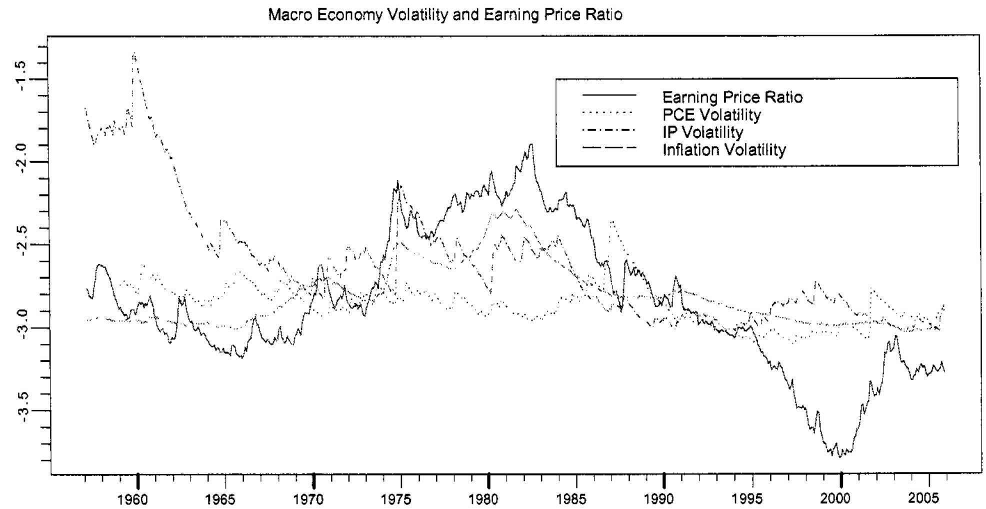


Figure 3.3 (Continued)

A.



B.

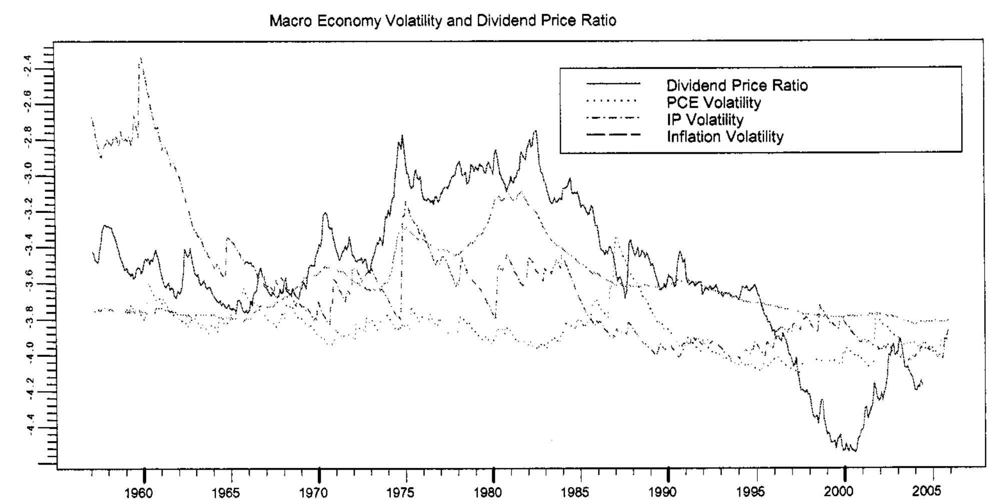
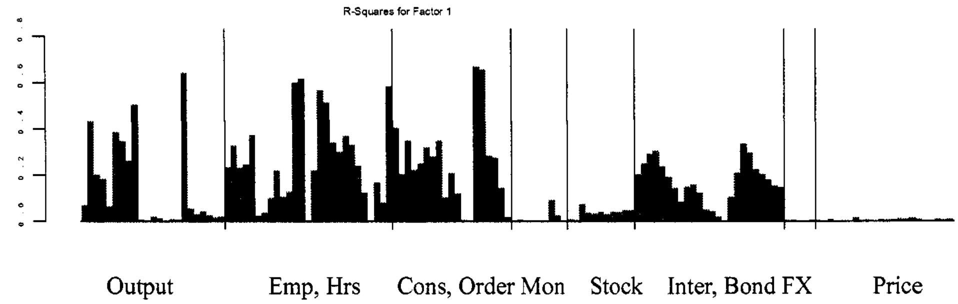
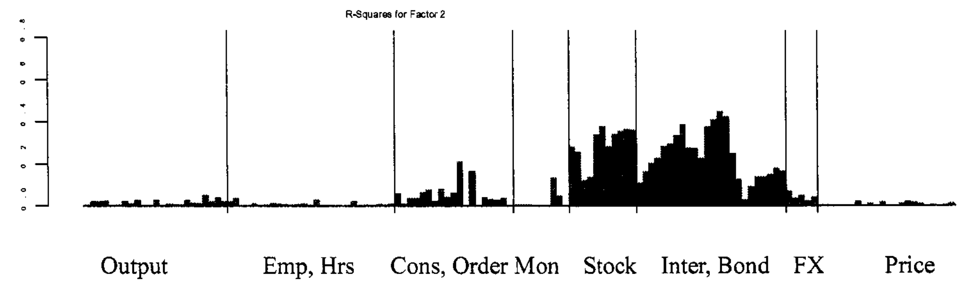


