Implications of news asymmetries in foreign exchange markets

by

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Abstract

We employ a multivariate BEKK GARCH model which allows news to affect conditional volatility in an asymmetric manner. The asymmetric model outperforms the standard symmetric model, implying that efficient financial decision makers should not treat good and bad news as homogenous. We estimate the conditional variance and covariance of the Japanese yen, Swiss franc and British pound *vis-à-vis* the US dollar from January 1971 to June 2005. We find that the volatility of foreign exchange market returns is persistent in response to news originating in own market and between markets. The dynamics of exchange rate volatility show that conditional volatility, covariance and correlation coefficients between exchange rate returns are time varying.

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1. Introduction

The selection of exchange rate regime together with increasing financial market integration, and a propensity towards systemic contagion following exogenous shocks, are renewing interest in the transmission of volatility between foreign exchange markets. Following the collapse of the Bretton Woods system of fixed exchange rates in 1971, leading international exchange rates have floated against one another. On the contrary, European policymakers resorted to fixed exchange rate arrangements to lessen volatility.[1] Nevertheless, foreign exchange markets have been characterised by substantial short-term volatility, large medium-term swings, and long-term trends in exchange rates since the 1970s (IMF, 2000). These issues interest international traders, investors, and portfolio managers because of volatility's impact on managing international financial risk, asset pricing, and asset allocation. Similarly, policymakers are concerned with exchange rate volatility because of its effect on financial stability.

In order to derive precise estimates of the volatility of exchange rate returns, volatility should be conditional upon "news" entering the market.[2] It is important to quantify how markets respond to the arrival of news if we are to understand and predict exchange rate movements. There are several studies of the effects of news announcements in the exchange rate literature.[3] The general implication is scheduled news announcements and time-of-the-day effects are important predictors of exchange rate changes. Recently, Evans and Lyons (2005) claim the information content of news does not decay as quickly as previously thought. Whilst foreign exchange markets do respond quickly to news, the effect persists as market participants adjust their positions *vis-à-vis* prior expectations.

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[1] In the European Community, policymakers created the European Monetary System (EMS) in March 1979 under which exchange rate determination was based on the exchange rate mechanism (ERM). This arrangement lasted until 1993. Policymakers decided exchange rate stability could be achieved through European Monetary Union (EMU) and the introduction of a single currency (in 1999).

[2] In studies of market microstructure and exchange rate volatility – which tend to employ intra day data - news is classified either as public or private news with public news referring mainly to [scheduled and unscheduled] announcements about macroeconomic events. Private news maybe divided into unreleased information held by public bodies like central banks, and private information held by traders. Humpage (2003) explains the tendency for central banks to sometimes operate in secret in the 1970s and 1980s they wanted to convince the market that observed changes in market activity emanated from the private sector.

[3] For instance, the Euro-dollar market (Omrane et al, 2003); yen-dollar market (DeGennarro and Shrieves, 1997; Melvin and Yin, 2000; Andersen et al, 2003); deutschemark-dollar market (Andersen and Bollerslev, 1998; Daníelsson and Payne, 2002; Andersen et al, 2003); and Norwegian krone (Bauwens et al, 2005).

It is important, therefore, to recognise the asymmetric effect of news in modelling volatility. Substantial empirical evidence exists that markets react differently to good and bad news. The importance of accounting for asymmetry is noted by Nelson (1991), Engle and Ng (1993), Glosten et al (1993), Bekaert and Harvey (1997), Brooks and Henry (2000), and Bekaert et al (2003). Failure to specify asymmetric effects can lead to model mis-specification. Kroner and Ng (1998) define the asymmetric volatility effect as implying that bad news shocks lead to higher volatility than good news shocks. This occurs because the flow of information increases following bad news announcements which affect covariance between returns. The transmission of news, and its processing and interpretation, is important because it conditions the expectations of market participants, which in turn influences the volatility of returns in a continual process.[4]

Researchers have identified two types of asymmetries: in individual returns; and in dependence between returns. Asymmetries are found in stock returns (see Kroner and Ng, 1998), optimal hedge ratios (Brooks et al, 2002), and exchange rate returns (Patton, 2006). The covariance of country returns with returns on the world stock market – an indicator of country risk – shows an asymmetric response to the arrival of new information, which will distort portfolio decisions and diversification effects unless asymmetry is accounted for (Henry et al, 2004). Asymmetric information effects are also found in macroeconomic variables like inflation which affect the rate of output growth (Shields et al, 2005; Grier et al, 2004). An asymmetric dependence between returns implies that correlations between returns are larger during episodes of financial distress compared to periods of relative stability (Patton, 2004; Hong et al. 2004).

