“Hot Markets”, Conditional Volatility, and Foreign Exchange

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Abstract

The existence of conditional volatility as a statistical property of the foreign exchange markets is well known, with ARCH-type models having been successfully applied to many time series. The present paper works toward an economic explanation of this property of the foreign exchange markets by examining the hypothesis that there are speculative noise traders that are attracted to “hot” markets. A simple model is offered of such a phenomenon, with the empirical implication that markets which are far away from their “fundamental values” will be characterized by high volatility.

This empirical implication is then tested using data for the U.S. dollar against each of the other G7 currencies. Fundamental values are estimated by applying filters to the data. To examine whether our model fits the data better than an ARCH/GARCH random walk, Monte Carlo simulations are used. In these simulations, random walks with the same (G)ARCH parameters as the actual data series are constructed. The empirical tests of the model show that the actual data includes the phenomenon that deviations from fundamentals are associated with subsequent high volatility, and that this phenomenon is more present in the actual data than in the (G)ARCH random walk simulations.

1 Introduction

The hypothesis that the innovation to prices in financial markets in each time period is independently and identically distributed has been long realized as a simplifying assumption. The proliferation of statistical models involving autoregressive conditional heteroskedasticity has been driven in large part by economists seeking to represent more accurately the observed process in many financial markets, including equity, debt, and currency markets.

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While a large amount of progress has been made in statistically characterizing volatility of key financial variables as having a variety of autoregressive properties, somewhat less progress has been made in understanding economically what drives this statistical property. The present paper presents a model of "public interest" in financial markets, and examines whether it can explain these statistical regularities in the foreign exchange market.

The model describes an environment in which non-informational trading has transitory impacts on market prices. This interest is self-sustaining, in the sense that a large amount of public interest in the market generates more publicity (for example, through news coverage). The result of this publicity is that in the next period, a greater segment of the public enters, either reinforcing the current trend or offsetting it. This means that "hot markets", or those markets priced far away from their "fundamental values", will have more volatile prices than markets for those assets which are currently priced close to their fundamental values.

This model is somewhat similar in spirit to DeLong, Shleifer, Summers, and Waldmann [6]. In DeLong et al., noise traders buy when prices have risen and sell when prices have fallen. This creates self-reinforcing trends away from fundamental value as smart traders anticipate their reactions and trade accordingly. The present model, however, has an infinite horizon and focuses on the connections between noise trading and the heteroskedasticity of returns.

Whether the "hot markets" phenomenon can explain the time-series properties of volatility is ultimately an empirical question. In order to test this empirically, both the "hot market" phenomenon and the autoregressive volatility phenomenon must be quantified. The volatility question is addressed by fitting the foreign exchange time series to ARCH and GARCH specifications in order to find a fitted measure of the conditional volatility time series. The "hot market" question requires a measure of the distance between the market price and the fundamental price. In order to find a measure of the fundamental price that does not involve the joint hypothesis of a specific exchange rate model (such as purchasing power parity) various filters are used to separate the permanent trend from a transitory component. The permanent component is taken to be the fundamental value, with the transitory component representing the effect on market price of transitory traders. Several filtering strategies are used to show that the empirical results are robust to the choice of filtering methods.

The next section presents a simple model of the hot markets phenomenon. Section three then describes in more detail the empirical testing strategy, while section four presents the result of those tests. Section five then concludes.

2 Model

This section outlines a general model of the market for a financial asset. The asset itself is a claim on a discrete cash flow stream $\{C_t\}$. The nature of this cash flow will depend on the financial asset. In the case of debt instruments, it would be interest payments. In the case of equity instruments, it may be dividend payouts. We focus on exchange rates, where a natural interpretation of this cash flow stream would be the relative nominal short-term interest rates of the two countries. The amount of this cash flow stream is known with certainty, and the amount of the asset outstanding has been normalized to one unit. The market participants are of two types: uninformed "noise traders", who have an inelastic net demand (or supply) for the asset, and "smart money", who buy (or sell) the asset based on its expected return[1].