Figure 3.4 Macroeconomic Volatility and Stock Market Valuation

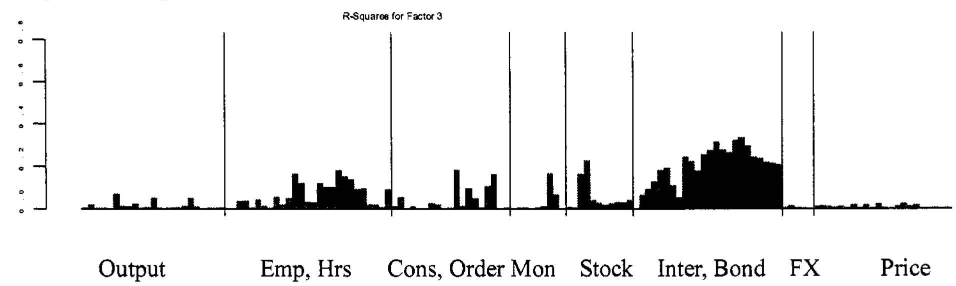
A. Marginal R-Squares for Factor 1: Real Factor



B. Marginal R-Squares for Factor 2: Interest Rate Factor



C. Marginal R-Squares for Factor 3: Bond Market Factor



D. Marginal R-Squares for Factor 4: Price Factor

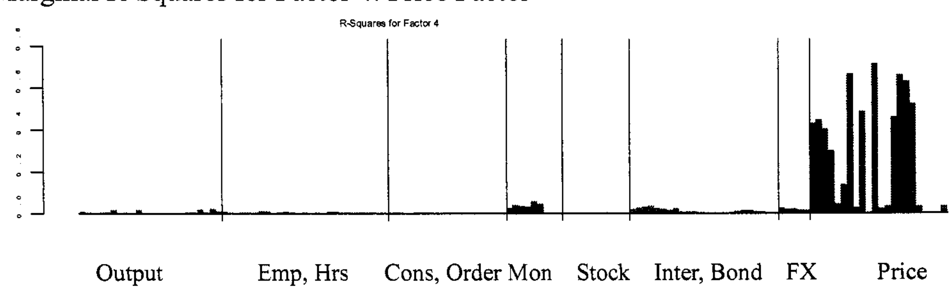
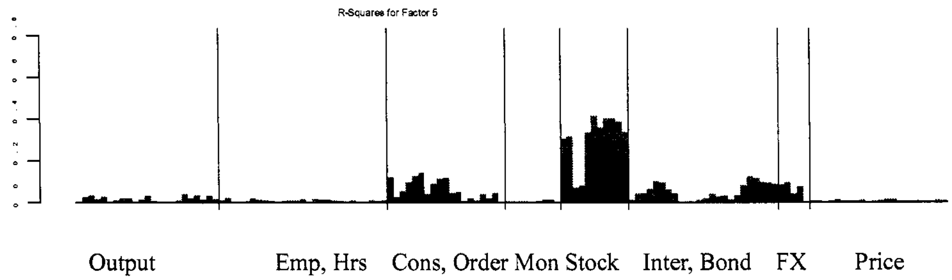
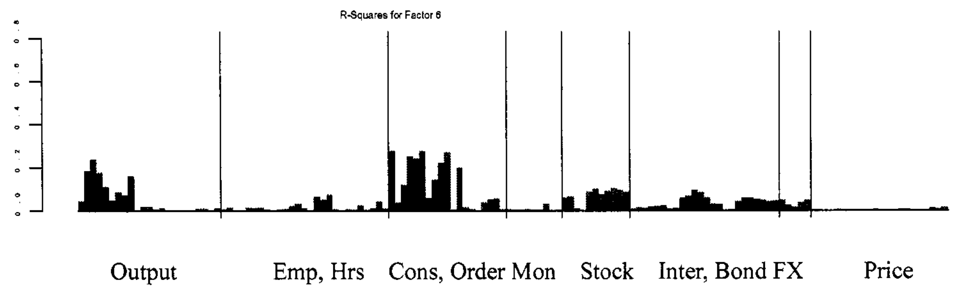


Figure 3.5 Marginal R-Squares for Factors

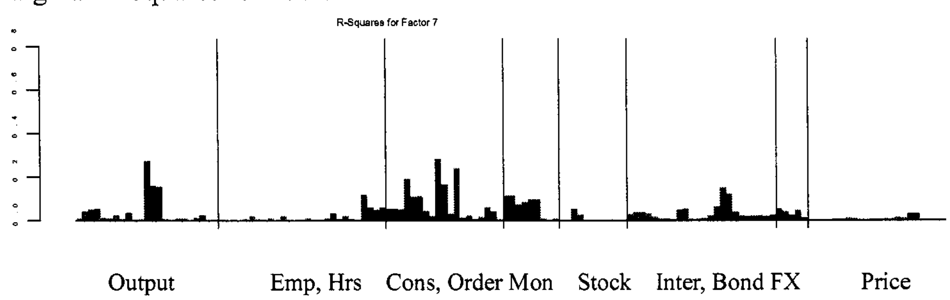
E. Marginal R-Squares for Factor 5: Stock Market Factor



