Asymmetric Volatility in the Foreign Exchange Markets

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Abstract

This paper explores the presence and characteristics of the asymmetric return-volatility relationship (i.e. asymmetric volatility) in bilateral exchange rates and trade weighted indices (TWI). We find evidence of asymmetric volatility in daily realized volatilities of AUD, GBP, and JPY against USD, as well as daily GARCH-estimated volatilities of their TWI. The asymmetry in bilateral exchange rates is weaker than it is in TWI. For a given currency, the asymmetry is stable in one direction and persists over periods of several years. It is driven by the continuous component, not the jump component, of realized volatility. However, for different currencies the asymmetry is in different directions: Volatilities of AUD and GBP increase when they depreciate against USD; but volatility of JPY increases following JPY appreciation. The statistical properties of EUR are quite different from the other currencies. Its returns against USD appear to be normally distributed with no fat tails. Its volatility has much lower short-term persistence. There is no asymmetric volatility in EUR against USD and its TWI. We also document a strong impact from long-run price trend to daily realized volatility. The impact is stronger than past volatilities aggregated at different time intervals. Our findings call for alternative economic explanations for asymmetric volatility in exchange rates.

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I. Introduction

It is well known that volatility in equity markets is asymmetric, i.e. negative returns are associated with higher volatility than positive returns. Robert Engle in his 2003 Nobel Lecture emphasizes the importance of asymmetric volatility. For a portfolio of S&P500 stocks, Engle (2004) shows that ignoring the asymmetry in volatility leads to a significant underestimation of the Value at Risk (VaR). In the foreign exchange markets, however, the consensus seems to be that there is no asymmetric volatility. Bollerslev, Chou, and Kroner (1992) suggest that "[W]hereas stock returns have been found to exhibit some degree of asymmetry in their conditional variances, the two-sided nature of the foreign exchange market makes such asymmetries less likely." All of the studies in their survey adopt symmetric models for exchange rate volatility. Since then the theoretical advances in volatility models, together with the availability of intraday exchange rate data, led to a proliferation of studies of exchange rate volatility. Almost all of them do not consider asymmetric volatility models. Recently Andersen, et al. (2001, 2003) (ABDL hereafter) provide an extensive examination of the statistical properties and the modeling and forecasting of realized volatility of foreign exchange rates. However the possibility of asymmetric volatility is yet to be investigated.

The "two-sided nature of the foreign exchange market" is probably the primary reason for the overwhelming choice of symmetric models for exchange rate volatility. By definition, bilateral exchange rates are ratios of currency values: positive returns for one currency are necessarily negative returns for the other. As such it seems that the link between exchange rate return and volatility should be symmetric. Furthermore, the standard explanations for asymmetric volatility in equity markets, i.e. the leverage effect and the volatility feedback effect, do not appear to be applicable to exchange

rates. The debt-to-equity ratios in equity markets vary from zero to several hundred percent. But the debt-to-GDP ratios for most countries are below 5%, and the debt-to-national asset ratios are much lower. If an investor anticipates higher volatility, say for USD/AUD rate, it is unclear whether she should sell USD or AUD if she holds both currencies. Empirically, the standard asymmetric GARCH models regularly detect asymmetric volatility in daily equity returns. However these models typically fail to detect asymmetry in daily exchange rate volatility. This may be an important factor in model selection in favor of symmetric volatility models.

Despite the apparent symmetry in bilateral exchange rates, currencies are not symmetric: some have greater economic importance than others. For example, many companies and financial institutions use USD as the base currency for profit and loss calculations but few uses AUD. For these institutions, higher expected USD/AUD volatility implies greater risk in AUD-denominated assets but not in USD-denominated assets. This may lead to the sale of AUD-denominated assets, which lowers USD/AUD exchange rate. This base-currency effect is similar to the volatility feedback effect in equity markets. It is likely to be stronger in some currencies than in others. For example, higher expected USD/EUR volatility may lead Europeans to sell USD-denominated assets and Americans to sell EUR-denominated assets. To the extent that the Euro area and the United States are of similar sizes and levels of economic development, the base-currency effect should be weaker for the USD/EUR rate than it is for other currencies. Another unique feature of the foreign exchange markets is central bank intervention. It is well known that interventions are associated with higher volatility. As central banks intervene on one side of the market but not the other, interventions may lead to an asymmetric relationship between exchange rate return and volatility. For example the Bank of Japan is known to be a heavy seller of JPY over

our sample period. If the selling slows down the speed of JPY appreciation, then the higher volatility from intervention is associated with a lower JPY/USD rate. If the selling leads to a lower value for JPY, thus a higher JPY/USD rate, then there should be a positive relationship between the JPY/USD rate and its volatility. Finally Avramov, et al. (2006) show that contrarian and herding investors can cause asymmetric volatility in stock markets: herding trades increase volatility as prices decline while contrarian trades reduce volatility following price increases. Since contrarian trading and herding are present in the foreign exchange markets, e.g. Gençay, et al. (2003) and Carpenter and Wang (2006), one would also expect the presence of asymmetric volatility.

This study tests for the presence of asymmetric volatility in major world currencies. The issue is important for several reasons. First, the foreign exchange markets are several times larger than the equity markets and present a substantial risk to investors. As argued by Engle (2004), the presence of asymmetric volatility, if unaccounted for, will lead to the underestimation of the Value at Risk. Second, an empirical examination of asymmetric volatility will enhance our understanding of exchange rate dynamics, particularly in the second moment. This in turn may improve volatility forecasting and derivative pricing. Third, the presence of asymmetric volatility invalidates the standard normality results associated with a continuous diffusion price process (Andersen, Bollerslev, and Dobrev, 2005, Barndorff-Nielsen and Shephard, 2006). These results are used in testing for jumps in volatility, e.g. Huang and Tauchen (2005). Last but not least, the presence of asymmetric volatility will challenge the traditional economic explanations for asymmetric volatility in equity markets and call for alternative explanations for the foreign exchange markets.

Studies on asymmetric volatility in the foreign exchange markets are relatively scarce. An early study by Hsieh (1989) shows that EGARCH models produce slightly

smaller residual kurtosis than GARCH models, while other diagnostics are similar. Byers and Peel (1995) document asymmetric volatility in European exchange rates during 1922-1925. Asymmetric volatility has been found in Malaysian ringgit (Tse and Tsui, 1997), Australian dollar (McKenzie, 2002), and Mexian peso (Adler and Qi, 2003), all against US dollar. Recently Ederington and Guan (2005) reports marginally smaller forecasting errors for JPY/USD using EGARCH relative to GARCH. While not directly examining exchange rate volatility, Andersen, et al. (2003) shows asymmetric responses of major exchange rates to economic announcements in the United States: bad news leads to greater exchange rate movements than good news. A natural question to ask is whether such asymmetry holds for exchange rate volatility.

Our study makes several contributions to the literature on exchange rate volatility. First, we test for the presence of asymmetric volatility in the trade weighted indices (TWI) and in realized volatility of bilateral exchange rates. TWI measures changes in the absolute value of a currency and is an important input for monetary policies as well as investment decisions. The dynamics of TWI, particularly in the second moment, has not been examined in the literature. Realized volatility is an unbiased and highly efficient estimator of the underlying integrated return volatility. It should capture any asymmetric relationship between return and integrated volatility that may have been missed in less-efficient volatility measures. This leads to our second contribution. We draw direct comparison between realized volatility and daily GARCH estimated volatility in terms of statistical properties and short-term dynamics. Despite a rapid expansion of studies on realized volatility, "the relationship between these models and the standard daily ARCH-type modeling paradigm is not yet fully understood, neither theoretically nor empirically." (Andersen, Bollerslev, and Dobrav, 2005). Third, our test for asymmetric volatility is based on a dynamic model of realized

volatility that encompasses the impact of the long-run volatility as well as the long-run price trend. The long memory in volatility has been documented by many studies since Ding, et al. (1993). The association between price trend and volatility has been explored by Müller, et al. (1997), Campa, et al. (1998), and Johnson (2002) among others. We separately identify the impact of long-term price trend from the asymmetric impact of return innovations. Fourth, using the nonparametric procedure proposed by Barndorff-Nielsen and Shephard (2006), we decompose realized volatility into a continuous component and a jump component. Understanding the jump component is important for a range of investment decisions, from asset allocation (Liu, Longstaff, Pan, 2003) to option pricing (Eraker, et al., 2003). We examine which component is associated with volatility asymmetry.