Noise traders, who inelastically demand or supply an asset, represent relatively uninformed public involvement in the financial market. In periods where a particular market is already attracting a lot of noise traders, the market is "hot" and receives a lot of publicity. The result is that many noise traders may be attracted, on either side of the market, in the next period. The net demand (in dollars) of these noise traders in time t is thus taken to be some fraction $0 < \alpha < 1$ of those noise traders remaining from period $t-1$, plus a new contingent of noise

[1] A model with "smart money" investors similar to those presented here but without the fad characteristics of the "noise traders" can be found in Shiller [13].

traders whose size is correlated with the previous supply of noise traders:

$$F_t = \alpha F_{t-1} + \delta_t |F_{t-1}| \tag{1}$$

where δ_t is normally distributed with mean zero and variance σ_δ^2. The value of δ_t is not known until period t. This means that the expected value of next period's noise demand is the fraction α of this period's noise demand:

$$E_t F_{t+1} = \alpha F_t \tag{2}$$

The expected value of any future period's noise demand can then be seen iteratively to be:

$$E_t F_{t+i} = \alpha^i F_t \tag{3}$$

The variance of next period's noise supply depends on the current absolute level of noise trading:

$$Var_t(F_{t+1}) = \sigma_\delta^2 (F_t)^2 \tag{4}$$

There are also "smart money" investors whose demand for stock is elastic and increasing in the expected return. Since this paper does not model fundamental risk, variability in the expected return is caused only by the price effects of the noise traders. The smart money demand for shares in any given period is linear in the expected return over the next period:

$$S_t = \frac{(E_t R_t - \rho)}{\varphi} \tag{5}$$

where ρ can be interpreted as a normal rate of return (the shadow cost of capital to the smart money traders) and φ a measure of the risk aversion of the smart money[2]. The expected real return on the asset is the cash flow for one period plus the expected capital gain, expressed as

[2]To traders with finite horizons, the noise traders create price risk even though the asset has no fundamental risk.

fraction of the purchase price:

$$E_t R_t = \frac{C_{t+1} + E_t P_{t+1} - P_t}{P_t} \tag{6}$$

This means the smart money demand can be restated as:

$$S_t = \frac{\left(\frac{C_{t+1}+E_t P_{t+1}-P_t}{P_t} - \rho\right)}{\varphi} \tag{7}$$

In equilibrium, the amount of the asset outstanding (which has been normalized to unity) must equal the smart money demand plus the noise trader net demand (expressed in shares).

$$1 = S_t + \frac{F_t}{P_t} \tag{8}$$

Using equation (7), this can be rewritten as

$$1 = \frac{1}{\varphi}\left(\frac{C_{t+1} + E_t P_{t+1} - P_t}{P_t} - \rho\right) + \frac{F_t}{P_t} \tag{9}$$

This can be solved for the current period's price P_t:

$$\begin{aligned} P_t &= \frac{1}{\varphi}(C_{t+1} + E_t P_{t+1} - P_t - \rho P_t) + F_t \\ \varphi P_t &= C_{t+1} + E_t P_{t+1} - (1+\rho)P_t + \varphi F_t \\ (1+\rho+\varphi)P_t &= E_t P_{t+1} + C_{t+1} + \varphi F_t \qquad (10) \end{aligned}$$

If P_t is unbounded, then (10) can have "bubble"-type solutions. However, we focus on the solution which is not characterized by these bubbles. A sufficient condition for this is to place any upper bound on the expected discounted price of the asset. This yields the unique solution:

$$P_t = \sum_{i=0}^{\infty} \frac{C_{t+i+1} + \varphi E_t F_{t+i}}{(1+\rho+\varphi)^{i+1}} \tag{11}$$