F. Marginal R-Squares for Factor 6: Real Factor



G. Marginal R-Squares for Factor 7: Real Factor



H. Marginal R-Squares for Factor 8: Money Market Factor

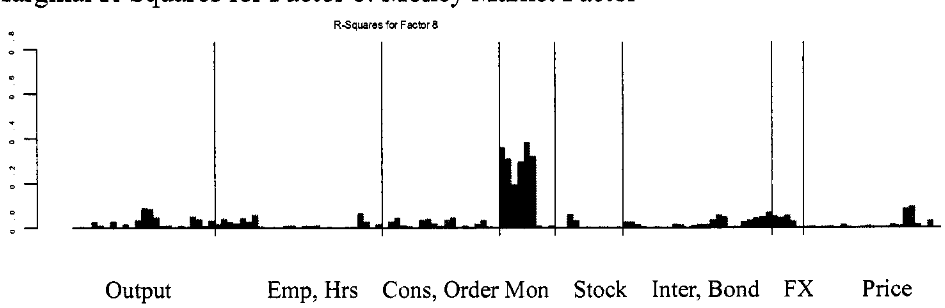
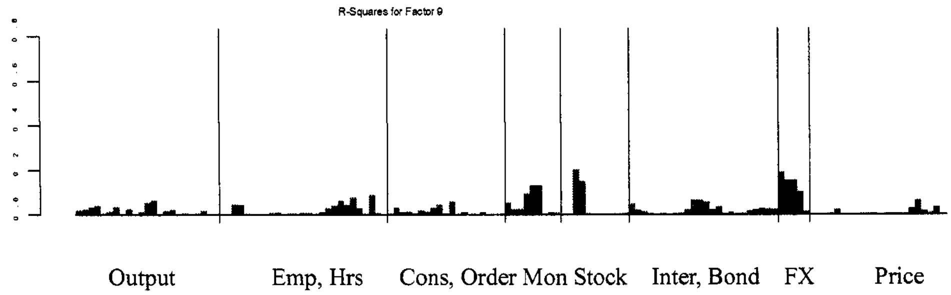
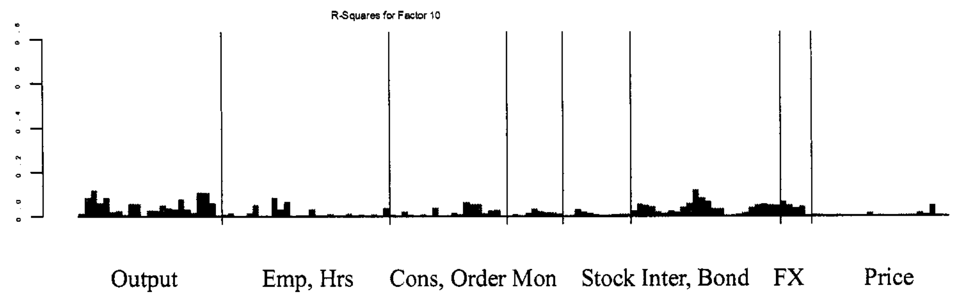


Figure 3.5 (Continued)

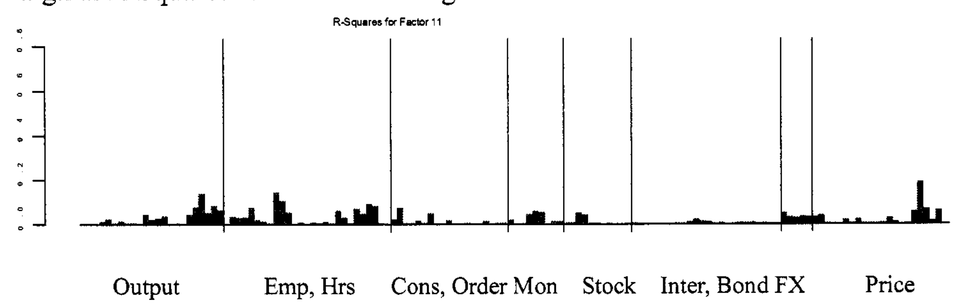
I. Marginal R-Squares for Factor 9: Foreign Exchange Factor



J. Marginal R-Squares for Factor 10: Real Factor



K. Marginal R-Squares for Factor 11: Wage Factor



L. Marginal R-Squares for Factor 12: Wage Factor

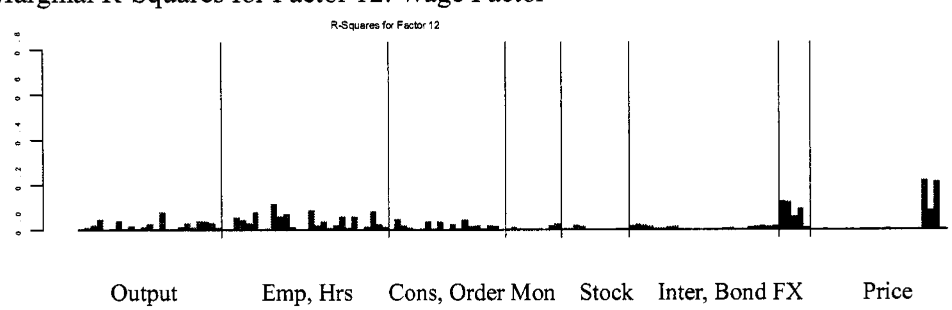


Figure 3.5 (Continued)

