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The Asymmetric Volatility of Euro Cross Futures

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ABSTRACT

I test for the presence of asymmetric volatility in the Euro cross-rate futures markets. My investigation is based on a variant of the heterogeneous autoregressive volatility model, using daily realized variance and return series. I find that appreciation against the Euro leads to less volatility for the EUR/GBP contract and significantly greater volatility for the EUR/JPY contract. Relative to volatility on days following a positive one-standard-deviation change, volatility on days following a negative one-standard-deviation return is -0.10% less for the CHF/EUR future, 12.42% lower for the EUR/GBP future and 5.81% greater for the EUR/JPY future. The results are robust to the removal of the jump component from the realized volatility.

Keywords: *Futures, cross rates, Euro, Volatility.*

INTRODUCTION

It is well known that volatility in equity markets is asymmetric, i.e. negative returns are associated with higher volatility than positive returns, but whether other asset markets, such as currency futures, exhibit volatility asymmetry is less well-known. Bollerslev at al. (1992) suggest that "The two-sided nature of the foreign exchange market makes such asymmetries less likely". Since then the theoretical advances in volatility models has led to a large literature on exchange rate volatility, almost exclusively concentrated on rates versus the US Dollar. However, the issue of volatility asymmetry has remained under-examined, as noted by Wang and Yang (2009).

The so-called "two-sided" nature of the foreign exchange market is the primary reason that symmetric models are chosen for modeling exchange rates and currency derivatives. The reasoning is that relative positive news for one currency must of necessity imply relative negative news for the other currency. This implies that currency rate volatility should have symmetric responses to shocks in the return on the underlying rate. Further, standard asymmetric GARCH models regularly fail to detect asymmetry in daily exchange rate volatility.

There are at least two reasons to suspect the presence of asymmetry in exchange rates. First, some currencies have greater economic importance than others. Many banks use the US dollar as their base currency for profit and loss calculation. Therefore, a higher than expected volatility in a dollar based exchange rate may imply greater risk in assets denominated in another currency, but not necessarily greater risk for dollar denominated assets. This can lead to sales of assets denominated in another currency, and a lower US dollar direct exchange rate. Though, with currencies of relatively similar importance, say the Japanese Yen/Euro cross rate, we should expect this effect to be weaker. Second, central bank intervention could lead to periods of volatility asymmetry. Higher volatilities could be a result of a central bank reacting to an undesired appreciation or depreciation of its currency. For Japanese Yen (JPY) cross-rate futures in the current case, this would be of particular emphasis since the Bank of Japan is well-known to have been a heavy seller of the JPY over much of my sample period.

McKenzie (2002) finds some support for the hypothesis that central bank intervention s cause asymmetric volatility in exchange rates using USD/AUD rates on a daily basis. Several authors have documented asymmetric volatility in exchange rates while studying other issues. Byers and Peel (1995) find volatility asymmetry in European exchange rates from 1922-1925.Andersen et al. (2003b) measure asymmetric responses in volatility for major exchange rates to US economic announcements.

Asymmetric volatility has also been documented in minor currencies, including the Malaysian ringgit (Tse and Tsui, 1997), Australian dollar (McKenzie, 2002) and the Mexican peso (Adler and Qi, 2003). Wang and Yang (2009) examine four major currencies (the Australian dollar, Euro, British pound and the Japanese yen) versus the dollar and find strong evidence for volatility asymmetry

This study tests for the presence of asymmetric volatility in Euro denominated cross-rate futures. The issue is important for several reasons. First, the currency futures markets present a substantial risk to investors as well as an opportunity to hedge for users and suppliers of currencies. 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 currency futures dynamics, particularly in the second moment and particularly for non-dollar denominated contracts. 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 and call for alternative explanations.

This study makes several contributions to the literature on currency futures volatility. First, I test for the presence of asymmetric volatility in realized volatility of currency futures returns. 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 my second contribution. I 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 Dobrev, 2005).

Third, my 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. I 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), I 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). I examine which component is associated with volatility asymmetry.

Fifth, by studying non-dollar denominated currency futures, we can investigate the presence of asymmetric volatility in less well-traded contracts, in terms of volume.