This price can be separated into a "fundamental value" deriving from the claim to the cash flow and a term reflecting the distortions of the transitory traders:

$$P_t = \sum_{i=0}^{\infty} \frac{C_{t+i+1}}{(1+\rho+\varphi)^{i+1}} + \varphi \sum_{i=0}^{\infty} \frac{E_t F_{t+i}}{(1+\rho+\varphi)^{i+1}} \tag{12}$$

Denoting this "fundamental value" as V_t and using equation (3), we can rewrite (12) as:

$$\begin{aligned} P_t &= V_t + \varphi \sum_{i=0}^{\infty} \frac{\alpha^i F_t}{(1+\rho+\varphi)^{i+1}} && (13) \\ &= V_t + \frac{\varphi F_t}{1+\rho+\varphi} \sum_{i=0}^{\infty} \left(\frac{\alpha}{1+\rho+\varphi} \right)^i \\ &= V_t + \frac{\varphi F_t}{1+\rho+\varphi} \left(\frac{1}{1-\frac{\alpha}{1+\rho+\varphi}} \right) \\ &= V_t + \frac{\varphi F_t}{1+\rho+\varphi} \left(\frac{1+\rho+\varphi}{1+\rho+\varphi-\alpha} \right) \\ P_t &= V_t + \frac{\varphi F_t}{1+\rho+\varphi-\alpha} && (14) \end{aligned}$$

Equation (14) means that next period's price is similarly given by:

$$P_{t+1} = V_{t+1} + \frac{\varphi F_{t+1}}{1+\rho+\varphi-\alpha} \tag{15}$$

The expected value of next period's price is increasing in the expected level of noise trader demand:

$$E_t P_{t+1} = V_{t+1} + \frac{\varphi \alpha F_t}{1+\rho+\varphi-\alpha} \tag{16}$$

The variance of next period's price, however, is increasing in the *absolute value* of the noise trader demand:

$$Var_t P_{t+1} = \frac{\varphi}{1+\rho+\varphi-\alpha}\sigma_\delta^2(F_t)^2 \tag{17}$$

Since equation (14) shows that noise traders distort the price P_t away from its fundamental value V_t , the variance of next period's price is increasing in the magnitude of the distortion of this period's price from fundamental value. Combining equations (14) and (17) shows this to be the case:

$$Var_t P_{t+1} = \frac{1+\rho+\varphi-\alpha}{\varphi}\sigma_\delta^2(P_t - V_t)^2 \tag{18}$$

3 Empirical Methods

3.1 Data Description

The previous section derived some theoretical results with testable empirical implications. The data on which this theory will be analyzed is weekly foreign exchange rates. The rates were collected for each Friday close from 1978 through 1997. The country pairs are the United States dollar against each of the other G7 currencies (Canada, France, (the Federal Republic of) Germany, Italy, Japan, and the United Kingdom). In each case, logarithms have been taken of the nominal exchange rate series.

3.2 Testing Strategy

Equation (18) is the key testable implication of this model. "Hot" markets, by virtue of the same public interest which made their prices diverge from fundamental values, are also likely to have more volatile returns. The goal will therefore be to determine whether deviations from fundamental value explain changes in asset price volatility. This introduces three empirical challenges: estimating fundamental value, estimating exchange rate volatility, and determining whether the two are related.

3.2.1 Estimating Fundamental Value

The first empirical challenge is to estimate the "fundamental value" of the asset in question, which in the case of this paper will be the exchange rate. As combining equations (1) and (14) implies, the noise trader's effects on the market price are transitory deviations from fundamental value. This means that a decomposition of the time series into permanent and transitory components offers a plausible method to determine the fundamental value. This will be done using a Hodrick-Prescott filter, a dynamic measure of central tendency which seeks to both match the movements in the time series while maintaining a smooth filtered value. The alternative to this statistical approach would be to pick a specific economic or structural model of "fundamental value". For example, in the context of exchange rates, one could estimate purchasing power parity. Unfortunately, this would then result in the empirical tests being tests of the joint hypothesis of the interpretation of autoregressive volatility offered by this paper and the economic model of fundamental value chosen. In order to focus on the question of time-varying volatility, therefore, a statistical filtering technique rather than a particular economic model has been chosen to estimate fundamental value.