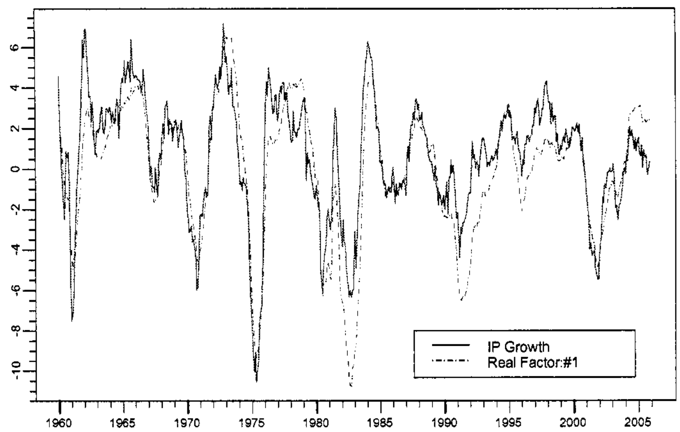
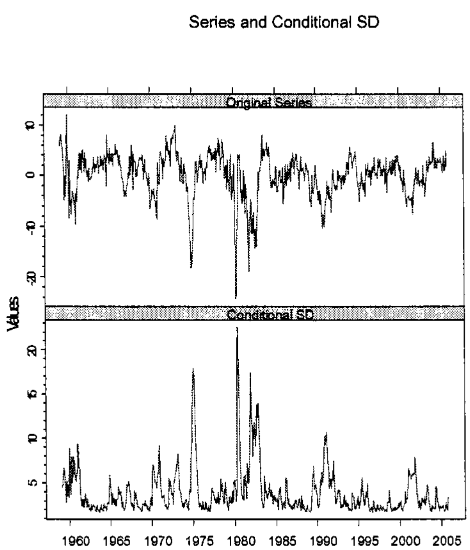


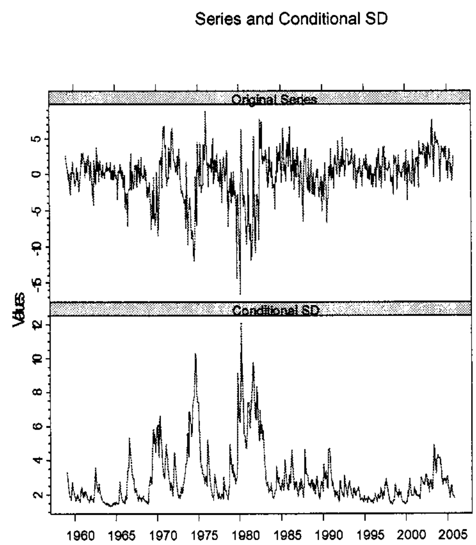
Figure 3.6 Factor 1: Real Factor and IP Growth

Note: The plots are 12 months moving average of both IP growth and real factor.

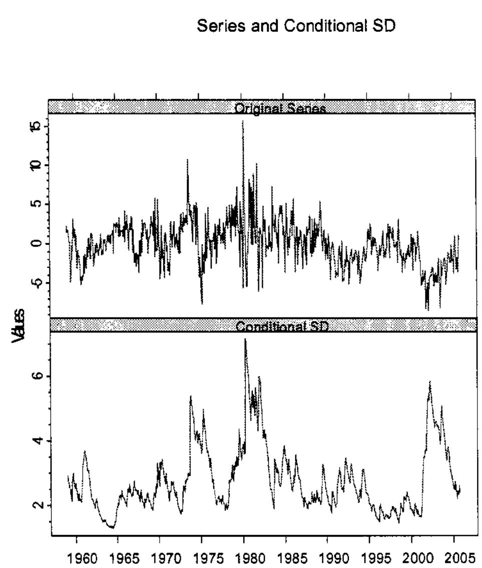
A. Factor 1: Real Factor



B. Factor 2: Interest Rate Factor



C. Factor 3: Bond Market Factor



D. Factor 4: Price Factor

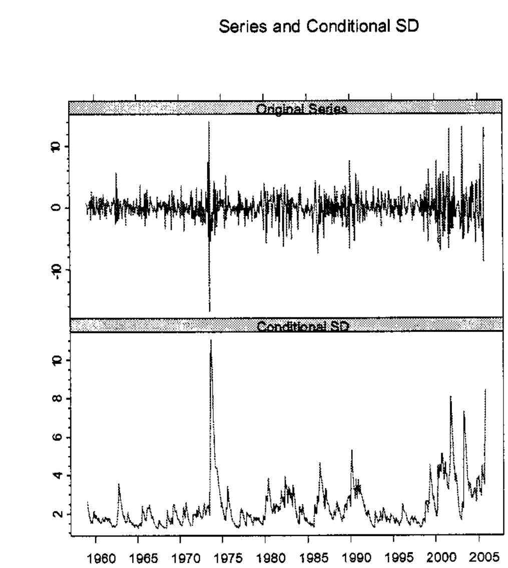
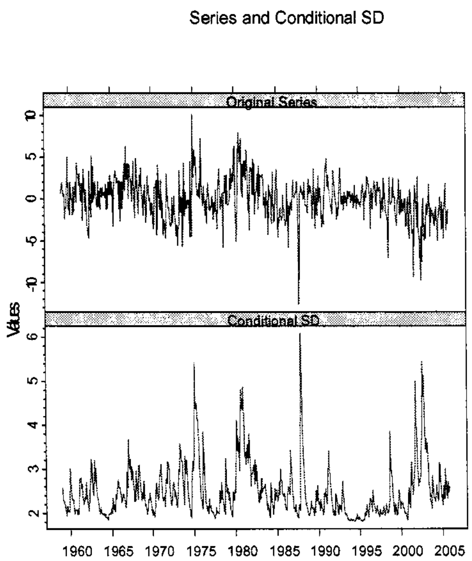
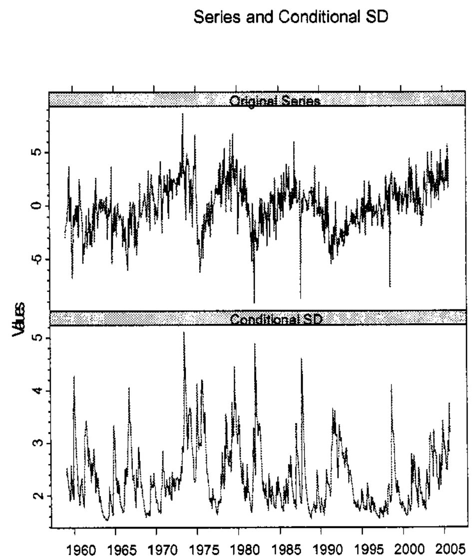