Data and Preliminary Analysis

The analysis is based on intraday quotes for Swiss franc (CHF/EUR), British pound (EUR/GBP) and Japanese yen (EUR/JPY) cross-rate futures versus the euro, over a period of more than 5 years from April 14, 2004 to October 22, 2009. The quotes are from the Chicago Mercantile Exchange.

Construction of Daily Return and Realized Volatility

The quotes are used for the construction of daily return and realized volatility. I adopt the same 30-minute sampling interval as Andersen et al (2003) 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." I 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 Andersen et al (2003), a trading day starts at 2100 GMT, or 4pm New York time, and ends at 2100 GMT on the next day. Weekend quotes, from 2100 GMT on Friday to 2100 GMT on Sunday, are excluded. Half-hourly returns are the log-difference of half-Q(20) and $Q^2(20)$ are Ljung-Box statistics for testing autocorrelation in return and squared return respectively for the first 20 lags. The 5% critical value of $\chi^2(20)$ distribution is 31.41.

Table1. *Daily Return Summary*

	CHF/EUR	EUR/GBP	EUR/JPY
Observations	1549	1549	1549
Median	0.000003	0.000000	0.000367
Mean	0.000008	0.000129	0.000047
S.D.	0.000022	0.004267	0.007251
Skewness	14.313942	0.149512	-0.198664
Kurtosis	317.467914	9.674794	12.272236
Q(20)	3470.1922	67.1158	61.2289
$Q^2(20)$	1797.1246	1196.6791	1936.3747

Table2. *Daily Realized Volatility Summary*

Realized volatility	**CHF/EUR**	**EUR/GBP**	**EUR/JPY**
Median	0.000003	0.000008	0.000013
Mean	0.000008	0.000019	0.000042
S.D.	0.000022	0.000098	0.000181
Skewness	14.313942	21.825368	16.150266
Kurtosis	317.467914	547.075027	325.955636
Q(20)	3470.1922	314.8694	1044.7889
Log realized volatility			
Median	-12.625061	-11.762089	-11.222382
Mean	-12.570978	-11.809692	-11.228104
S.D.	1.224222	1.246816	1.390930
Skewness	-0.074213	-0.373526	-0.238106
Kurtosis	1.739039	2.625211	2.703263
Q(20)	4139.3664	3310.6771	4359.2251
EGARCH cond. variance			
Median	0.000000	0.000000	0.000000
Mean	0.000009	0.000017	0.000050
S.D.	0.000013	0.000018	0.000075
Skewness	3.886028	4.156875	4.611883
Kurtosis	16.723525	20.290054	24.433633
Q(20)	25311.6303	28273.2288	22988.6150

Q(20) and $Q^2(20)$ are Ljung-Box statistics for testing autocorrelation in returns for the first 20 lags. The 5% critical value of $\chi^2(20)$ distribution is 31.41. EGARCH conditional variance series are based on the point estimates reported in Table 3.

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. Sometimes a trading day has less than 48 half-hourly observations due to holiday in part of the world, slow trading, or a recording system stoppage. If a trading day has more than 3.5 hours of missing data, I exclude the day from our sample. This process leads to 1549 daily observations.

Data summary

Table 1 exhibits summary statistics for daily returns based on the quotes. For all contracts, the means and the medians are several orders smaller than the standard deviation of the measured returns. The standard deviations of the two contracts are very close to each other. Both returns series display departures from normality, exhibiting positively skewed and lepto-kurtopic distributions. The Ljung-Box statistics indicate significant autocorrelation in the return series and in the squared return series for both contracts.

Table 2 reports the summary statistics for the daily realized volatility series of both contracts. The mean and standard deviations of the realized volatility for both contracts are very similar, as are the skewness statistics. The Ljung-Box statistics indicate significant autocorrelations in all series, but it is less pronounced in the realized volatility series that has been constructed. The realized volatility series are clearly non-normal in terms of their underlying distribution.

The middle panel of Table 2 summarizes the log realized volatility on a daily basis, which is the primary variable used in our study. The skewness and kurtosis are much smaller than for the realized volatility. The log realized volatility has higher Ljung-Box statistics than the realized volatility, a characteristic consistent with previous studies using realized volatility (Anderson et al (2001,2003) and Wang and Yang (2009)).