Our analysis is based on intraday quotes for AUD, EUR, GBP, and JPY against USD, over a period of eight years from January 1996 to March 2004. The empirical results reveal several new regularities in exchange rate volatilities. First asymmetric volatility is present in bilateral rates of AUD, GBP, and JPY against USD. For a given bilateral rate, the asymmetry is stable in one direction and persists over periods of several years. It is driven by the continuous component, not the jump component, of realized volatility. However, the asymmetry is in different directions for different currencies: volatility is higher for AUD and GBP when these currencies depreciate against USD, but is higher for JPY when JPY appreciates against USD. To our knowledge this has not been documented elsewhere and the economic explanations are yet to be explored. Second, we find a strong and increasing impact from weekly, monthly, and quarterly absolute returns to daily realized volatility, and the impacts of long-run absolute returns are larger than those of lagged realized volatilities aggregated at different time intervals. Although Müller, et al. (1997) document a significant impact

from squared long-run return (up to 12 weeks) to half-hourly volatility, the impact coefficients diminish with time aggregation and past volatilities are not included. Our finding is clearly different from GARCH models where daily volatility is mostly explained by past daily volatility. Third, the statistical properties of EUR appear to defy the stylized facts for other currencies and financial assets, e.g. fat tails and volatility clustering. Its returns appear to be normally distributed with no significant skewness and kurtosis. Its realized volatility has much lower short-term persistence. Contrary to the idea of information spillover from major to minor currencies, e.g. Hong (2001) and Evans and Lyons (2002), we find no volatility spillover from EUR to any of the other currencies at daily frequency; there is no asymmetric volatility in EUR. Overall these findings call for theoretical exploration for the presence of asymmetric volatility in exchange rates and for the relationship between price trend and volatility.

Section II provides details on the data, the calculation of daily realized volatility, and summary statistics of daily returns and realized volatility. Section III compares daily realized volatility with GARCH-estimated volatility and explores why asymmetric GARCH models fails to capture the asymmetry in realized volatility. Tests and robustness checks for asymmetric volatility are carried out in section IV. We conclude in section V.

II. Data and Preliminary Analysis

Our primary data are intraday Reuters FXFX quotes for AUD, EUR, GBP, and JPY, all against USD, kindly provided by the Securities Industry Research Center of Australia (SIRCA). The samples for AUD, GBP, and JPY are from 1 January 1996 to 31 March 2004 for a period over eight years. The sample for EUR goes from 1 January 1999 to 31 March 2004 for a period over five years. AUD, GBP and EUR are quoted as USD/AUD, USD/GBP, and USD/EUR respectively, while JPY is quoted as

JPY/USD. Quotes are filtered for anomalies, e.g. out-of-range price or spread. Daily exchange rates and the trade-weighted indices (TWI) are also used for our analysis and are downloaded from DataStream for the same currencies and over the same sample periods as above. DataStream provides daily exchange rates on all weekdays sampled at different times over the trading day for different currencies.

Construction of Daily Return and Realized Volatility

Reuters quotes are used for the construction of daily return and realized volatility. We adopt the same 30-minute sampling interval as ABDL (2003) as they argue that "the use of equally-spaced thirty-minute returns strikes a satisfactory balance between the accuracy of the continuous-record asymptotics underlying the construction of our realized volatility measures on the one hand, and the confounding influences from microstructure frictions on the other."[1] We first calculate the midpoint of the bid and ask quotes at each 30-minute interval as the linear interpolation of the quotes immediately before and after the 30-minute time stamp. Following the convention in Bollerslev and Domowitz (1993) and ABDL (2003), a trading day starts at 21 GMT, or 4pm New York time, and ends at 21 GMT on the next day. Weekend quotes, from 21 GMT on Friday to 21 GMT on Sunday, are excluded. Half-hourly returns are the log-difference of half-hourly prices. Daily returns are the sum of half-hourly returns over the trading day. Daily realized volatility is the sum of squared half-hourly returns over a trading day. Numerically the return series are expressed in percentage, not decimals; therefore the volatility series contain a factor of 10^4. Sometimes a trading day has less

[1] Recently several studies have proposed procedures for removing microstructure noise, e.g. Ait-Sahalia, et al. (2005), Bandi and Russel (2005), and Hansen and Lunde (2006). Hansen and Lunde (2006) report that at 20-30 minute sampling intervals, microstructure noise is independent of asset prices, and such independence fails at higher frequencies. Barndoraff-Nielsen and Shaphard (2006) show that the difference in realized volatilities from alternative sampling frequencies, e.g. 1 minute versus 10 minutes, is theoretically small. Empirically correcting microstructure noise does not appear to improve volatility forecasting, according to Ghysels and Sinko (2006).

than 48 half-hourly observations due to holiday in part of the world, slow trading, or Reuters system stoppage. If a trading day has more than 3.5 hours of missing data, we exclude the day from our sample. This process leads to 1920 daily observations for AUD, 1925 for GBP, 1935 for JPY, and 1217 for EUR.

Descriptive Analysis

Table 1 provides a brief summary of quote activities. Based on a sample from December 1986 to June 1999, ABDL (2003) report the average daily number of quotes around 2000 for JPY and 4500 for Deutschemark. The quote intensity has increased substantially since. EUR is clearly the most active currency. The median number of quotes for EUR is over three times the quotes for JPY, over five times the quotes for GBP, and approximately twenty-five times the quotes for AUD.

Figure 1 depicts the exchange rates and the realized volatility over the sample period. The most notable feature from Figure 1 is the exceptionally high volatility for JPY in early October 1998. On October 7, 1998, JPY jumped from around 130 to 120 in one day. Our realized volatility measure is 11.3 for October 7 and 34.6 for October 8. Both AUD and GBP experienced high volatility on these days. Since this is regarded as "once-in-a-generation" volatility[2], these two days are treated as outliers and are removed for the econometric analysis in the following sections.

Table 2 provides some summary statistics for three daily samples: (1) daily returns based on Reuters quotes at 21 GMT, (2) daily returns sampled at different times by DataStream, and (3) daily TWI returns from DataStream. Our EGARCH estimation is based on daily bilateral and TWI returns from DataStream. The statistical properties of all three samples are very similar. Compared to standard deviations, the daily means are approximately zero. Volatility and kurtosis rankings are the same for all three

[2] See Cai, et al. (2001) for events surrounding these days.

samples. GBP has the lowest volatility; EUR has the lowest kurtosis; and JPY is the highest in both. JPY returns are left skewed partially due to the large one-day jump in October 1998[3]. The Ljung-Box statistics show not significant autocorrelation in daily returns but strong autocorrelation in squared returns. As expected, TWI return volatilities are lower than volatilities against USD. AUD TWI returns show negative skewness not present in USD/AUD rate. Interestingly the raw daily return distribution of EUR appears to be different from the other currencies. Its kurtosis is less than 3, indicating no fat tails in return distribution. The Ljung-Box statistics for squared returns are much lower than other currencies and is marginally significant (critical value is 40 at 99.5% significance), indicating relatively little persistence in volatility.