There are various explanations for asymmetric dependence in exchange rates. Evans and Lyons (2004) discuss differences in volatility emanating from micro and macro news, and suggest that [private, short-term] trading (micro news) explains exchange rate volatility to a greater extent than public news concerning economic fundamentals (macro

[4] A voluminous literature considers whether private or public information is the more important channel of transmission. For instance, future changes in exchange rates cannot be predicted using publicly available information because rates follow a martingale process. When news arrives, market participants process the new information often with reference to earlier priors which could be based on private information. It is these market dynamics that lead to a continuation of volatility (Engle et al, 1990).

news). This is because micro news concerning market transactions accumulates and renders minimal the short-term impact of public macro news. However, Evans and Lyons discuss an embedding effect which occurs because markets gradually absorb and process macro news. This causes rational exchange rate errors in portfolio allocations and explains the medium-term to long-term effect of macro news on exchange rate volatility. On the contrary, Andersen and Bollerslev (1998) find larger returns are positively related to macro news announcements – about economic and trade fundamentals in the US and monetary aggregates in Germany. Patton (2006) suggests asymmetric dependence in exchange rates can be explained by central bank management of the exchange rate, and re-balancing of currency portfolios following exchange rate movements.

There is empirical evidence to suggest that volatility responds asymmetrically to changes in exchange rate regime. For instance, Bollerslev (1990) examines the effects of an increase in policy co-ordination on exchange rate volatility. Bollerslev estimates the volatility of five European exchange rates *vis-à-vis* the US dollar before and after the creation of the EMS (European Monetary System) in March 1979, and he finds exchange rate volatility and conditional covariance between rates increased following policy co-ordination.[5] Kearney and Patton (2000) examine exchange rate volatility transmission amongst the most important EMS currencies (*vis-à-vis* the ECU – European currency unit).[6] Their results suggest the deutschemark plays a pivotal role in transmitting volatility; transmission effects are evident in daily data which implies markets are more likely to transmit volatility when they are active, rather than calm. Similarly, Laopodis (1998) examines volatility transmission between EMS and non-EMS exchange rates *vis-à-vis* the German mark before and after the unification of Germany in 1990.[7] In this case, significant spillover effects between EMS currencies disappeared after unification.

[5] The EMS currencies are the French franc, German mark and Italian lira whilst the other European currencies are the British pound and Swiss franc. The pre-EMS period runs from July 1973 to March 1979 and the post EMS period from March 1979 to August 1985, thereby allowing for a comparison of volatilities under floating and fixed exchange rate regimes (see Bollerslev, 1990).

[6] The currencies are the German mark, British pound, French franc, Italian lira, and the European Currency Unit (ECU). The analysis covers the period from April 1979 to March 1997.

[7] The EMS currencies are the Belgian franc, Dutch guilder, and French franc; and the non-EMS currencies the Canadian dollar, Japanese yen, and US dollar. The period of analysis covers March 13th, 1979 to December 30th, 1996. In order to investigate the effects of German reunification, two sub-samples are

Our principal objective is to estimate foreign exchange market volatility across a lengthy time series, and to consider exchange rate dynamics in three international exchange rates: Japanese yen, Swiss franc, and British pound *vis-à-vis* the US dollar from 1971 to mid-2005. We employ a multivariate asymmetric GARCH model with the BEKK formulation for twin reasons. First, and as suggested by the established literature, news enters the model asymmetrically. Due to difficulties associated with estimating multivariate asymmetric GARCH models, only a few studies have employed this methodology. Second, the BEKK formulation enables us to identify whether volatility is transmitted across foreign exchange markets. It is an empirical issue whether volatility is determined by news originating in the home market or upon news originating in other markets. These hypotheses are referred to as the heat wave and meteor shower (see Engle et al, 1990; Ito et al, 1992). We consider the dynamics of volatility in exchange rate returns by calculating the conditional covariance and correlation between exchange rate returns and examining whether volatility, covariance, and correlation are time-varying.

The remainder of the paper is organised as follows. The specification of the multivariate asymmetric GARCH model is presented in Section 2. An analysis of the data and tests for the appropriateness of employing a GARCH model are discussed in Section 3. The empirical estimates of volatility transmission effects are presented in Section and some conclusions are offered in Section 5.