The bottom panel reports the basic statistics for the estimated conditional variance of an EGARCH model, whose estimation details are provided below. Compared to the realized variance, the EGARCH variance has a higher mean and median and exhibit much less skewness and kurtosis. On the other hand, the EGARCH estimated variances also show a much larger degree of autocorrelation as shown by the Ljung-Box statistics.

Table3. *GARCH Models*

EGARCH	CHF/EUR	EUR/GBP	EUR/JPY
μ	-0.00004(0.00005)	-0.00003(0.00008)	0.0003***(0.0001)
δ	-0.1394***(0.0420)	-0.0755*(0.0403)	-0.2729***(0.0595)
α	0.1012***(0.0199)	0.0772***(0.0184)	0.1201***(0.0268)
β	0.9948***(0.0029)	0.9983***(0.0031)	0.9827***(0.0048)
γ	0.0589***(0.0132)	0.0229*(0.0133)	-0.1024***(0.0179)
v	6.5509***(1.0110)	5.7185***(0.8741)	6.0254***(0.8817)
GJR			
μ	-0.00004(0.00005)	-0.00002(0.00007)	0.0003**(0.0001)
δ	0.0000001***(0.00000001)	0.00000005 (0.00000005)	0.0000007***(0.0000002)
α	0.0871***(0.0035)	0.0443***(0.0122)	0.0008(0.0183)
β	0.9273***(0.0030)	0.9682***(0.0103)	0.9118***(0.0169)
γ	**-0.0491***(0.0069)**	**-0.0275*(0.0155)**	**0.1256***(0.0283)**
v	6.4608***(0.8623)	5.7817***(0.9588)	6.4255***(1.0627)

Asymmetric GARCH Models for Daily Returns

Previous studies using GARCH type models have reported mixed results in volatility asymmetry in the oil futures markets. I revisit this issue by estimating GARCH models that allow for asymmetry in the return series. I then draw comparisons between the realized volatility and the GARCH-estimated daily volatility in terms of statistical properties and short-term dynamics; I use two asymmetric GACRH models. The first is the exponential GARCH, EGARCH hereafter, model of Nelson (1991) and the second is the Glosten, Jaganathan and Runkle model, hereafter GJR. Given that there is autocorrelation in the return series, the mean specification is:

$$r_t = \mu + \delta r_{t-1} \varepsilon_t \sim \text{iid } t(v) \qquad (1)$$

where ht is the conditional variance of the daily return series rt and t(v) is Student's t-distribution with degree of freedom v. The t-distribution is suitable for capturing the lepto-kurtosis of the underlying distribution in the return series.

The EGARCH specification is

$$\ln(h_t) = \omega + \alpha\left(\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}}\right) + \gamma\left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \beta \ln(h_{t-1}) \qquad (2)$$

and the GJR specification is

$$\ln(h_t) = \omega + \alpha\varepsilon_{t-1}^2 + \gamma S_{t-1}\varepsilon_{t-1}^2 + \beta h_{t-1} \qquad (3)$$

Where, St =1 if rt<0; St =0 otherwise. Engle and Ng (1993) show that EGARCH and GJR are superior to other asymmetric volatility models. For both models, the γ term captures the asymmetric effects.

The results of the GARCH estimations are reported in Table 3. The results are consistent with the stylized characteristics of daily GARCH models. The coefficients α and β are significant and β is close to one for all contracts.. The asymmetry effect, γ, is significant for all contracts under all models, but there is a sign change depending on the model. The EGARCH model exhibits a negative asymmetry coefficient, while the coefficient estimated for the GJR model is positive.

However, the asymmetric effects found here are very transitory. All of the estimated coefficients are very small.

Figure 1 provides a visual comparison of realized volatility and EGARCH volatility for the EUR/JPY futures. EGARCH volatility is often viewed as predicted volatility based solely on past returns whereas realized volatility may be viewed as an observation on the current volatility. Figure 1 makes plain that EGARCH volatility captures the low frequency component of volatility adequately, but represents the high frequency component poorly. On the other hand, realized volatility, which converges in probability to the underlying volatility when the sampling frequency increases, carries much more information about the underlying volatility than the EGARCH return.