Table 3 reports summary statistics for daily realized volatility and logarithmic daily realized volatility. The ranking of the average realized volatility is consistent with daily return statistics in Table 2. The average realized volatility for JPY, 0.540, is very similar to the average realized volatility for the 1986-1996 period, 0.538, reported in ABDL (2001). However JPY has the highest "volatility of volatility", partially due to the "once-in-a-generation" volatility in October 1998. EUR has much lower realized volatility and "volatility of volatility" than Deutsch Mark (DEM) in the earlier sample. The Ljung-Box statistics shows that realized volatility is highly persistent after 20 days for all four currencies. The volatility of JPY was highly correlated with those of AUD and GBP before the introduction of EUR in 1999. But the correlations dropped sharply after EUR. The correlation between JPY and EUR volatilities (0.252) is much lower than the correlation between JPY and DEM volatilities (0.539) reported by ABDL (2001). The bottom panel summarizes logarithmic daily realized volatility, which is the primary variable we study. The skewness and the kurtosis indicate that logarithmic

[3] After removing the outliers, the skewness of JPY drops -1.004 to -0.513.

realized volatility is approximately normally distributed. Logarithmic realized volatility has higher Ljung-Box statistics than realized volatility, which in turn has higher Ljung-Box statistics than squared returns. These characteristics are consistent with the findings for DEM/USD and JPY/USD by ABDL (2001, 2003). Figure 2 shows the autocorrelation function of the logarithmic volatility for lags up to 100 days. AUD has the slowest decay among four currencies. JPY appears to have slower decay than reported in ABDL (2001, 2003). EUR has lower autocorrelations in the first 15 lags than the other currencies. This is reflected in the lower Q(20) values. But in the long run, it has similar autocorrelation function as GBP. The autocorrelations are significantly different from zero even after 100 days.

III. Asymmetric GARCH Models and Realized Volatility

Previous studies have found no persistent volatility asymmetry in the foreign exchange markets. We revisit this issue using daily exchange rates from DataStream. Two asymmetric GARCH models are deployed to test for asymmetric volatility. The first is the exponential GARCH model of Nelson (1991) with the following specification for the variance equation:

(1) $$\ln(h_t) = \omega + \alpha \ln(h_{t-1}) + \beta\left[\left| r_{t-1} \right| \Big/ \sqrt{h_{t-1}} - \sqrt{2/\pi} \right] + \gamma\left(r_{t-1} \Big/ \sqrt{h_{t-1}} \right)$$

where h_t is the estimated daily return variance and r_t is daily return. The second model is that of Glosten, Jaganathan, and Runkle (1993, GJR hereafter):

(2) $$h_t = \omega + \alpha h_{t-1} + \beta r_{t-1}^2 + \gamma S_{t-1} r_{t-1}^2$$

where S_t=1 if r_t<0; S_t=0 otherwise. Engle and Ng (1993) show that EGARCH and GJR are superior relative to other asymmetric volatility models. In both models, the coefficient γ captures the asymmetric effect of return on volatility.

The EGARCH estimation results are reported in top panel of Table 4. The covariance matrix is estimated via Newey-West covariance matrix with the bandwidth selected by the automatic bandwidth estimator of Andrews (1991) using the Bartlett kernel. The coefficients ω, α, and β are highly significant for almost all currencies. EUR shows some differences from the other currencies. Its parameters are noisier, resulting in an insignificant ω and lower t-statistics for α and β than the others. The coefficient for asymmetric volatility, γ, is only significant for JPY. The GJR estimation results (not reported here) show that none of the coefficients for asymmetric volatility is significant. Overall the results show no significant asymmetry in the GARCH-estimated volatility in the foreign exchange markets.

The traditional explanation for the lack of asymmetric volatility is that exchange rates are relative prices: good news for AUD is bad news for USD and vice versa. The rise and fall of a currency is not measured by changes in bilateral exchange rates, but rather by changes in the trade-weighted index (TWI). Therefore any asymmetric relationship between currency value and its volatility should be reflected in the volatility of TWI returns. We test this hypothesis and report the EGARCH estimation results for TWI returns in the middle panel of Table 4. Indeed TWI return volatilities show significant asymmetry for AUD, GBP, and JPY. The asymmetry is not in the same direction. When AUD depreciates, its volatility is higher than normal. But when GBP and JPY depreciate, their volatilities are actually lower. There is no asymmetric volatility in the TWI returns of EUR. The results confirm that volatility asymmetry is stronger in TWI than it is in bilateral exchange rates.

An alternative explanation for failing to detect asymmetric volatility is that the GARCH-estimated daily volatility is not a good volatility measure. A better volatility measure, such as the realized volatility estimated from intraday returns, may capture the

asymmetric relationship between return and volatility. This conjecture is tested using the EGARCH specification for daily realized volatility, rv_t:

$$\ln(rv_t) = \omega + \alpha \ln(rv_{t-1}) + \beta\left(\left| r_{t-1} \right| \Big/ \sqrt{rv_{t-1}} \right) + \gamma\left(r_{t-1} \Big/ \sqrt{rv_{t-1}} \right) + \xi_t \tag{3}$$

The results are shown in the bottom panel of Table 4. Indeed when volatility is measured using intraday returns, we find that the asymmetric coefficient γ is highly significant for AUD, GBP, and JPY, as in the case for TWI[4]. The EGARCH-RV model of equation (3) produces smaller but more significant unconditional volatility e^{ω}. It has much lower α therefore the realized volatility is less persistent than the EGARCH-estimated volatility. Even though that volatility asymmetry is weaker in bilateral exchange rates, the results suggest that it is present in realized volatility for bilateral exchange rates, but not in GARCH-based volatility estimates. The exception is EUR, which does not show any asymmetry.

Why do asymmetric GARCH models fail to capture the asymmetry that appears to be in the realized volatility? The realized volatility is constructed using high frequency observations and in theory, it can capture all available information in a trading day. As such it is an unbiased and highly efficient estimator of the daily integrated volatility, and is able to reveal the subtle volatility-return asymmetry. On the other hand, the GARCH models may be interpreted as consistent filters for the conditional volatility (Nelson, 1992). As the length of the time interval for returns approaches to zero, the GARCH volatility approaches the true conditional volatility in continuous time, comparable to the fitted portion on the right hand side of equation (3).

[4] GBP TWI and the USD/GBP rate have opposite asymmetries: volatility is higher when GBP rises in TWI and when GBP falls against USD. This highlights the difference between bilateral rates and TWI. One possible explanation is that a rising USD, measured by USD TWI, is associated with a lower USD/GBP rate (daily return correlation -0.459). A higher USD/GBP volatility may reflect the market's concern over high USD value. Indeed an EGARCH estimation for USD TWI shows that USD TWI volatility rises with USD TWI value, same as GBP TWI. The daily return correlation between USD TWI and GBP TWI is 0.119, so there is little spillover between them.

One would expect that GARCH models at high frequencies to capture return-volatility asymmetry as in (3). However, when GARCH models are based on daily returns, there is no reason to expect the GARCH volatility to be close to the fitted portion of equation (3), which is asymmetrically related to the lagged return.

In Figure 3, which depicts the realized volatility and EGARCH-based volatility for AUD, the contrast between the two measures of volatility is dramatic. The summary statistics of EGARCH volatility are presented at the bottom panel of Table 3. Compared to realized volatility, EGARCH volatility has similar medians but much smaller standard deviations. The skewness and kurtosis of EGARCH volatility are much lower than realized volatility, but the autocorrelations at 20 lags are much larger than realized volatility. As conditional expected volatility, EGARCH volatility is much smoother and more persistent than realized volatility. The realized volatility mainly consists of three components: the true conditional volatility, the contemporaneous disturbance (approximately ξ_t in (3)), and a jump component (large unexpected change in price). One might suspect that the asymmetry identified in (3) was caused by the jump component. However, we show later on (Table 10) that the asymmetry found in (3) remains when the jump component is eliminated from the realized volatility.

IV. Testing for Asymmetric Volatility

The EGARCH(1,1) specification for realized volatility in equation (3) serves to draw direct comparison with the EGARCH-estimated volatility. However it does not capture some important features in volatility such as the long-memory effect in volatility demonstrated in Figure 2. Traditionally the long-memory effect is captured by fractional integration models. Müller, et al. (1997) proposes a Heterogeneous ARCH (HARCH) model for volatilities of different time resolutions. The model has its root in the "heterogeneous market hypothesis" of Müller, et al. (1993). It provides an

easy way to capture the long-memory effect in volatility. Corsi (2004) adapts the HARCH specification to realized volatility and shows that the HAR-RV model provides superior volatility forecasting performance. A nice feature of the HAR-RV model is that testing for asymmetry, which in GARCH models requires an auxiliary regression (see Engle and Ng, 1993), simply becomes a regression coefficient significance test. In this section we propose a modified HAR-RV model to test for asymmetric volatility in exchange rates.