2. Model Specification

A wealth of literature is devoted to modelling temporal dependence in the second order moments of asset returns. The seminal works are Engle (1982) and Bollerslev (1986) which presented the ARCH and GARCH methodologies. A multitude of methodological developments and empirical applications have emerged since.[8] We estimate a multivariate GARCH using the BEKK[9] model of Engle and Kroner (1995), where the restriction of a symmetrical variance-covariance structure is removed and news is

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created: from March 13th 1979 to June 30th, 1990; and July 1st 1990 to December 30th, 1996. The data exclude exchange rate realignments and speculative attacks (see Laopodis, 1998).

[8] For excellent reviews of theoretical developments in modelling conditional heteroskedasticity and associated empirical evidence, see Bollerslev et al (1992) and Bauwens et al (2003).

[9] BEKK stands for Baba, Engle, Kraft and Kroner.

allowed to behave in an asymmetric manner following Glosten et al. (1993). Thus, the paper contributes to a limited set of studies which estimate asymmetric GARCH models in applications to stock market volatility and spillovers (Ng, 2000), optimal hedge ratios (Brooks et al., 2002), asset returns (Kroner and Ng, 1998), and stock and bond returns (De Goeij and Marquering, 2004).

Let r_t equal the continuously compounded return on a currency exchange rate over the period t–1 to t. The information set available to investors at time t–1, when investment decisions are taken, is denoted Ω_{t-1}. The expected return and volatility of returns based on those decisions are the conditional mean and variance of r_t given Ω_{t-1}, denoted $y_t = E(r_t \mid \Omega_{t-1})$ and $h_t = var(r_t \mid \Omega_{t-1})$, respectively. The unexpected return at time t is $\varepsilon_t = r_t - y_t$. Following Engle and Ng (1993), ε_t can be interpreted as a measure of news. An unexpected increase in returns ($\varepsilon_t>0$) indicates the arrival of good news, whilst an unexpected decrease in returns ($\varepsilon_t<0$) indicates bad news.

The conditional variance h_t may be modelled as a function of the lagged ε_t, implying that predictable volatility is dependent on past news, with the effect of any piece of news upon current volatility decreasing as the news becomes older or decays (Engle, 1982). In the GARCH specification introduced by Bollerslev (1986), the effect of a shock to returns decreases geometrically over time. In its simplest form, the univariate GARCH(p,q) model may be specified as follows:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \qquad [1]$$

where $\omega > 0$; $\alpha_1, \ldots, \alpha_p \geq 0$; and $\beta_1, \ldots, \beta_q \geq 0$ are constant parameters, and the non-negativity conditions ensure the conditional variance is positive. Equation [1] imposes a restriction of symmetry on the conditional variance structure. This restriction is undesirable in view of the *a priori* assumption that markets do not treat good and bad news, or small and large news shocks, in an equal manner. For an asymmetric effect, the impact of a shock of any given magnitude on the covariance equation differs depending upon whether the shock is positive (good news) or negative (bad news).

Following Glosten et al. (1993), equation [1] can be re-specified to account for the possibility of asymmetric effects. Let $k_{t-1}=1$ if $\varepsilon_{t-1}<0$, and $k_{t-1}=0$ otherwise. For ease of exposition we assume p=q=1, or a GARCH(1,1) specification:

$$h_t = \omega + (\alpha + \delta k_{t-1})\varepsilon_{t-1}^2 + \beta h_{t-1} \qquad [2]$$

$\delta>0$ implies a bad news shock has a greater impact on volatility than a good news shock. The conditions $\omega>0$, $\alpha\geq 0$, $\alpha+\delta\geq 0$ and $\beta\geq 0$ must be satisfied in order to ensure a positive conditional variance.

For a multivariate model, let $r_{m,t}$ denote the continuously compounded return on the m'th country's exchange rate over the period t–1 to t, for m=1 ... M. The expected return is the conditional mean of $r_{m,t}$ given Ω_{t-1}, denoted $y_{m,t} = E(r_{m,t} \mid \Omega_{t-1})$. The unexpected return at time t is $\varepsilon_{m,t} = r_{m,t} - y_{m,t}$. As before, the conditional variance-covariance matrix is measurable with respect to the information set, Ω_{t-1}, such that $\varepsilon_t \mid \Omega_{t-1} \sim N(0, H_t)$, where ε_t is an $M\times 1$ vector containing $\{\varepsilon_{m,t}\}$ for m=1 ... M, and H_t is an $M\times M$ matrix containing the conditional variances and covariances for the disturbance terms of the M equations.