GARCH family models with $r_t = \mu + \delta r_{t-1}\varepsilon_t \sim \text{iid } t(v)$

EGARCH

$$\ln(h_t) = \omega + \alpha\left(\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}}\right) + \gamma\left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \beta\ln(h_{t-1})$$

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

The asterisks *, ** and *** represent statistical significance at 10%, 5% and 1% respectively. Standard errors are in parentheses. Coefficients measuring asymmetry results are in bold.

TESTING FOR ASYMMETRY IN REALIZED VOLATILITY

As I argued in the previous section, daily realized volatility is a better means of examining the structure of daily volatility and its relationship with lagged returns. In the following section, I model the daily realized volatility and test for volatility asymmetry.

Long-memory and HAR-RV model

As shown by the Ljung-Box statistics, the autocorrelations in daily realized volatility decays very slowly. This long-memory dependence is a common characteristic of daily realized volatility, To account for this, Andersen et al (2003a) model realized volatilities as a fractionally integrated process. Recently, Corsi (2004) and Andersen et al (2005) adapt a heterogeneous ARCH model (HARCH), based on their heterogeneous market hypothesis to capture this long-memory dependency. An adaption of this model, the heterogeneous autoregressive realized volatility model, (HAR-RV) is found by Corsi and Andersen et al to provide superior forecasting performance. I use a variant of this model to describe the realized volatility series similar to that employed by Wang and Yang (2009).

The Modified HAR-RV Model

The basic HAR-RV model includes past volatilities aggregated over different time horizons as explanatory variables. Let rv^D_t be the realized volatility on day t. The average realized volatility in the past *h* days (including day t) is $rv_{t,h} = 1/h \sum^{t}_{s=t-h+1} rv^D_s$. I denote the average weekly (h=5), monthly (h=22), and quarterly (h=66) volatilities as $rv^W_{t,}$, rv^M_t, and rv^Q_t respectively. The HAR-RV model of Corsi (2004) is given by

$$rv_t^D = \omega + \sum_{k=D}^{Q} \beta^k\, rv_{t-1}^k + \xi_t \qquad (4)$$

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

$$ln(rv_t^D) = \omega + \sum_{k=D}^{Q} \beta^k\, ln(rv_{t-1}^k) + \alpha^D |r_{t-1}^D| + \gamma^D r_{t-1}^D + \xi_t \qquad (5)$$

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, I expected the coefficient of the lagged return, γ, to be negative and significant. In addition, I 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)