Figure 3.7 Factor Series and Its GARCH Volatility

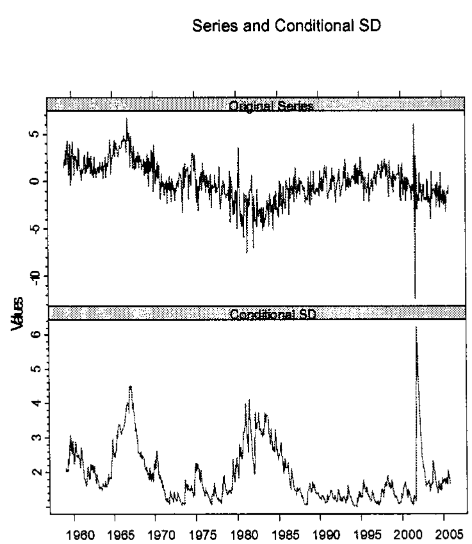
E. Factor 5: Stock Market Factor



F. Factor 6: Real Factor



G. Factor 7: Real Factor



H. Factor 8: Money Market Factor

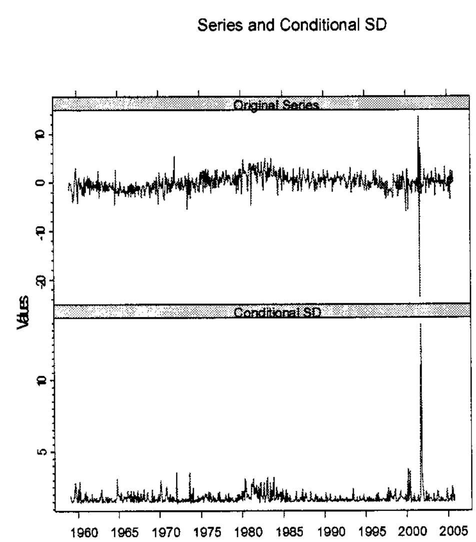
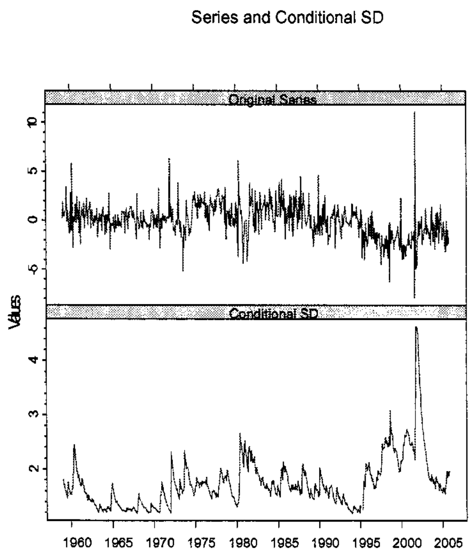
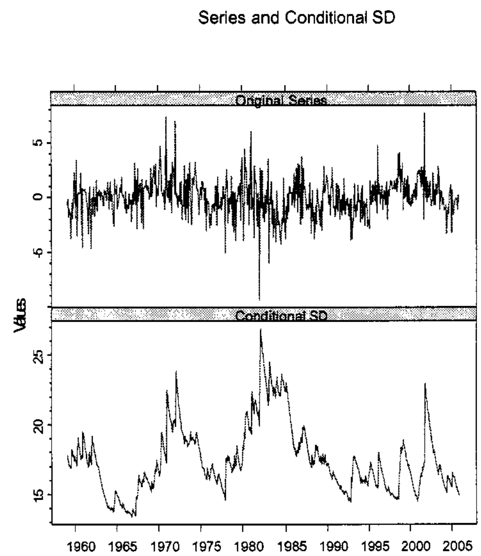


Figure 3.7 (Continued)