The robustness of the results will be checked by separately subjecting the data to high-pass filters with the threshold set at 26 weeks. The high-pass filter proposed by Baxter and King [1] will be used as well as the modification to the Baxter and King filter proposed by Woitek [14].

3.2.2 Estimating Volatility

The second challenge is to estimate the volatility of the financial market price. It is well known that time series in many financial markets including foreign exchange appear to be heteroskedastic. We therefore seek to control for this effect by fitting the data to a heteroskedastic specification in order to better represent these properties. In order to do this, autoregressive conditional heteroskedasticity (ARCH)[3] and generalized autoregressive conditional heteroskedasticity

[3] See Engle [7]

(GARCH)[4] statistical models have been applied to the data and the resulting fitted variances are used to represent the volatility of the underlying series. The model to be estimated for the innovations to the asset price will be an AR(n) model with ARCH or GARCH errors. Specifying the time series as s_t, this implies that the process is given by:

$$\Delta s_t = a_0 + a_1 \Delta s_{t-1} + a_2 \Delta s_{t-2} + \ldots + a_n \Delta s_{t-n} + \epsilon_t \tag{19}$$

The variance h_t of ϵ_t is given in an ARCH(q) process:

$$h_t = c + q_1 \epsilon_{t-1}^2 + q_2 \epsilon_{t-2}^2 + \ldots + q_q \epsilon_{t-q}^2 \tag{20}$$

Alternatively, a GARCH(p,q) specification that allows for two channels of volatility persistence is also used. Specifically, a GARCH(p,q) specification is one in which an ARCH(q) model is augmented with p lagged terms of the variance term h_t itself, and is given by:

$$h_t = c + p_1 h_{t-1} + p_2 h_{t-2} + \ldots p_p h_{t-p} + q_1 \epsilon_{t-1}^2 + q_2 \epsilon_{t-2}^2 + \ldots + q_q \epsilon_{t-q}^2 \tag{21}$$

Based on the exchange rate data, we find that an AR(2) specification is an adequate time-series representation of the change in the log spot exchange rate.[5] Meanwhile, ARCH(2), ARCH(3), and GARCH(2,3) processes are used to model the conditional variance function.[6] Naturally, the entire data set is used to estimate the parameters in equations (20) and (21). However, once these parameters have been chosen, the fitted variance for each period depends only on lagged disturbance realizations. The present model predicts that deviations from fundamentals impact future volatility. This effect therefore will not appear fully in the ARCH and

[4]See Bollerslev [2]

[5]In most cases, an AR(1) would suffice, but the costs of overparameterizing slightly are small compared to the alternative.

[6]A GARCH(1,3) model yielded unstable results for some currencies due to underparameterization. Hence, an extra lag of h_t was needed.

GARCH specifications for several periods.

3.2.3 Do Deviations from Fundamentals Influence Volatility?

Equation (18) implies that a large (in magnitude) difference between market price P_t and fundamental value V_t will create a large future volatility in the market price. Specifically, the variance should be a linear function of the squared deviation $(P_t - V_t)^2$. To incorporate the lagged effect of observed variance on ARCH-fitted variance and the time needed for a price move to attract public interest, the squared deviation has been lagged by 4 weeks. The ARCH-fitted variance is then regressed on the lagged squared deviation.

3.2.4 Monte Carlo Estimation

An empirical finding that a large deviation from fundamentals results in high subsequent volatility validates the model and thereby provides an economic explanation for the ARCH characteristics of the data.