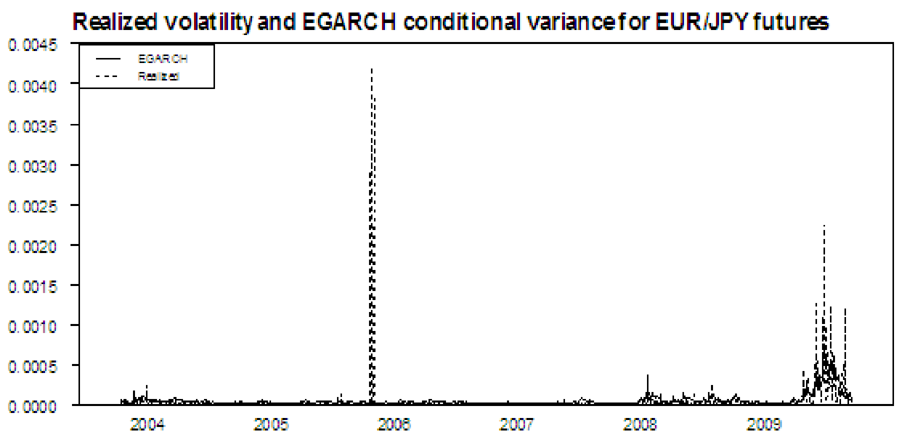

Figure1

Table4. *HAR-logRV-R models*

	CHF/EUR	EUR/GBP	EUR/JPY
ω	-2.6234***(0.5806)	-3.8164***(0.5931)	-3.1767***(0.5035)
β^D	0.0613**(0.0270)	0.0085(0.0250)	0.0798***(0.0271)
β^W	0.4602***(0.0663)	0.3984***(0.0813)	0.4627***(0.0859)
β^M	0.0505(0.0953)	0.1344(0.1017)	0.0939(0.1037)
β^Q	0.2467***(0.0864)	0.1707***(0.0615)	0.1185*(0.0609)
α^D	55.8026***(14.7623)	55.2186***(9.7354)	32.5738***(6.6223)
γ^D	21.7490**(9.1377)	15.5440**(6.3078)	-12.5575***(3.8898)
corr(r_t,ξ_t)	0.1333	0.0993	0.3241
adj. R^2	0.3433	0.2582	0.3273
Q(20)	0.5139	0.5642	0.5289

Table 4 reports the estimation results of model (5), where the standard errors are computed using the Newey-West correction for heteroscedasticity and autocorrelation (HAC) to obtain robust estimates. The null hypothesis of no asymmetry, γ=0, can be rejected for all futures contracts. As shown by Wang and Yang, the relative asymmetric effect of r^D_{t-1} on rv^D_t can be measured as exp(-2$\gamma^D\sigma$)-1, where σ is the standard deviation of the daily return. Based on the sample standard deviation of the returns in Table 1 and the point estimate in Table 4, the value of this measure would be -0.10%, -12.42% and 5.81% for the CHF/EUR, EUR/GBP and EUR/JPY future respectively. Thus asymmetric returns are of little economic significance for the CHF/EUR futures and of some significance for the remaining futures contracts.

Sensitivity Analysis

In this section I examine an alternative specification of the HAR-logRV model and the removal of the jump component from realized volatility. This will serve as a robustness check on the findings in the previous section.

Modified HAR-logRV-R models

Forsberg and Ghysels (2004) and Ghysels et al (2006) both suggest that absolute returns have predictive power for realized volatility. One way to view this is that long-term absolute returns may be viewed as price trends, or momentum, that increases volatility. Thus, lagged weekly, monthly and quarterly absolute returns are relevant explanatory variables in explainingdaily log realized volatility. I check the sensitivity of the asymmetric effects to the

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

The asterisks *, ** and *** represent statistical significance at 10%, 5% and 1% respectively. Q(20) are Ljung-Box statistics for testing autocorrelation in returns for the first 20 lags. The 5% critical value of χ2(20) distribution is 31.41.The standard errors are the Newey-West HAC robust estimates and are in parentheses.

Inclusion of long-term absolute returns in the HAR-logRV model by estimating the following version:

$$rv_t^D = \omega + \sum_{k=D}^{Q} \beta^k \ln\left(rv_{t-1}^k\right) + \alpha^k\left|r_{t-1}^k\right| + \gamma^k r_{t-1}^k + \xi_t. \quad (6)$$

where rkt = (1/h)Σts=t-h-1rDs and h=1 for k=D, 5 for k =W, 22 for k=M and 66 for k=Q. The hypothesis of symmetric volatility is again that γ=0. The estimation results for model (6) are presented in Table 5. The hypothesis of symmetric volatility is rejected for all of the contracts except for the CHF/EUR contract.

As a further test of robustness, I now examine the model when lagged weekly, monthly and quarterly returns are included:

$$rv_t^D = \omega + \sum_{k=D}^{Q} \beta^k \ln\left(rv_{t-1}^k\right) + \alpha^k\left|r_{t-1}^k\right| + \gamma^k r_{t-1}^k + \xi_t. \quad (7)$$

The estimation results of model (7) are reported in Table 6. I test the joint null hypothesis Ho: γD= γW= γM= γQ=0. The joint null is rejected for all contracts again except for the CHF/EUR contract.

5.2 Continuous and jump components of realized volatility

Recently, Barndorff-Nielsen and Shepard (2004,2006) have proposed a procedure that allows for a direct non-parametric decomposition of realized volatility into a continuous component and a jump component. If jumps are viewed as infrequently observed large-magnitude intraday returns, it is of interest to determine the effects of these jumps on asymmetric volatility, especially, if these jumps may be causing us to detect asymmetry. That, I check to see if the asymmetric effects in Table 4 are sensitive to the removal of the jump component from the realized volatility.