The Modified HAR-RV Model

The basic HAR-RV model includes past volatilities aggregated over different time horizons as explanatory variables. Let rv_t^D be the realized volatility on day t. The average realized volatility in the past h days (including day t) is $rv_{t,h} = \frac{1}{h}\sum_{s=t-h+1}^{t} rv_s^D$. We denote the average weekly (h=5), monthly (h=22), and quarterly (h=66) volatilities as rv_t^W, rv_t^M, and rv_t^Q respectively. The HAR-RV model of Corsi (2004) is given by $rv_t^D = \omega + \sum_{k=D}^{Q} \alpha^k rv_{t-1}^k + \xi_t$ where k = D (day), W (week), M (month), and Q (quarter).

To test for any asymmetric impact from return to volatility, we modify the basic HAR-RV model by including the lagged daily return as an explanatory variable:

$$\ln(rv_t^D) = \omega + \sum_{k=D}^{Q} \alpha^k \ln(rv_{t-1}^k) + \gamma r_{t-1}^D + \xi_t$$

The use of the logarithmic volatility is motivated by its approximately normal distribution, as documented in Table 3 and by ABDL (2001, 2003). When negative returns lead to greater volatility than positive returns, as in equity markets, we expected the coefficient of the lagged return γ to be negative and significant. In addition, we propose to include past absolute returns at daily, weekly, monthly, and quarterly

intervals. Theory (e.g. Forsberg and Ghysels, 2004) and empirical evidence (e.g. Ghysels, et al., 2006) suggest that absolute returns outperform square return-based volatility measures in predicting future increments in quadratic variation. Long-run absolute returns also captures price trends that increase volatility; see Campa, et al. (1998) and Johnson (2002). Our modified HAR-RV model is given by

$$\ln(rv_t^D) = \omega + \sum_{k=D}^{Q} \alpha^k \ln(rv_{t-1}^k) + \sum_{k=D}^{Q} \beta^k \,|\, r_{t-1}^k \,| + \gamma r_{t-1}^D + \xi_t \tag{4}$$

where $r_t^k = \frac{1}{h} \sum_{s=t-h+1}^{t} r_s^D$ and h=1 for k=D, 5 for k=W, 22 for k=M, and 66 for k=Q. Following Corsi (2004) and the GARCH-family notations, we label the modified model as HAR-RV(4,4). Although the same model is fitted for all four currencies here, it is possible that the best HAR-RV(p,q) is different for different currencies. We also use returns standardized by the corresponding realized volatility as in the EGARCH specification. The results for standardized returns are qualitatively the same.

Table 5 reports the estimation results. The unconditional volatility, given by e^{ω}, is highly significant. The coefficients for lagged volatilities at different intervals are almost all positive and significant[5]. The finding of strong impact from long-horizon volatilities to daily volatility is consistent with Müller, et al. (1997), Corsi (2004), and Andersen, et al. (2005). The model does a good job in removing any long-run dependence in logarithmic volatility. The Q(20) statistics for residuals is drastically reduced relative to Table 3 and is no longer significant. The lagged quarterly volatility, not examined in previous studies, is significant for AUD, GBP, and JPY. In Corsi (2004) and Andersen, et al. (2005), the lagged daily volatility has the largest impact on today's volatility, and the size of the coefficient declines from daily to weekly to monthly. That pattern does not hold for the four currencies in our sample. Our results

[5] When the lagged half-yearly volatility is included, only AUD shows significant impact.

indicate that the lagged weekly volatility has the largest impact. It is unclear whether it is the currency or the sample period caused the difference. Our results are in line with the results for S&P500 examined by Andersen, et al. (2005) where the lagged weekly volatility has the largest impact on both the current daily and weekly volatilities.

The size of past returns at different intervals has a significant impact on daily volatility, independent of the past volatility measures. In general, monthly or quarterly absolute returns have greater impact than daily or weekly absolute returns. For AUD and EUR, the impact of past absolute returns increases monotonically with time interval. To compare the impact of past volatility with past absolute return, we rewrite rv_t^D as squared daily standard deviation and divide both sides of Eq (4) by 2. Realized volatilities are now realized standard deviations which have the same percentage measure as absolute returns. The coefficients of lagged standard deviation remain the same but the coefficients of lagged absolute returns are halved. The impact of absolute returns at monthly or quarterly intervals has greater impact than any of the lagged standard deviations. For example, $\beta^M/2 = 0.3815$ is still larger than any of the α^k for GBP. It appears that the size of long-turn returns contains more information about short-run volatility than past volatilities at various horizons. This finding calls for further theoretical exploration of the dynamics of exchange rate volatility.

As in the EGARCH-RV model in Table 4, the asymmetric coefficient γ is significant for AUD, GBP, and JPY, but not EUR. Therefore negative returns at t-1 leads to greater volatility in these bilateral rates regardless the long-run trend. We also find evidence of a strong and negative contemporaneous relationship between return and volatility in AUD and JPY. Given that JPY is quoted in the opposite way as AUD and GBP, it is puzzling to see that the sign of γ for JPY is the same as those for AUD and GBP: AUD volatility is higher when AUD depreciates against USD, but JPY

volatility is higher when JPY appreciates. One plausible explanation is the intervention by the Bank of Japan (BOJ) in the JPY/USD market. Data from BOJ show that with the exception of a short period from December 1997 to June 1998, BOJ was mostly selling JPY and buying USD. The selling became more intense from January 2003 to March 2004. When the BOJ interventions are included in Eq (4)[6], the size of the asymmetric coefficient γ drops by 20% to -0.102 with a t-statistics of 5.40. On the other hand, when AUD reached the historical low in 2001, the Reserve Bank of Australia (RBA) intervened in support of the Australian currency. The ad hoc evidence is consistent with the conjecture that intervention in JPY is associated with JPY appreciation, and intervention in AUD is associated with AUD depreciation. As discussed before, central bank intervention is not the only source for asymmetric volatility. Other factors, e.g. exchange rate level, may also affect market expectations and the volatility-return relationship.

Robustness Check

Our first robustness check is to test the stability of the asymmetric coefficient γ over the sample period. We use both the classic CUSUM test and the test for multiple breaks proposed by Bai and Perron (1998). The Bai-Perron tests endogenously identify the number of structural breaks as well as the break points from historical data. The UDmax and WDmax statistics test the null hypothesis of no break against the alternative hypothesis of at least one break. The SupF(k+1|k) tests the null of k breaks against the alternative of k+1 breaks. The critical values for these test statistics are given in Bai and Perron (1998, 2003). The Appendix provides a brief description of the test procedure. More details on implementation can be found in Bai and Perron (2003).

[6] Let x_t be the JPY amount, in billion yen, purchased by BOJ on day t, therefore $x_t < 0$ when BOJ sells JPY. Let $y_t = \text{sign}(x_t)\ln|x_t|$. We include the contemporaneous and lagged $|y_t|$ and y_t in Eq (4). The coefficients of $|y_t|$ and y_t are positive and significant.

The CUSUM statistics and the SupF statistics are plotted in Figure 4. The CUSUM test fails to identify any structural break in Eq (4) for all four currencies. The Bai-Perron procedure fails to detect any structural break for GBP and EUR[7]. Table 6 reports Bai-Perron test statistics for structural breaks and parameter estimates for AUD and JPY. UDmax and WDmax are significant at 5% for both currencies. The SupF(2|1) statistics tests the null hypothesis of one break versus the alternative of two breaks. The critical value at 5% is 27.64 therefore the test fails to reject the null. The break for AUD occurred early in the sample around 4 September 1998, and the break for JPY occurred at the end of 2002. The confidence interval for the break date is not symmetric around the dates and is much larger for AUD. Asymmetric volatility is present in AUD in the five and half years after the break point, and is present in JPY in the seven years before the break point. Even though the asymmetries for different currencies are in different direction, for a given currency, the asymmetry is stable in one direction and persists for several years. Given the small sample size after the break for JPY and the need for a long lag of 66 days, we do not fit Eq. (4) to JPY's post-break period.