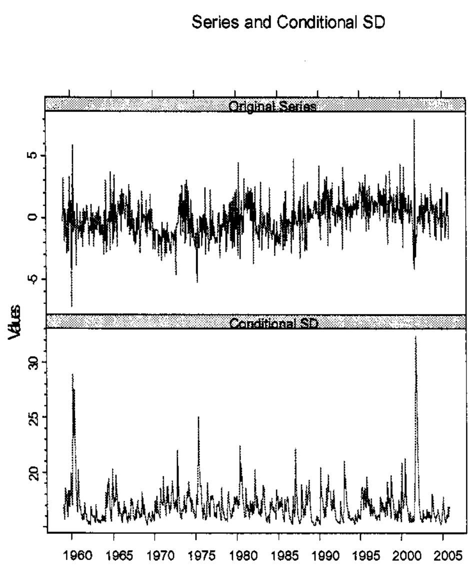
I. Factor 9: Foreign Exchange Factor



J. Factor 10: Real Factor



K. Factor 11: Wage Factor



L. Factor 12: Wage Factor

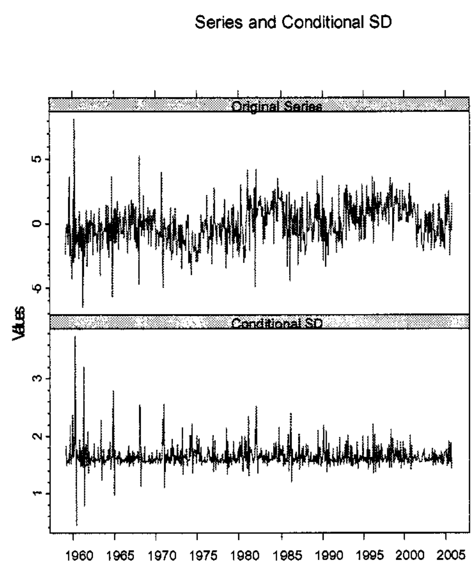


Figure 3.7 (Continued)

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APPENDIX A. Stochastic Volatility Model

We use stochastic volatility model following geometric random walks described by Stock and Watson (2002) to estimate the smoothed instantaneous standard deviations (σ_t) with random-walk time-varying autoregressive coefficients (ϕ_{jt}) as shown in Figure 1.2.

$$y_t = \mu_t + \sum_{j=1}^{4} \phi_{jt} y_{t-j} + \sigma_t e_t$$
$$\phi_{jt} = \phi_{jt-1} + \gamma_t v_{jt}$$
$$\ln \sigma_t^2 = \ln \sigma_{t-1}^2 + \omega_t$$

where $e_t, v_{1t}, \ldots v_{4t}$ are $i.i.d. N(0,1)$. And ω_t is $N(0, \omega_1^2)$ with probability p and $N(0, \omega_2^2)$ with probability *1-p*. The model shows the output shock is the sum of two underlying shocks. One is from a normal distribution (e_t); the other is from a mixture of normal distribution with smaller variance (ω_1^2) with probability p and larger variance (ω_2^2) with probability 1-p to catch fat-tailed disturbancees. The series y_t is standardized before the computations, and we set, scale factor, γ_t = 7 / T, which is consistent with Stock and Watson's previous estimates of parameter drift in autoregressions. We set ω_1^2 = 0.04, ω_2^2 = 0.2 and p = 0.95. This nonGaussian smoother for the time-varying parameters is computed using Markov Chain Monte Carlo (MCMC) method. Assume Y denotes $y_1, \ldots. y_T$; A denotes {ϕ_{jt}, where j = 1, …4, t = 1, …T}; and S denotes $\sigma_1, \ldots. \sigma_T$. The MCMC iterates between the three conditional distributions of Y| A, S; of A| Y, S; and S| A, Y. The first and second distributions are normal but the third one is nonnormal which is computed by a mixture of normal distribution. We use the log chi-square distribution to match the first four moments for the mixture means and variances. Initial conditions were set by a flat prior and a diffuse conjugate prior was used for the parameter values.

APPENDIX B. Data Transformation, Description and Sources

Table A lists the name, transformation, description, and sources of the data. In the transformation column, *lev* denotes the level of the series, *ln* denotes taking logarithms, *dlev* denotes the first difference of the series, *dln* denotes the first difference of the logarithm, *ddln* denotes the second difference of the series. All series are from DRI Basic Economics Database by Global Insights, Inc. unless the sources are listed in parentheses as FRED (Federal Reserve Economic Data from http://research.stlouisfed.org/FRED2/), CRSP (Center for Research in Security Prices) or AC (author's calculation from the based on the above data). And sa denotes seasonal adjustment saar denotes seasonal adjustment with annual rate.

Table A. Data transformation, description and sources

Number	Series	Trans.	Description
Real Output, Income, and Consumption			
1	ipn10	*dln*	industrial production index - total index
2	ips11	*dln*	industrial production index - products, total
3	ips12	*dln*	industrial production index - consumer goods
4	ips13	*dln*	industrial production index - durable consumer goods
5	ips18	*dln*	industrial production index - nondurable consumer goods
6	ips25	*dln*	industrial production index - business equipment
7	ips34	*dln*	industrial production index - durable goods materials
8	ips38	*dln*	industrial production index - nondurable goods materials
9	ips43	*dln*	industrial production index - manufacturing (sic)
10	ips306	*dln*	industrial production index - fuels
11	ips307	*dln*	industrial production index - residential utilities
12	cap11	*dln*	industrial capacity index - manufacturing
13	cap21	*dln*	industrial capacity index - motor vehicles and parts naics=3361-3
14	cap31	*dln*	industrial capacity index - petroleum and coal products naics=324
15	cap44	*dln*	industrial capacity index - primary & semifinished processing (capacity)
16	cap45	*dln*	industrial capacity index - finished processing (capacity)
17	pmp	*lev*	napm production index (percent)
18	pi	*dln*	personal income (FRED, saar)
19	dspic	*dln*	real disposable income (FRED, saar, chained 2000)
20	pcec	*dln*	personal consumption expenditures (FRED, saar, chained 2000)
21	Pcedgc	*dln*	personal consumption expenditures - durable goods (FRED, saar, chained 2000)
22	pcendc	*dln*	personal consumption expenditures - nondurable goods (FRED, saar, chained 2000)
23	pcesc	*dln*	personal consumption expenditures - services (FRED, saar, chained 2000)