Intuitively, one would expect even a simple random walk to produce some correlation between its ARCH-fitted variance and its deviation from a filtered trend if the data in fact follow an ARCH specification. This is because a filter which seeks to smooth the series will tend to produce large deviations in the regions of large jumps in the series: at the same time, the ARCH specification necessarily predicts a large variance following large jumps in the series. A random walk with ARCH innovations may have this property to an even greater degree than a random walk with i.i.d. innovations. In order to account for this, Monte Carlo simulations have been run in which a random walk is calibrated to have the same sort of innovations (including both unconditional and conditional variances) as the underlying data series. The possibility that the "hot markets" phenomenon merely a result of this spurious random walk correlation can then be examined by comparing the coefficients from these random walk regressions of conditional variance on filter deviations with the coefficients obtained from the actual foreign exchange data.[7]

This Monte Carlo testing procedure asks not only whether the present model can explain the (G)ARCH properties in the data, but also whether it can improve on this statistical representation. This is done by comparing actual data to a (G)ARCH-calibrated random walk. Indeed, this empirical strategy is quite friendly to the hypothesis that the ARCH specification is complete and the current model has nothing to add. Instead of merely asking whether the present model can improve upon an ARCH model, we are asking whether the present model can improve upon an ARCH model *within an ARCH framework.* Any improvements over the ARCH specifications that the theoretical model predicts that may not be captured by the fitted ARCH variance will not show up in the empirical results. To the extent that the model improves our ability to forecast ARCH variance, then, presents striking evidence in favor of the endogenous noise trading model being offered.

4 Empirical Results

The general result of equation (18) can be tested with a variety of filtering techniques and heteroskedasticity specifications in order to analyze the robustness of the result. If the results are robust to these alternative specifications, then the results can be seen as properties of the data rather than specific techniques.

For each example, logs have been taken of the six nominal exchange rate series. Table 1 shows results for an ARCH(2) specification for the conditional variance. The first results shown use a Hodrick-Prescott filter [12] with the smoothing parameter λ set to 57600.[8] The Hodrick-Prescott filter separates the series into a permanent and transitory component, and this transitory component is used as a measure of the deviation from fundamentals. In accordance

[7]This Monte Carlo specification is even more important when a GARCH specification of variance is used. This is because a large innovation in one period will directly affect the GARCH-estimated variance four periods later. With our four-period lag between deviations and the resulting variance, ARCH(2) and ARCH(3) specifications have too short a memory to for the large innovation to directly affect the ARCH-estimated variance four periods later.

[8]Alternative values for λ were also used and do not qualitatively affect the results.

with equation (18), this deviation is then squared.

The innovations of each series are fitted to an ARCH(2) process, and the q_1 and q_2 terms from equation (20) are shown in the first two rows. This generates a fitted conditional variance series, which is then regressed on the squared deviation (lagged four weeks) and twelve lagged values of the fitted conditional variance (to eliminate serial correlation). The β value shown in the third row of Table 1 is the coefficient on the lagged squared deviation, and the standard error is shown below, with the associated and p-value for the hypothesis that $\beta = 0$. Notice that in each case, these results are statistically significant at the 5% level, and generally at statistical significance levels well above that. This evidence is supportive of the hypothesis of the present model, that deviations from fundamentals affect future volatility in prices.

However, this evidence is not sufficient in itself to distinguish from an alternative, less well-defined hypothesis: that there is some other unobserved force which happens to generate ARCH properties in the data, and that ARCH innovations *inherently* generate the sort of results for β being generated here. Indeed, at least the second half of this alternative hypothesis has intuitive appeal: a large shock in one period will tend to generate a large deviation from the smooth trend. At the same time, with an ARCH process, the same large shock will generate high future conditional variance. Deviations and future conditional variance will therefore be correlated.