We express the multivariate counterpart of equation [1] using the GARCH-BEKK specification, which guarantees that H_t is positive-definite through the imposition of quadratic forms upon the matrices of coefficients:

$$H_t = C'C + \sum_{i=1}^{p} A_i \varepsilon_{t-i}\varepsilon_{t-i}' A_i' + \sum_{j=1}^{q} B_j H_{t-j} B_j' \qquad [3]$$

C is an $M\times M$ upper-triangular matrix of coefficients, and A_i and B_j are (unrestricted) $M\times M$ matrices of coefficients. The GARCH-BEKK specification permits the estimation of spillover effects between equations. One drawback of [3], however, is it implies that only the magnitude of previous news is important in determining the current conditional variances and covariances. This is excessively restrictive because it does not allow for the very real possibility of asymmetric effects, defined as before. For a multivariate model, these can be specified as follows:

$$\text{Let } k_{m,t-1}=1 \text{ if } \varepsilon_{m,t-1}<0 \text{ and } k_{m,t-1}=0 \text{ if } \varepsilon_{m,t-1}\geq 0 \text{ for } m=1,\ldots,M.$$

Let K_{t-1} be an $M\times M$ diagonal matrix containing $k_{m,t-1}$ in the main diagonal elements, and 0's in the off-diagonal elements; and let $\xi_{t-1} = K_{t-1}\varepsilon_{t-1}$. As before, for ease of exposition we assume a GARCH(1,1) specification with p=q=1:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}'A' + D\xi_{t-1}\xi_{t-1}'D' + BH_{t-1}B' \qquad [4]$$

In [4], D is the matrix of coefficients for the asymmetric effects. Since the symmetric and linear GARCH-BEKK model (i.e. [3] with p=q=1) is a restricted version of [4] in which D = 0, a likelihood ratio test can be used to determine the more appropriate model specification.

In the estimations that are reported below, the number of equations is M=3. We let $r_{m,t}$ denote the continuously compounded returns for the Japanese yen-US dollar rate (m=1), the Swiss franc-US dollar rate (m=2), and the British pound-US dollar rate (m=3).

3. Data Description

The literature reports that exchange rates display similar features to equities: volatility clustering, persistence, skewness, kurtosis, as well as spillovers or volatility transmission between markets.[10] The data employed in the present study comprise 8,998 daily observations on three exchange rates from January 4th, 1971 to June 29th, 2005. The exchange rates are *vis-à-vis* the US dollar and the currencies are the Japanese yen, Swiss

[10] See Engle and Bollerslev, 1986; Boothe and Glassman, 1987; Hsieh, 1989; Baillie and Bollerslev, 1989, 1990; Bollerslev and Engle, 1993; Engle et al, 1990; and Ito et al, 1992. Generally, these studies examine volatility transmission between the US dollar and the currencies of other industrial nations.

franc, and British pound. The data are the H.10 Foreign Exchange Rate series produced by the Board of Governors of the Federal Reserve System in the US. The exchange rates are noon buying rates in New York for cable transfers payable in foreign currencies.

Figure 1 shows the evolution of exchange rates and returns over time. The return series are calculated as 100 x $ln(R_t / R_{t-1})$ where R is the exchange rate at time t. The left hand side of Figure 1 shows different patterns in exchange rate movements. Generally speaking, the US dollar depreciates from 1971 to the late 1970s, following the collapse of the Bretton Woods system. Short sharp dollar depreciation takes place in the mid-to-late 1980s followed by a more gradual depreciation to the mid 1990s. Over the past decade to 2005, exchange rates appear relatively more stable. The Japanese yen appreciates against the dollar between 1971 and 1978 but gradually depreciates from 1978 to 1985. Thereafter, the yen appreciates from around ¥250:$ towards its highest value at around ¥80:$ against the dollar in 1995. Although the yen gradually depreciates after 1995, the yen-to-dollar rate is relatively stable. Similar to the yen, the Swiss franc appreciates considerably against the dollar between 1971 and 1978. Although the dollar wiped out around 50% of the earlier franc appreciation in the early-to-mid 1980s, the trend is reversed between 1985 and 1987 with the rate remaining relatively stable to the present. On the contrary, the British pound depreciates against the dollar in two intervals over 1971 to 1985; between 1971 and 1976, and 1981 to 1985 (following an appreciating pound circa 1977 to 1980). Another large appreciation of the pound occurred over 1985 to 1988 after which its relationship with the dollar is less volatile. The pound has been floating since it left the ERM in September 1992 and it is relatively stable against the dollar with some evidence of strengthening from around 2001 to the present.