Barndorff-Nielsen and Shepard (2004) show that as the intra-day sampling length shrink to zero the realized volatility rvDt converges in probability to the sum of a component associated with a continuous diffusion process and a component associated with a jump process. The bi-power variation, bvDt = (π/2)Σmj=2 |rt,j||rt,j-1| where m is the number of intraday sampling intervals and rt,j is the intraday return for interval j. The bi-power variation is shown to converge in probability to the integrated volatility component, or the component associated with the continuous diffusion process.

To test for the presence of a jump component in the daily realized volatility, Barndorff-Nielsen and Shepherd (2006) suggest the following test statistic:

$$Z_t = \frac{m^{1/2}\left({bv_t^D}/{rv_t^D} - 1\right)}{\left({\pi^2}/{4} + \pi - 5\right).\max\left\{1, {(qv_t^D)^{1/2}}/{bv_t^D}\right\}} \quad (8)$$

where qvDt = (π2/4)mΣmj=42 |rt,j||rt,j-1| |rt,j-2||rt,j-3| (a quad-power variation). The Z statistic converges in probability to a standard normal random veritable when the lengths of the sampling intervals shrink to zero and there are no jumps. Therefore, the null of no jump is rejected if Zt is too negative.. Following Andersen et al (2005), I let zα be the standard normal upper tail critical interval for a given significance level α, z0.001=3.09. As suggested by Andersen et al (2005), the jump and continuous components of daily realized volatility are then constructed by

$$J_t^D = I\{Z_t < z_a\}\left(rv_t^D - bv_t^D\right)$$

$$\text{and } C_t^D = rv_t^D - J_t^D \quad (9)$$

respectively, where I{A} is an indicator function that is 1 if A is true and zero otherwise.

I construct the continuous and jump components as described above choosing the significance level of α = 0.001. Some descriptive statistics of JDt are given in Table 7. To test whether the HAR-logRV model (5) results are driven by infrequent jumps, I replace the rvDt in model (5) with the continuous component CDt. I report these results in Table 8.

Since the results in Table 8 are qualitatively the same as the results in Table 4, I conclude that the asymmetric effects noted in Table 4 are not caused by infrequent jumps in the returns series.

Conclusions

I present in this paper new evidence for the presence of asymmetric volatility in Euro cross-rate futures contracts. The results are robust to a number of model variations and data series. The CHF/EUR futures are found to have no significant volatility asymmetry, while the remaining contracts exhibit small, but significant, volatility asymmetries. The underlying economic rationale is not clear, but central bank intervention may play a role in volatility asymmetry. This explanation left to future investigation

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

The asterisks *, ** and *** represent statistical significance at 10%, 5% and 1% respectively. Q(20) are Ljung-Box statistics for testing autocorrelation in returns for the first 20 lags. The 5% critical value of $\chi^2(20)$ distribution is 31.41.The standard errors are the Newey-West HAC robust estimates and are in parentheses.

Table5. *HAR-logRV-R models with long term absolute returns*

	CHF/EUR	EUR/GBP	EUR/JPY
ω	-3.6190***(0.7406)	-4.6876***(0.7296)	-5.8509***(0.6789)
β^D	0.05636**(0.0270)	0.0044(0.0249)	0.0542**(0.0251)
β^W	0.4213***(0.0673)	0.3434***(0.0853)	0.3627***(0.0842)
β^M	0.0074(0.0965)	0.1296(0.1015)	0.0289(0.1053)
β^Q	0.2601***(0.0854)	0.1672***(0.0607)	0.0889(0.0596)
α^D	51.5942***(15.3305)	52.1073***(9.8803)	23.3419***(6.9452)
α^W	-966.8313(738.3341)	29.8172(27.7169)	58.7586***(13.7871)
α^M	212.7449**(97.2874)	100.2011(69.7569)	94.8546**(40.4486)
α^Q	1022.1706(729.2369)	-4.8377(109.5706)	170.5151***(62.3639)
γ^D	14.5924(11.0849)	15.9701**(6.4334)	-12.8212*** (4.1190)
corr(r_t,ξ_t)	0.1365	0.1003	-0.0297
adj. R^2	0.3460	0.2601	0.3495
Q(20)	0.5165	0.5764	0.5709

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

The asterisks *, ** and *** represent statistical significance at 10%, 5% and 1% respectively. Q(20) are Ljung-Box statistics for testing Auto correlation in returns for the first 20 lags. The 5% critical value of $\chi 2(20)$ distribution is 31.41.The standard errors are the Newey-West HAC robust estimates and are in parentheses. The p-value is for the hypotheses test H0: $\sum_{k=D}^{Q} \gamma^k = 0$.