In order to control for this alternative hypothesis, Monte Carlo simulations have been run. In each case, a random walk calibrated with the ARCH parameters q_1 and q_2 found in the actual data is generated. This random series is then treated just as if it was actual data: first the series is detrended to calculate squared deviations and the conditional variance series is estimated. Then the conditional variance is regressed on the lagged squared deviation (with lagged dependent variables, as above) regressed for a β_{MC} coefficient. 1,000 iterations were conducted for each currency, and the results are shown as the Monte Carlo β_{MC} values. P-values are then presented for the hypothesis that the actual data β_D values equal the Monte Carlo β_{MC} values, based on the actual data standard errors.

The results are that for each of the six currencies, as the model predicts, the β_D value is a larger positive number with the actual data than in a Monte Carlo simulation, or $\beta_D > \beta_{MC}$. The statistical significance of this result varies, being significant at the 1% level for four of the six currencies but not significant for the other two. Taken as a whole, however, these results represent broad support for the model, particularly given the stringent nature of the empirical strategy discussed earlier. The "hot markets" phenomenon appears to be an empirical regularity of the exchange rate data, beyond what a random walk with ARCH errors could account for.

The next part of Table 1 presents results of the same process using a high-pass filter in place of the Hodrick-Prescott filter. As outlined in Baxter and King [1], a high-pass filter attempts to separate the dynamics having a frequency below some threshold (in this case, 26 weeks) from dynamics having a frequency above that threshold. Separating low from high frequency movements thus determines the series' permanent and transitory components.

The same ARCH parameters obtain since the series has its conditional volatility estimated separately from the detrending calculations. Again, the data coefficients β_D are positive for each currency, and significantly (at 1%) greater than zero for five of the six currencies (the Deutsche mark just misses the 5% level). The significance level against the Monte Carlo values β_{MC}, however, is different. The yen, pound, and lire continue to be highly significant, with p-values of no more than 0.1%. The French franc is now also significant at the 5% level. However, the Deutsche mark and Canadian dollar coefficients are insignificant, and the Canadian dollar is now (by a small margin) generating a result (which is not significant) on the "wrong" side of its Monte Carlo simulations. Taken as a whole, however, the results remain reasonably encouraging.

Table 2 repeats the same process as Table 1, except that the conditional volatility is now modeled as an ARCH(3) process. With the Hodrick-Prescott filters, the results are strikingly similar to Table 1. The parameter values β_D from the actual data, the parameter values β_{MC} from the generated data, and the statistical coefficients are quite similar to the ARCH(2) results.

The inference is that the results are robust to alternative ARCH specifications. Similarly, the results using the Baxter-King high-pass filter are similar to those in Table 1. The only dramatic change is in the case of the Deutsche mark, which is now showing *more* signs of "hot markets" than its Monte Carlo counterpart. All six currencies now have a stronger "hot markets" effect in the actual data than in calibrated ARCH(3) random walks, and in four of the six cases the results are statistically significant. This suggests that the insignificance (and marginal failure of the ARCH(2)-calibrated Deutsche mark) of some results may be due primarily to excessively parsimonious representations of the conditional variance.

Finally, a GARCH(2,3) has been analyzed and the results reported in Table 3. For the Hodrick-Prescott filters, the data reports results which are always greater than zero at a 5% significance level, and aside from the Canadian dollar, at a 0.1% significance level. Four of the six currencies show results different than their Monte Carlo estimates at the 1% significance level, and all currencies have results whose point estimates are stronger than the GARCH random walk can explain. The qualitative results are quite similar when the Baxter-King high pass filter is applied instead.

Woitek [14] has proposed a modification to the Baxter-King filter to ameliorate side lobe problems. As a further robustness check, the results have been computed once again using his algorithm. The bottom of each of Tables 1, 2, and 3 show the results, which are very close to the unmodified Baxter-King filter results, demonstrating further robustness of the results.

5 Conclusion

This paper has presented a model of "hot markets". In the model presented, non-informational "noise traders" are attracted in larger number (on either side of the market) to markets which are currently "hot", that is, moving away from their long-term fundamental values. The model generates the testable prediction that a large deviation from fundamentals will increase future volatility in the prices.