Figure 1 here

The returns are shown in the right hand side of Figure 1. The autocorrelation of returns and squared returns imply unpredictability and volatility clustering are features of each series. If returns are predictable, the autocorrelations should be significant, whilst volatility clustering will appear as significant autocorrelations in the squared returns.

Table 1 shows the return autocorrelations to be insignificant and the squared returns autocorrelations to be significant.

Table 1 here

The Ljung-Box Q statistic is calculated at various lag lengths ranging from 6 to 30 days for the returns and squared returns series. For returns, a significant Q statistic implies rejection of the null hypothesis of no serial correlation, whilst a significant Q statistic for squared returns implies rejection of the null hypothesis of homoskedasticity. Table 2 shows significant Q statistics at different lag lengths for each exchange rate. Thus, returns are characterised by the presence of higher order serial correlation (autocorrelation) and non randomness, and squared returns display non-linear dependency. This implies that it is appropriate to model exchange rate volatility using GARCH methods.

Table 2 here

Table 3 presents descriptive statistics for returns. The sample means show the yen and franc with small, negative yet significant, returns of around one-seventy fifth of a percent per day. The mean return on the pound is positive but insignificant at just under one-three hundredths of a per cent per day. The unconditional variances are 0.3977, 0.514, and 0.33, for the yen, franc, and pound, respectively. Re-expressing these data as average annualised volatilities, we find the franc to be the more risky currency with annualised volatility of 11.38% compared to 10.01% and 9.12% for the yen and pound, respectively. The distributional features of returns are as expected. The null hypothesis of normally distributed returns is rejected by the Jarque-Bera, skewness, and kurtosis statistics. Yen returns are negatively skewed whereas pound returns are positive. Kurtosis measures the extremes compared with what would be expected from a normal random variable. Under normality the kurtosis coefficient should be three. However, it is greater than three for each currency with yen returns much more extreme than returns on francs and pounds. Extreme kurtosis indicates currency returns are fat tailed.

Table 3 here

4. Empirical Results

Diagnostic Tests of Model Specification

To begin with, we use statistical methods to identify whether news should be treated as symmetric or asymmetric, and test whether cross-market spillover effects should be specified. We estimate the symmetric and asymmetric models shown in equations [3] and [4], and use a likelihood ratio to test the null hypothesis that the joint significance of the asymmetric effects is equal to zero, that is, $\delta_{m,n} = 0$. The data strongly reject the null implying that the asymmetric model is the more appropriate model specification. We test whether the joint significance of the cross-market spillover effects is equal to zero by estimating equation [4] and employing an F-test procedure. The data overwhelmingly reject the null hypothesis. This implies that volatility is transmitted between foreign exchange markets and is consistent with the meteor shower hypothesis of Engle et al (1990) and Ito et al (1992). Equation [4] was estimated using the BFGS (Broyden, Fletcher, Goldfarb, and Shanno) algorithm to maximise the log likelihood function. We also employ the quasi-maximum likelihood (QML) estimation of Bollerslev and Wooldridge (1992) which allows inference when the conditional distribution of the residuals is non-normal. The model converged after 70 iterations. The number of optimal lags in the model specification is determined by the Schwartz Information Criterion.

Since the asymmetric model is the preferred specification, the following presentation and discussion of results are based on estimates obtained from equation [4]. Table 4 shows the distributional features of the model residuals. The standardised residuals $(\varepsilon_1, \varepsilon_2, \varepsilon_3)$ are skewed and exhibit kurtosis. The model specification in terms of adequately capturing the dynamics of the data is checked by testing the standardised residuals for the presence of serial correlation and heteroskedasticity. A correctly specified model implies the standardised residuals will be *iid* standard normal variables. Typically, univariate tests are applied independently to each series although multivariate tests have been developed but are less frequently employed (see, Kroner and Ng, 1998; Ding and Engle, 2001). We follow the former approach and carry out independent residual diagnostic tests using the Ljung-Box test and the residual or LM ARCH test (see Engle, 1982).