As a further test for the robustness of the asymmetric volatility, we test whether incorporating the cross-currency impact on return and volatility eliminates the asymmetric volatility[8]. It is motivated by the Evans and Lyons (2002) finding of significant cross-currency impact of order flows. Returns are driven by own lagged returns and past returns of other currencies: $r_{i,t} = \sum_{s=1}^{10} \sum_{j=AUD}^{EUR} \beta_{j,s} r_{j,t-s} + \varepsilon_{i,t}$. The volatility

[7] We use 10% trimming of the sample, therefore the minimum length of each regime is 10% of the sample size, i.e. 119 days for EUR. The SupF, UDmax, WDmax statistics are significant for EUR, with a break point occurs at the 206th sample point. After trimming 66 days for lagged volatility and 119 days for the test, the break point is less than 119 days from the start of the sample, therefore is discarded.

[8] To facilitate the examination of cross-currency volatility impact, we synchronize the sample across currencies by keeping days when all three (four) currencies have observations before (after) the introduction of EUR in 1999. Our sample has 1908 daily observations for AUD, GBP, JPY, and 1193 observations for EUR.

equation now includes the day-of-the-week effect D_d, d=MON, TUE, …, FRI, as well as volatility spillover from other currencies at daily interval:

$$\text{(5)} \qquad \ln(rv_{i,t}^{D}) = \sum_{d=MON}^{FRI} \omega_d D_d + \sum_{j=AUD}^{EUR} \alpha_j^D \ln(rv_{j,t-1}^{D}) + \sum_{k=M}^{Q} \alpha^k \ln(rv_{i,t-1}^{k}) + \sum_{k=D}^{Q} \beta^k \,|\, \varepsilon_{i,t-1}^{k} \,| + \gamma \varepsilon_{i,t-1}^{D} + \xi_{i,t}$$

The results for equation (5) are reported in Table 7. The coefficients of the day-of-the-week dummies, not reported here, are highly significant. Friday has the highest unconditional volatility except for EUR where the highest volatility tends to be on Thursday. For AUD, GBP, and JPY, the own lagged daily volatility has stronger impact than spillover from other currencies. EUR is different again. Its own lagged daily volatility has no impact in both Table 5 and Table 7, and it has no impact on other currencies. Again the asymmetric coefficients for AUD, GBP, and JPY survive the new specification and are negative and significant. Removing cross-currency impact in returns also seems to reduce autocorrelation in volatility. The Q(20) statistics are even lower than in Table 5. It also appears to strengthen the negative contemporaneous correlation between return and volatility innovations in AUD and JPY.

Continuous and Jump Components of Realized Volatility

Recently Barndorff-Nielsen and Shephard (2004, 2006) propose a procedure that allows for a direct nonparametric decomposition of the realized volatility into a continuous component and a jump component. Volatility jumps have significant impact on asset allocation (Liu, Longstaff, Pan, 2003) and option pricing (Eraker, et al., 2003). Andersen et al. (2005), Huang and Tauchen (2005), and Tauchen and Zhou (2005) demonstrate that the decomposition significantly improve volatility forecasts. Therefore we examine whether both components, or only one of them, drive the asymmetry in realized volatility.

The continuous component of realized volatility is approximated by the bipower variation proposed by Barndorff-Nielsen and Shephard (2004):

$$BV_t = \frac{\pi}{2} \times \frac{m}{m-1} \sum_{j=2}^{m} | r_{t,j} || r_{t,j-1} |$$

where m is the number of intraday sampling intervals, $r_{t,j}$ is the intraday return for interval j. In our study, the intraday sampling interval is 30 minutes. Therefore m = 48 on most days and $r_{t,j}$ is the 30-minute return for j^{th} interval. Barndorff-Nielsen and Shephard (2004) show that as $m \to \infty$, BV_t converges to the volatility component associated with the continuous diffusion process. The jump component is then given by the limit (as the sampling interval tends to zero) of the difference between realized volatility and bipower variation: RV_t-BV_t.

The descriptive statistics of BV, ln(BV) and ln(RV/BV) for the currencies AUD, GBP, JPY and EUR are given in Table 8. Compared to RV in Table 3, BV has smaller mean, median, and standard deviation as expected. Similar to ln(RV), ln(BV) is approximately normally distributed with much smaller skewness and kurtosis than BV. Note that ln(BV) of EUR has much larger skewness and kurtosis than the other currencies. Huang and Tauchen (2005) show by simulation that the log difference ln(RV)-ln(BV) is an empirically more robust measure for volatility jumps. We adopt the same jump measure as do Andersen, et al. (2005). Not surprisingly, the jump component ln(RV/BV) has larger skewness and kurtosis than the continuous component ln(BV), but has no persistence.

To test for asymmetry in ln(BV) and ln(RV/BV), we re-estimate the baseline model of equation (4) using both variables and present the results for ln(BV) in Table 9. Qualitatively the results for ln(BV) are the same as for ln(RV) in Table 6. The only noticeable difference is the t-ratio of γ for GBP, which is smaller for ln(BV) than it is

for ln(RV). The estimation results for jumps ln(RV/BV) are not reported here. Most coefficients are mostly not significant, including the coefficient for volatility asymmetry γ. It appears that the asymmetry in realized volatility is entirely driven by the continuous component measured by the bi-power variation. Bollersleve et al. (2005) report similar results for realized volatility of the S&P500 index futures.

V. Conclusion

This paper presents some new evidence on asymmetric volatility in realized exchange rate volatilities. The asymmetry in exchange rates is more complex than it is in stocks and equity indices. It varies in direction between bilateral rates and TWI, and across different currencies. The presence of asymmetric volatility in exchange rates calls for alternative economic explanations to those based on equity markets. One possible explanation is the direction and size of central bank interventions. Another is the base-currency effect in which the base currency is used for profit and loss calculation, therefore the variations in the bilateral rate becomes risk of the other currency. Future research should also explore the impact of asymmetric volatility on volatility forecasting and option pricing.

Appendix: The Bai-Perron Test

Without presenting the full range of the Bai-Perron tests, we choose the following procedure for our study. We use 10% trimming at both ends of the sample period, which implies that the minimum length of a regime is 10% of the sample size. The first step is to test the null hypothesis of no break against the alternative hypothesis of at least one break. An F-test in the spirit of the Chow test is constructed for a given set of k breaks. The SupF(k) statistic is the highest value of the F statistics from all possible combinations of the k breaks. By varying k from one to an upper bound M, the double maximum statistic is calculated as the highest value of a_kSupF(k) for a set of fixed weights a_k, k=1,..,M. The UDmax statistic is when the weights are equal to unity. The WDmax statistic is given by the set of weights such that the marginal p-values are equal for different k. When the test statistics exceed the critical values given in Bai and Perron (1998, 2003), we reject the null of no break in favor of at least one break.

If there is evidence of at least one break, the second step is to implement the sequential procedure to test m versus m+1 breaks. The test statistic is constructed by comparing the sum of squared residuals (SSR) from the estimation of the best (in the sense of minimum SSR) m-break model to the best (m+1)-break model, starting from m=1. The number of breaks is given by the first m for which the test fails to reject the null of m breaks in favor of m+1 breaks.

Given the number of breaks, m, the break dates are estimated by minimizing the SSR over different partitions of the sample period. Confidence intervals are then constructed for the break dates. Minimizing the SSR also produces parameter estimates with robust (heteroskedasticity and autocorrelation consistent) covariance estimation. Note that the variance of the error term is different in each of the break periods, resulting in asymmetric confidence intervals around the break dates.