The model therefore offers an economic interpretation of autoregressive conditional heteroskedasticity (ARCH) and generalized autoregressive conditional heteroskedasticity (GARCH) models. Importantly, however, the empirical tests on G7 foreign exchange rate data not only validate this economic interpretation, but also show that the model can improve on statistical ARCH/GARCH models which do not incorporate this economic phenomenon.

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ARCH(2) Parameters						
	Japan	Germany	Britain	France	Canada	Italy
Q_1	0.1210	0.1557	0.1947	0.2108	0.2158	0.3543
Q_2	0.0549	0.1754	0.0832	0.1289	0.0240	0.1454
Hodrick-Prescott Filter						
	Japan	Germany	Britain	France	Canada	Italy
β_D	0.00595	0.00512	0.01757	0.01027	0.00599	0.04510
	(0.00103)	(0.00172)	(0.00152)	(0.00211)	(0.00295)	(0.00351)
$p(\beta_D = 0)$	0.000	0.003	0.000	0.000	0.042	0.000
β_{MC}	0.00180	0.00351	0.00328	0.00391	0.00349	0.00930
$p(\beta_D = \beta_{MC})$	0.000	0.351	0.000	0.003	0.397	0.000
Baxter-King Filter						
	Japan	Germany	Britain	France	Canada	Italy
β_D	0.02215	0.00998	0.07049	0.02903	0.02107	0.18008
	(0.00358)	(0.00541)	(0.00620)	(0.00665)	(0.00787)	(0.01388)
$p(\beta_D = 0)$	0.000	0.065	0.000	0.000	0.008	0.000
β_{MC}	0.00817	0.01417	0.01396	0.01543	0.01513	0.03248
$p(\beta_D = \beta_{MC})$	0.000	*0.439*	0.000	0.041	0.451	0.000
Baxter-King-Woitek Filter						
	Japan	Germany	Britain	France	Canada	Italy
β_D	0.02340	0.01004	0.07376	0.02997	0.02220	0.18880
	(0.00379)	(0.00566)	(0.00656)	(0.00696)	(0.00827)	(0.01469)
$p(\beta_D = 0)$	0.000	0.077	0.000	0.000	0.007	0.000
β_{MC}	0.00857	0.01477	0.01457	0.01607	0.01583	0.03366
$p(\beta_D = \beta_{MC})$	0.000	*0.404*	0.000	0.046	0.441	0.000

Notes: The top panel contains the ARCH(2) parameters Q_1 and Q_2, as described in the text. The next panel has the results of regressing conditional variance on squared deviations, where deviations have been calculated using the Hodrick-Prescott [12] filter. The deviations are lagged four periods. The results are shown both for the actual data (β_D) and for the Monte Carlo results (β_{MC}) of random walks with the same ARCH coefficients. The third panel repeats the analysis of the second panel using the Baxter-King [1] high-pass filter with a threshold of 26 weeks. The bottom panel repeats this analysis again using Woitek's [14] modifications to the Baxter-King filter.