Employment and Hours

24	lhel	*dlev*	index of help-wanted advertising in newspapers (1967=100;sa)
25	lhelx	*dlev*	employment: ratio; help-wanted ads:no. unemployed clf
26	lhem	*dln*	civilian labor force: employed, total (thous.,sa)
27	lhnag	*dln*	civilian labor force:employed in nonag,both sexes 16-19yrs(thou.,
28	lhur	*dlev*	unemployment rate: all workers, 16 years & over (%,sa)
29	lhu680	*dlev*	unemploy.by duration: average(mean)duration in weeks (sa)
30	lhu5	*dln*	unemploy.by duration: persons unempl.less than 5 wks (thous.,sa)
31	lhu14	*dln*	unemploy.by duration: persons unempl.5 to 14 wks (thous.,sa)
32	lhu15	*dln*	unemploy.by duration: persons unempl.15 wks + (thous.,sa)
33	lhu26	*dln*	unemploy.by duration: persons unempl.15 to 26 wks (thous.,sa)
34	lhu27	*dln*	unemploy.by duration: persons unempl.27 wks + (thous,sa)
35	ces002	*dln*	employees on nofarm: total private
36	ces003	*dln*	employees on nonfarm: goods-producing
37	ces006	*dln*	employees on nonfarm: mining
38	ces011	*dln*	employees on nonfarm: construction
39	ces015	*dln*	employees on nonfarm: manufacturing
40	ces017	*dln*	employees on nonfarm: durable goods
41	ces033	*dln*	employees on nonfarm: nondurable goods
42	ces046	*dln*	employees on nonfarm: service-producing
43	ces048	*dln*	employees on nonfarm: trade, transportation, and utilities
44	ces049	*dln*	employees on nonfarm: wholesale trade
45	ces053	*dln*	employees on nonfarm: retail trade
46	ces088	*dln*	employees on nonfarm: financial activities
47	ces140	*dln*	employees on nonfarm: government
48	ces151	*lev*	avg wkly hours, prod wrkrs, nonfarm - goods-producing
49	ces155	*dlev*	avg wkly overtime hours, prod wrkrs, nonfarm - mfg
50	pmemp	*lev*	napm employment index (percent)

Construction, Inventories and Orders

51	hsfr	*ln*	housing starts:nonfarm(1947-58);total farm&nonfarm(1959-)(thous.,sa
52	hsne	*ln*	housing starts:northeast (thous.u.)s.a.
53	hsmw	*ln*	housing starts:midwest(thous.u.)s.a.
54	hssou	*ln*	one-family houses sold:south(thou.u.,s.a.)
55	hswst	*ln*	housing starts:west (thous.u.)s.a.
56	hsbr	*ln*	housing authorized: total new priv housing units (thous.,saar)
57	hsbne	*ln*	houses authorized by build. permits:northeast(thou.u.)s.a
58	hsbmw	*ln*	houses authorized by build. permits:midwest(thou.u.)s.a.
59	hsbsou	*ln*	houses authorized by build. permits:south(thou.u.)s.a.
60	hsbwst	*ln*	houses authorized by build. permits:west(thou.u.)s.a.
61	hnr	*ln*	new 1-family houses, month's supply @ current sales rate(ratio)
62	hniv	*ln*	new 1-family houses for sale at end of month (thous,sa)
63	ivm	*dln*	inventories - all manufacturing industries naics (m3)
64	pmi	*lev*	purchasing managers' index (sa)
65	pmno	*lev*	napm new orders index (percent)
66	pmdel	*lev*	napm vendor deliveries index (percent)
67	pmnv	*lev*	napm inventories index (percent)
68	mocmq	*dln*	new orders (net) - consumer goods & materials, 1996 dollars (bci)

69	msondq	*dln*	new orders, nondefense capital goods, in 1996 dollars (bci)

Money, Credit, and Finance

Money Market

70	fm1	*ddln*	money stock: m1(curr,trav.cks,dem dep,other ck'able dep)(bil$,sa)
71	fm2	*ddln*	money stock:m2(m1+o'nite rps,euro$,g/p&b/d mmmfs&sav&sm time dep(bil$,
72	fm3	*ddln*	money stock: m3(m2+lg time dep,term rp's&inst only mmmfs)(bil$,sa)
73	fmfba	*ddln*	monetary base, adj for reserve requirement changes(mil$,sa)
74	fmrra	*ddln*	depository inst reserves:total,adj for reserve req chgs(mil$,sa)
75	fmrnba	*ddln*	depository inst reserves:nonborrowed,adj res req chgs(mil$,sa)
76	busloans	*dln*	commercial and industrial loans at all commercial banks (FRED, sa)
77	fclbmc	*lev*	wkly rp lg com'l banks:net change com'l & indus loans(bil$,saar)
78	ccinrv	*ddln*	consumer credit outstanding - nonrevolving(g19)