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Table 1: Summary Statistics for Reuters Quotes

	AUD	GBP	JPY	EUR
Total Quotes (million)	2.49	13.6	18.1	27.6
Quotes per Weekday				
Average	1,238	6,777	9,064	22,048
Median	845	3,920	5,775	20,763
Maximum	5,841	34,101	32,794	59,798

Table 2: Daily Return Summary

	AUD	GBP	JPY	EUR
Return based on prices at 21 GMT				
Mean	0.009	0.015	-0.01	0.016
St Dev	0.679	0.481	0.718	0.674
Skewness	0.007	0.013	**-1.004**	0.022
Kurtosis	**5.79**	**4.02**	**10.9**	**2.14**
Q(20)	16.3	27.5	26.8	11.8
$Q^2(20)$	**90.3**	**90.2**	**132.3**	**50.8**
Return based on prices from DataStream				
Mean	0.0014	0.0087	0.00017	0.0038
St Dev	0.686	0.502	0.754	0.673
Skewness	0.088	**-0.163**	**-0.781**	**0.099**
Kurtosis	**6.3**	**5.34**	**11.3**	**2.56**
Q(20)	27.3	18.7	25.1	15.3
$Q^2(20)$	**109.2**	**117.3**	**85.9**	**43.0**
TWI returns from DataStream				
Mean	0.0032	0.0064	0.0041	0.0017
St Dev	0.594	0.384	0.655	0.423
Skewness	**-0.281**	**-0.320**	**0.432**	0.017
Kurtosis	**5.89**	**4.73**	**7.06**	**4.49**
Q(20)	35.5	22.4	23.7	28
$Q^2(20)$	**131.1**	**267.4**	**522.6**	**199.1**

Q(20) and $Q^2(20)$ are Ljung-Box statistics for autocorrelation in return and squared return for the first 20 lags. Bold numbers indicate significantly different from zero (3 for kurtosis) at 5%.

Table 3: Daily Realized Volatility Summary

	AUD	GBP	JPY	EUR
Realized Volatility				
Mean	0.527	0.260	0.540	0.466
Median	0.397	0.217	0.357	0.387
St Dev	0.521	0.202	0.996	0.364
Skewness	**4.58**	**6.56**	**22.43**	**3.99**
Kurtosis	**37.7**	**103.2**	**728.2**	**56.5**
Q(20)	**2934**	**1345**	**1229**	**621**
Cross-Cor before EUR				
GBP	0.365			
JPY	0.407	0.508		
Cross-Cor after EUR				
GBP	0.360			
JPY	0.186	0.146		
EUR	0.433	0.599	0.252	
Logarithmic Volatility				
Mean	-0.936	-1.536	-0.981	-0.953
Median	-0.924	-1.529	-1.030	-0.950
St Dev	0.753	0.607	0.771	0.602
Skewness	**0.103**	-0.009	**0.518**	0.048
Kurtosis	**3.31**	**3.80**	**4.26**	**2.26**
Q(20)	**8991**	**3730**	**6047**	**1516**
EGARCH Volatility				
Mean	0.420	0.219	0.536	0.396
Median	0.392	0.209	0.454	0.390
St Dev	0.182	0.065	0.358	0.067
Skewness	**0.963**	**0.762**	**3.24**	**0.336**
Kurtosis	**3.96**	**4.03**	**17.66**	**2.14**
Q(20)	**27704**	**24733**	**29032**	**19471**

Table 4: Exponential GARCH Estimations

$$\text{EGARCH:}\quad \ln(h_t) = \omega + \alpha \ln(h_{t-1}) + \beta\left[\left| r_{t-1} \right| \Big/ \sqrt{h_{t-1}} - \sqrt{2/\pi} \right] + \gamma\left(r_{t-1} \Big/ \sqrt{h_{t-1}} \right)$$

$$\text{EGARCH\_RV:}\quad \ln(rv_t) = \omega + \alpha \ln(rv_{t-1}) + \beta\left(\left| r_{t-1} \right| \Big/ \sqrt{rv_{t-1}} \right) + \gamma\left(r_{t-1} \Big/ \sqrt{rv_{t-1}} \right) + \xi_t$$

	ω	α	β	γ
EGARCH				
AUD	**-0.007**	**0.987**	**0.093**	-0.010
t-stat	**-2.34**	**329**	**7.91**	-1.51
GBP	**-0.035**	**0.974**	**0.099**	-0.007
t-stat	**-3.03**	**131**	**6.19**	-0.93
JPY	**0.002**	**0.997**	**0.070**	**-0.008**
t-stat	**2.83**	**701**	**11.9**	**-1.91**
EUR	-0.016	**0.981**	**0.050**	-0.007
t-stat	-1.35	**77.9**	**2.65**	-0.83
EGARCH-TWI				
AUD	**-0.043**	**0.952**	**0.120**	**-0.030**
t-stat	**-4.70**	**113**	**8.63**	**-3.46**
GBP	**-0.027**	**0.985**	**0.098**	**0.032**
t-stat	**-3.05**	**222**	**7.76**	**3.84**
JPY	**-0.013**	**0.982**	**0.107**	**0.032**
t-stat	**-3.84**	**303**	**9.66**	**4.33**
EUR	**-0.008**	**0.994**	**0.049**	-0.008
t-stat	**-1.86**	**361**	**4.53**	-1.52
EGARCH_RV				
AUD	**-0.391**	**0.631**	**0.064**	**-0.032**
	-12.1	**27.8**	**2.60**	**-2.28**
GBP	**-0.844**	**0.480**	**0.057**	**-0.029**
	-19.2	**19.9**	**2.60**	**-2.29**
JPY	**-0.484**	**0.570**	**0.079**	**-0.076**
	-11.8	**21.1**	**2.80**	**-4.57**
EUR	**-0.663**	**0.368**	**0.062**	-0.004
	-14.6	**11.2**	**2.39**	-0.23

Table 5: Modified HAR-RV Estimation

$$\ln(rv_t^D) = \omega + \sum_{k=D}^{Q} \alpha^k \ln(rv_{t-1}^k) + \sum_{k=D}^{Q} \beta^k \,|\, r_{t-1}^k \,| + \gamma r_{t-1}^D + \xi_t$$

	AUD		GBP		JPY		EUR	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
ω	**-0.409**	**-9.08**	**-0.544**	**-7.91**	**-0.571**	**-9.77**	**-0.589**	**-8.08**
α^D	**0.192**	**6.77**	**0.160**	**5.42**	**0.156**	**4.38**	0.040	0.94
α^W	**0.249**	**5.18**	**0.275**	**4.97**	**0.287**	**5.49**	**0.314**	**4.27**
α^M	**0.202**	**3.16**	**0.154**	**2.21**	0.011	0.17	**0.171**	**1.72**
α^Q	**0.203**	**3.75**	**0.216**	**3.04**	**0.319**	**5.55**	**0.237**	**2.44**
β^D	**0.108**	**3.65**	**0.174**	**4.01**	**0.122**	**3.75**	**0.126**	**3.32**
β^W	**0.163**	**2.04**	**0.229**	**2.44**	**0.287**	**3.67**	**0.290**	**2.92**
β^M	**0.387**	**2.63**	**0.763**	**3.88**	**0.686**	**4.26**	**0.682**	**4.08**
β^Q	**0.853**	**3.28**	0.477	1.45	**0.585**	**2.03**	**0.810**	**2.39**
γ	**-0.046**	**-2.69**	**-0.049**	**-2.10**	**-0.128**	**-6.41**	-0.010	-0.39
R^2	0.504		0.347		0.472		0.294	
Q(20)	17.85		**29.4**		7.9		13.14	
$Cor(r_t, \hat{\xi}_t)$	**-0.075**		-0.0094		**-0.175**		0.0132	

Table 6: Endogenous Breaks

$$\ln(rv_t^D) = \omega + \sum_{k=D}^{Q} \alpha^k \ln(rv_{t-1}^k) + \sum_{k=D}^{Q} \beta^k \,|\, r_{t-1}^k \,| + \gamma r_{t-1}^D + \xi_t$$

Break points are selected by the sequential method at 10% significance level.