Table 1: ARCH(2) Results

	Japan	Germany	Britain	France	Canada	Italy
ARCH(3) Parameters						
Q_1	0.1230	0.1164	0.1959	0.1866	0.1453	0.3433
Q_2	0.0547	0.1430	0.0497	0.1233	0.0326	0.1324
Q_3	0.0002	0.1342	0.1647	0.0787	0.1337	0.1848
Hodrick-Prescott Filter						
	Japan	Germany	Britain	France	Canada	Italy
β_D	0.00606	0.00555	0.01807	0.00908	0.00443	0.04399
	(0.00104)	(0.00132)	(0.00152)	(0.00187)	(0.00206)	(0.00342)
$p(\beta_D = 0)$	0.000	0.000	0.000	0.000	0.032	0.000
β_{MC}	0.00164	0.00293	0.00364	0.00364	0.00282	0.01027
$p(\beta_D = \beta_{MC})$	0.000	0.047	0.000	0.004	0.436	0.000
Baxter-King Filter						
	Japan	Germany	Britain	France	Canada	Italy
β_D	0.02257	0.01731	0.07354	0.02568	0.01616	0.17562
	(0.00365)	(0.00413)	(0.00621)	(0.00590)	(0.00551)	(0.01350)
$p(\beta_D = 0)$	0.000	0.000	0.000	0.000	0.003	0.000
β_{MC}	0.00779	0.01163	0.01729	0.01408	0.01270	0.03052
$p(\beta_D = \beta_{MC})$	0.000	0.169	0.000	0.049	0.531	0.000
Baxter-King-Woitek Filter						
	Japan	Germany	Britain	France	Canada	Italy
β_D	0.02384	0.01799	0.07697	0.02652	0.01708	0.18412
	(0.00386)	(0.00432)	(0.00658)	(0.00617)	(0.00578)	(0.01428)
$p(\beta_D = 0)$	0.000	0.000	0.000	0.000	0.003	0.000
β_{MC}	0.00818	0.01215	0.01836	0.01466	0.01337	0.03140
$p(\beta_D = \beta_{MC})$	0.000	0.177	0.000	0.055	0.522	0.000

Notes: See the notes to Table 1, except that the conditional variance is now modeled as an ARCH(3) process.

Table 2: ARCH(3) Results

GARCH(2,3) Parameters						
	Japan	Germany	Britain	France	Canada	Italy
Q_1	0.1390	0.1152	0.1547	0.1840	0.1157	0.3300
Q_2	0.0000	0.0704	0.0000	0.1143	0.0317	0.0000
Q_3	0.0089	0.0956	0.0416	0.0143	0.1049	0.0507
P_1	0.4706	0.4003	0.3579	0.0000	0.0668	0.4370
P_2	0.0122	0.0000	0.3567	0.3830	0.2863	0.1497
Hodrick-Prescott Filter						
	Japan	Germany	Britain	France	Canada	Italy
β_D	0.00685	0.00458	0.01423	0.00897	0.00353	0.04238
	(0.00118)	(0.00114)	(0.00122)	(0.00184)	(0.00164)	(0.00329)
$p(\beta_D = 0)$	0.000	0.000	0.000	0.000	0.032	0.000
β_{MC}	0.00217	0.00265	0.00313	0.00359	0.00245	0.00978
$p(\beta_D = \beta_{MC})$	0.000	0.090	0.000	0.003	0.510	0.000
Baxter-King Filter						
	Japan	Germany	Britain	France	Canada	Italy
β_D	0.02555	0.01269	0.05842	0.02542	0.01300	0.16990
	(0.00412)	(0.00359)	(0.00497)	(0.00582)	(0.00437)	(0.01300)
$p(\beta_D = 0)$	0.000	0.000	0.000	0.000	0.003	0.000
β_{MC}	0.00932	0.01019	0.01103	0.01286	0.01045	0.02570
$p(\beta_D = \beta_{MC})$	0.000	0.486	0.000	0.031	0.559	0.000
Baxter-King-Woitek Filter						
	Japan	Germany	Britain	France	Canada	Italy
β_D	0.02699	0.01314	0.06094	0.02625	0.01376	0.1775
	(0.00436)	(0.00376)	(0.00525)	(0.00608)	(0.00459)	(0.0137)
$p(\beta_D = 0)$	0.000	0.005	0.000	0.000	0.003	0.000
β_{MC}	0.00976	0.01065	0.01153	0.01337	0.01103	0.02645
$p(\beta_D = \beta_{MC})$	0.000	0.509	0.000	0.034	0.553	0.000

Notes: See the notes to Table 1, except that the conditional variance is now modeled as a GARCH(2,3) process.

Table 3: GARCH(2,3) Results