Stock Market

79	fspcom	*dln*	s&p's common stock price index: composite (1941-43=10)
80	fspin	*dln*	s&p's common stock price index: industrials (1941-43=10)
81	fsdxp	*lev*	s&p's composite common stock: dividend yield (% per annum)
82	fspxe	*lev*	s&p's composite common stock: price-earnings ratio (%,nsa)
83	vwindd	*dln*	nyse value-weighted market index, excluding dividends (CRSP)
84	ewindd	*dln*	nyse equal-weighted market index, excluding dividends (CRSP)
85	nyca1	*dln*	nyse cap 1 market index (CRSP)
86	nyca2	*dln*	nyse cap 3 market index (CRSP)
87	nyca3	*dln*	nyse cap 5 market index (CRSP)
88	nyca4	*dln*	nyse cap 7 market index (CRSP)
89	nyca5	*dln*	nyse cap 9 market index (CRSP)

Interest Rate and Bond Market

90	fyff	*dlev*	interest rate: federal funds (effective) (% per annum,nsa)
91	fygm3	*dlev*	interest rate: u.s.treasury bills,sec mkt,3-mo.(% per ann,nsa)
92	fygm6	*dlev*	interest rate: u.s.treasury bills,sec mkt,6-mo.(% per ann,nsa)
93	fygt1	*dlev*	interest rate: u.s.treasury const maturities,1-yr.(% per ann,nsa)
94	fygt5	*dlev*	interest rate: u.s.treasury const maturities,5-yr.(% per ann,nsa)
95	fygt10	*dlev*	interest rate: u.s.treasury const maturities,10-yr.(% per ann,nsa)
96	fyaaac	*dlev*	bond yield: moody's aaa corporate (% per annum)
97	fybaac	*dlev*	bond yield: moody's baa corporate (% per annum)
98	sfygm3	*lev*	fygm3-fyff (AC)
99	sfygm6	*lev*	fygm6-fyff (AC)
100	sfygt1	*lev*	fygt1-fyff (AC)
101	sfygt5	*lev*	fygt5-fyff (AC)
102	sfygt10	*lev*	fygt10-fyff (AC)
103	sfyaaa	*lev*	fyaaac-fyff (AC)
104	sfybaa	*lev*	fybaaac-fyff (AC)
105	t30ret	*lev*	u.s.treasury bills 30 days return (CRSP)
106	t90ret	*lev*	u.s.treasury bills 90 days return (CRSP)
107	b1ret	*lev*	u.s.treasury bond l year return (CRSP)
108	b2ret	*lev*	u.s.treasury bond 2 year return (CRSP)
109	b5ret	*lev*	u.s.treasury bond 5 year return (CRSP)
110	b7ret	*lev*	u.s.treasury bond 7 year return (CRSP)

111	b10ret	*lev*	u.s.treasury bond l0 year return (CRSP)
112	b20ret	*lev*	u.s.treasury bond 20 year return (CRSP)
113	b30ret	*lev*	u.s.treasury bond 30 year return (CRSP)
Exchange Rate Market			
114	exrus	*dln*	united states;effective exchange rate(merm)(index no.)
115	exrsw	*dln*	foreign exchange rate: switzerland (swiss franc per u.s.$)
116	exrjan	*dln*	foreign exchange rate: japan (yen per u.s.$)
117	exruk	*dln*	foreign exchange rate: united kingdom (cents per pound)
118	exrcan	*dln*	foreign exchange rate: canada (canadian $ per u.s.$)
Price and Wage Indexes			
119	pwfsa	*ddln*	producer price index: finished goods (82=100,sa)
120	pwfcsa	*ddln*	producer price index:finished consumer goods (82=100,sa)
121	pwimsa	*ddln*	producer price index:intermed mat.supplies & components(82=100,sa)
122	pwcmsa	*ddln*	producer price index:crude materials (82=100,sa)
123	psccom	*ddln*	spot market price index:bls & crb: all commodities(1967=100)
124	pmcp	*ddln*	napm commodity prices index (percent)
125	punew	*ddln*	cpi-u: all items (82-84=100,sa)
126	pu83	*ddln*	cpi-u: apparel & upkeep (82-84=100,sa)
127	pu84	*ddln*	cpi-u: transportation (82-84=100,sa)
128	pu85	*ddln*	cpi-u: medical care (82-84=100,sa)
129	puc	*ddln*	cpi-u: commodities (82-84=100,sa)
130	pucd	*ddln*	cpi-u: durables (82-84=100,sa)
131	pus	*ddln*	cpi-u: services (82-84=100,sa)
132	puxf	*ddln*	cpi-u: all items less food (82-84=100,sa)
133	puxhs	*ddln*	cpi-u: all items less shelter (82-84=100,sa)
134	puxm	*ddln*	cpi-u: all items less midical care (82-84=100,sa)
135	pcepi	*ddln*	personal consumption expenditures: chain-type price index (FRED, sa)
136	pcepilfe	*ddln*	pce: chain-type price index less food and energy (FRED, sa)
137	ces275	*ddln*	avg hrly earnings, prod wrkrs, nonfarm - goods-producing
138	ces277	*ddln*	avg hrly earnings, prod wrkrs, nonfarm - construction
139	ces278	*ddln*	avg hrly earnings, prod wrkrs, nonfarm - mfg
140	hhsntn	*lev*	u. of mich. index of consumer expectations(bcd-83)

VITA

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