AUD	Tests:	UDmax	WDmax	SupF(2|1)							
	5% sig.	**32.8**	**36.5**	26.8							
	Break Dates:	T_B = 1998.9.4									
	95% Conf. Int:	[1998.2.24, 1999.5.13]									
	Sub-periods	ω	α^D	α^W	α^M	α^Q	β^D	β^W	β^M	β^Q	γ
	[1996.1.1, T_B]	**-0.556**	**0.173**	**0.292**	-0.040	**0.403**	**0.162**	**0.449**	**0.558**	**1.290**	-0.047
		-6.22	**3.31**	**3.66**	-0.40	**3.99**	**2.59**	**2.97**	**1.72**	**2.12**	-1.25
	[T_B+1, 2004.4.14]	**-0.388**	**0.182**	**0.194**	**0.373**	0.050	**0.095**	0.062	**0.369**	**0.630**	**-0.044**
		-7.49	**5.08**	**3.52**	**5.34**	0.80	**2.72**	0.77	**2.18**	**2.18**	**-2.25**
JPY	Tests:	UDmax	WDmax	SupF(2|1)							
	5% sig.	**53.1**	**53.1**	22.6							
	Break Dates:	T_B = 2002.12.23									
	95% Conf. Int:	[2002.10.1, 2002.12.26]									
	Sub-periods	ω	α^D	α^W	α^M	α^Q	β^D	β^W	β^M	β^Q	γ
	[1996.1.1, T_B]	**-0.555**	**0.169**	**0.281**	-0.002	**0.322**	**0.104**	**0.257**	**0.597**	**0.879**	**-0.139**
		-10.19	**4.66**	**5.23**	-0.03	**5.54**	**2.98**	**3.37**	**3.58**	**3.21**	**-7.25**

Table 7: The Modified HAR-RV Model with Cross-currency Impact

Return: $$r_{i,t} = \sum_{s=1}^{10} \sum_{j=AUD}^{EUR} \beta_{j,s} r_{j,t-s} + \varepsilon_{i,t}$$

Realized Volatility: $$\ln(rv_{i,t}^{D}) = \sum_{d=MON}^{FRI} \omega_d D_d + \sum_{j=AUD}^{EUR} \alpha_j^D \ln(rv_{j,t-1}^{D}) + \sum_{k=M}^{Q} \alpha^k \ln(rv_{i,t-1}^{k})$$

$$+ \sum_{k=D}^{Q} \beta^k \,|\, \varepsilon_{i,t-1}^{k} \,| + \gamma \varepsilon_{i,t-1}^{D} + \xi_{i,t}$$

where i = AUD, GBP, JPY, EUR.

	AUD		GBP		JPY		EUR	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
α_{AUD}^{D}	**0.191**	**6.27**	**0.039**	**2.14**	0.024	1.26	**0.052**	**1.84**
α_{GBP}^{D}	**0.067**	**3.01**	**0.163**	**5.34**	**0.074**	**2.90**	0.045	1.11
α_{JPY}^{D}	**0.037**	**1.89**	0.017	0.99	**0.130**	**3.45**	0.021	0.71
α_{EUR}^{D}	-0.022	-1.15	-0.002	-0.13	0.023	1.09	0.006	0.10
α^{W}	**0.223**	**4.63**	**0.264**	**4.66**	**0.267**	**5.24**	**0.314**	**4.30**
α^{M}	**0.212**	**3.28**	**0.142**	**2.04**	0.007	0.12	0.156	1.62
α^{Q}	**0.188**	**3.40**	**0.180**	**2.55**	**0.337**	**6.02**	**0.184**	**2.02**
β^{D}	**0.074**	**2.60**	**0.171**	**3.88**	**0.126**	**4.02**	**0.126**	**3.36**
β^{W}	**0.171**	**2.05**	**0.196**	**2.03**	**0.280**	**3.62**	**0.229**	**2.34**
β^{M}	**0.379**	**2.47**	**0.734**	**3.67**	**0.689**	**4.15**	**0.631**	**3.58**
β^{Q}	**0.922**	**3.33**	0.436	1.18	**0.778**	**2.59**	**0.725**	**2.02**
γ	**-0.049**	**-2.96**	**-0.041**	**-1.79**	**-0.128**	**-6.31**	0.007	0.31
R^2	0.528		0.366		0.487		0.322	
Q(20)	3.26		20.76		10.04		5.85	
$Cor(\hat{\varepsilon}_t, \hat{\xi}_t)$	**-0.080**		-0.0045		**-0.184**		0.0184	

Table 8: Bi-power Variations and Jumps

	Mean	Median	St Dev	Skewness	Kurtosis	Q(20)
AUD						
bv_t	0.450	0.340	0.448	4.904	43.78	2757
$Ln(bv_t)$	-1.099	-1.078	0.767	0.007	3.33	8520
$Ln(rv_t/bv_t)$	0.152	0.128	0.190	1.046	5.05	20.1
GBP						
bv_t	0.233	0.194	0.179	4.83	48.37	1246
$Ln(bv_t)$	-1.656	-1.642	0.628	-0.275	5.55	2738
$Ln(rv_t/bv_t)$	0.111	0.081	0.211	4.223	66.20	19.6
JPY						
bv_t	0.469	0.312	0.717	15.364	407.07	2086
$Ln(bv_t)$	-1.122	-1.165	0.788	0.353	4.27	5771
$Ln(rv_t/bv_t)$	0.122	0.092	0.197	1.629	9.12	16.1
EUR						
bv_t	0.401	0.334	0.313	5.014	53.58	768
$Ln(bv_t)$	-1.131	-1.098	0.706	-1.368	11.82	933
$Ln(rv_t/bv_t)$	0.144	0.098	0.284	7.808	141.22	22.0

Table 9: Dynamics of Bi-power Variations

$$\ln(bv_t) = \omega + \sum_{k=D}^{Q} \alpha^k \ln(bv_{t-1}^k) + \sum_{k=D}^{Q} \beta^k \mid r_{t-1}^k \mid + \gamma r_{t-1}^D + \xi_t$$

	AUD		GBP		JPY		EUR	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
ω	**-0.466**	**-9.56**	**-0.601**	**-7.86**	**-0.627**	**-9.91**	**-0.646**	**-7.72**
α^D	**0.160**	**5.96**	**0.168**	**5.35**	**0.165**	**4.63**	0.067	1.53
α^W	**0.261**	**5.34**	**0.236**	**4.40**	**0.264**	**5.41**	**0.242**	**3.27**
α^M	**0.193**	**2.86**	**0.188**	**2.47**	0.003	0.05	0.126	1.11
α^Q	**0.230**	**4.14**	**0.194**	**2.61**	**0.342**	**6.15**	**0.331**	**2.77**
β^D	**0.149**	**4.92**	**0.175**	**3.90**	**0.135**	**4.22**	**0.188**	**4.06**
β^W	**0.181**	**2.18**	**0.264**	**2.71**	**0.324**	**4.36**	0.199	1.68
β^M	**0.385**	**2.63**	**0.575**	**2.71**	**0.726**	**4.51**	**0.612**	**3.11**
β^Q	**0.778**	**2.92**	0.606	1.52	**0.566**	**1.90**	**0.876**	**2.10**
γ	**-0.049**	**-2.71**	**-0.050**	**-1.75**	**-0.117**	**-6.14**	-0.002	-0.06
R^2	0.483		0.30		0.459		0.239	