Table6. *HAR-logRV-R models with long term returns and absolute returns*

	CHF/EUR	EUR/GBP	EUR/JPY
ω	-3.9503***(1.0593)	-1.2694(1.1564	-4.6285***(0.8533)
β^D	0.0526**(0.0268)	-0.0112(0.0242)	0.0451*(0.0248)
β^W	0.3908***(0.0677)	0.2921***(0.0850)	0.3314***(0.0852)
β^M	-0.0403(0.1018)	0.1101(0.0978)	0.0296(0.1052)
β^Q	0.3133***(0.1147)	0.5415***(0.1217)	0.2320***(0.0827)
α^D	46.4514***(15.4742)	55.7505***(10.2046)	19.8228***(7.0645)
α^W	-1038.9954(736.5642)	36.1346(27.1340)	42.1249***(15.1352)
α^M	176.0081*(98.0107)	165.2907**(69.2054)	67.0330(42.0483)
α^Q	914.4649(722.3355)	71.6174(117.6591)	232.7113***(86.0177)
γ^D	15.9106(10.9901)	15.8692**(6.4627)	-12.9815***(4.1823)
γ^W	-0.1308(30.7097)	-1.0982(3.3992)	-3.8817*(2.3206)
γ^M	7.2983**(3.0644)	-0.4563(2.0524)	-2.0508(1.4173)
γ^Q	67.6645(92.0984)	213.3612***(59.6801)	-31.7207*(16.6049)
corr(r_t,ξ_t)	0.1387	0.0996	-0.0268
adj. R^2	0.3480	0.2659	0.3540
Q(20)	0.5131	0.5842	0.5829
p-value	0.3228	0.0009	0.0024

Table7. *Jump Components in realized volatility* $J_t^D = I\{Z_t < z_a\}(rv_t^D - bv_t^D)$

	CHF/EUR	EUR/GBP	EUR/JPY
Proportion of days with jumps	0.0168	0.0168	0.0749
Number of Days with jumps	26	28	116
No-zero jumps			
Min.	-0.0001	-0.00007	-0.0006
Median	-0.000002	-0.000004	-0.00001
Max.	-0.000001	-0.000001	-0.000002
Mean	-0.00001	-0.00001	-0.00003
S.D.	0.00003	0.00002	0.00006

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

The asterisks *, ** and *** represent statistical significance at 10%, 5% and 1% respectively. Q(20) are Ljung-Box statistics for testing autocorrelation in returns for the first 20 lags. The 5% critical value of $\chi 2(20)$ distribution is 31.41.The standard errors are the Newey-West HAC robust estimates and are in parentheses.

Table8. *HAR-logRV-R models with continuous component*

	CHF/EUR	EUR/GBP	EUR/JPY
ω	-4.1186***(0.8131)	-7.8940***(0.8040)	-8.2583***(0.6067)
β^D	0.2172***(0.0492)	0.0862**(0.0399)	0.1338***(0.0313)
β^W	0.3191***(0.0507)	0.1765***(0.0425)	0.1461***(0.0342)
β^M	0.0619(0.0385)	0.0483(0.0349)	-0.0028(0.0286)
β^Q	0.1028**(0.0437)	0.0734**(0.0397)	0.0471(0.0309)
α^D	63.0414***(20.5684)	57.2378***(11.9938)	22.8768***(8.2023)
γ^D	20.9722*(11.8734)	20.1526***(7.7715)	-14.7031***(4.7074)
corr(r_t,ξ_t)	0.1340	0.1045	-0.0412
adj. R^2	0.2664	0.2138	0.3238
Q(20)	0.4987	0.6058	0.6442

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