Figure 1: Exchange Rates and Realized Volatility

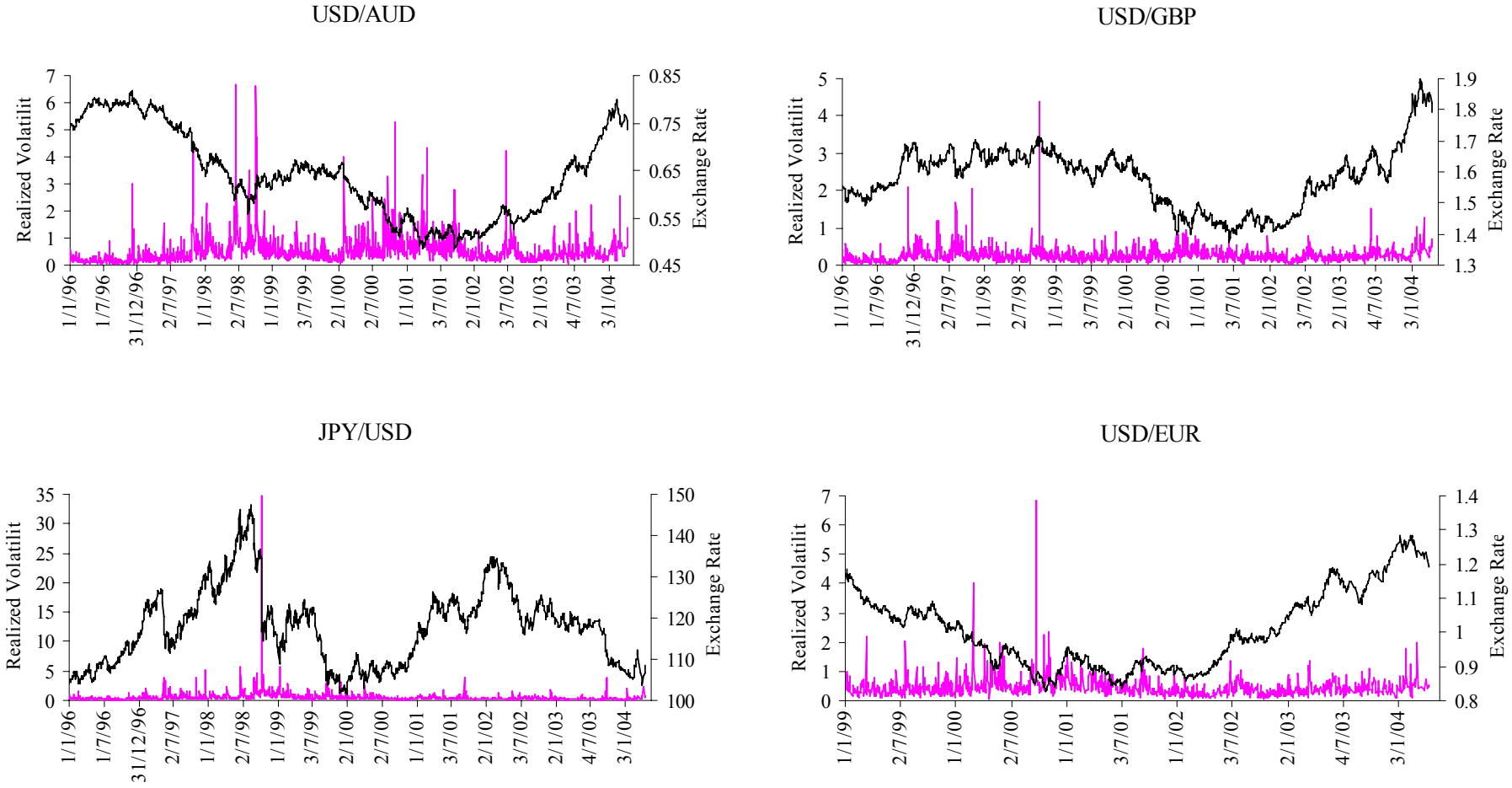

Figure 2: Autocorrelation of Realized Volatility

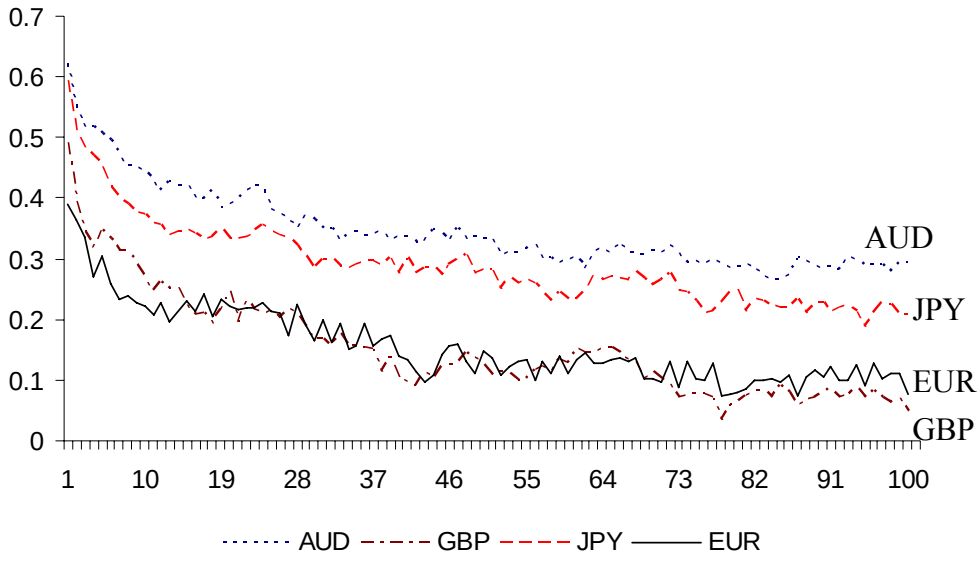

Figure 3: Realized Volatility and EGARCH-estimated Volatility for AUD

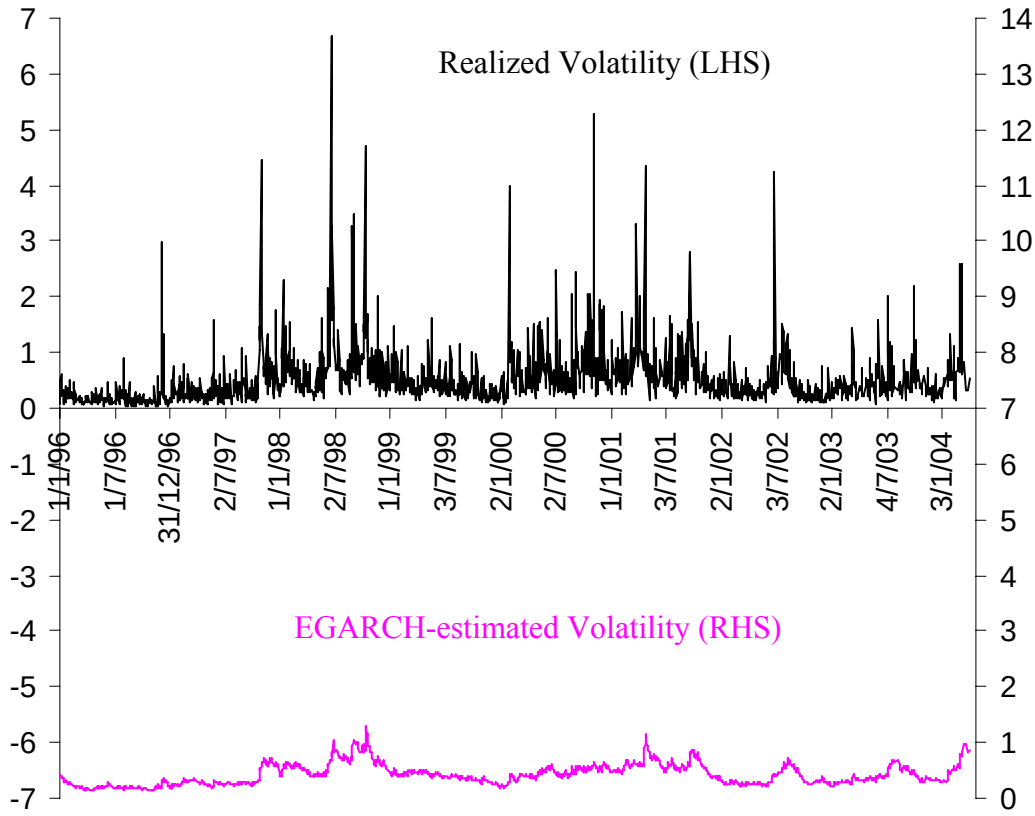

Figure 4: CUSUM and SupF Statistics for Structural Breaks