Table 4 here

Ljung-Box Q statistics are calculated on the standardised residuals ($\varepsilon_1, \varepsilon_2, \varepsilon_3$), standardised squared residuals ($\varepsilon_1^2, \varepsilon_2^2, \varepsilon_3^2$), and cross-products of the standardised residuals ($\varepsilon_1\varepsilon_2, \varepsilon_1\varepsilon_3, \varepsilon_2\varepsilon_3$). The Q statistics test for the presence of higher order serial correlation. Whereas we do not accept the null hypothesis in the standardised residuals is not accepted it is accepted in the cross-products. Arguably, it is unreasonable to expect the model to completely account for serial correlation since the daily returns are highly leptokurtic. The model adequately captures the persistence in the variance of returns since the standardised squared residuals, in general, are serially uncorrelated (with some exceptions in ε_2^2). The residual ARCH test can also be used to determine the presence of autocorrelation in squared residuals. Autocorrelation is not detected in ε_1^2 and ε_2^2, but it is found in ε_3^2. The final diagnostic test follows the recommendation of De Goeij and Marquering (2004). If the QML estimates are consistent then we should accept the following null hypotheses: $\varepsilon_i = 0$, $\varepsilon_i^2 = 1$, and $\varepsilon_i \varepsilon_j = 1$ where i,j = 1 … 3. We accept $\varepsilon_3 = 0$ in the case of the standardised residuals whereas we accept the null for each of squared standardised residuals and the cross-products of the standardised residuals.

Volatility transmission and the effect of asymmetric news

GARCH models show the persistence of volatility following innovations in returns. We consider innovations to be the continual arrival of news to which foreign exchange markets respond by adjusting the prices of currencies in line with *a priori* expectations. Generally speaking, the established literature finds that the conditional variance or volatility of returns is influenced to a larger degree by news emanating from the “home” market (the heat wave) rather than news arriving from other markets (the meteor shower). The statistical test reported above supports the specification of volatility transmission effects between foreign exchange markets. In Table 5, we present the estimates of each coefficient in equation [4] and show estimates from equation [3] for comparison.

The coefficients in Matrix A, α_{mn}, represent ARCH effects, that is, innovations in lagged squared error terms. As expected and consistent with the literature, the magnitude of the coefficients is larger when innovations originate in an exchange rate's own market compared with the case when news arrives from another foreign exchange market. Nevertheless, we observe a bi-directional interaction between the Yen-dollar market and the pound-dollar market. The coefficients α_{13} and α_{31} are significant and imply that news originating in the Japanese market affects the market for British pounds and vice-versa. There is also evidence that news originating in the market for Swiss francs significantly influences the Japanese yen market α_{12}. Similarly, there is a uni-directional news impact from the pound to the franc α_{23}.

The coefficients that measure shocks emanating from asymmetric news are contained in Matrix D and denoted by δ_{mn}. We consider a depreciating exchange rate to be bad news although we are aware of possible limitations associated with this type of generalisation. Only in the case of δ_{33} is bad news originating in own foreign exchange market a significant shock, that is, in the market for pounds. The δ_{mn} shows there are sizeable asymmetric news effects between foreign exchange markets. For instance, from franc and pound markets to the yen (δ_{12} and δ_{13}), and from the Japanese market to the Swiss (δ_{21}). Summing the α_{mn} and δ_{mn} gives a complete representation of good and bad news shocks within and between foreign exchange markets. News emanating in individual foreign exchange markets constitute the largest shock particularly in the market for pounds and less so for francs. Nevertheless, we observe relatively large coefficients on news emanating in European markets and impacting in Japan.

In Matrix B, the coefficients, β_{mn}, indicate the persistence of news or the rate at which news decays – GARCH effects. Although we may observe significant news shock, its effect in terms of its persistence may or may not be significant. That is to say, the news content is absorbed by the market and decays immediately. As expected, news originating in each foreign market is highly persistent and lasts for at least one day (see β_{11}, β_{22}, and β_{33}). There is evidence that cross-market news is persistent and does not decay (at least for one day). For instance, we observe significant bi-directional interdependence between the Swiss franc and British pound. The arrival in the franc market of news of the pound leads to an increase in the variation of returns on the franc (β_{23}) and vice-versa (β_{32}). One explanation for this finding is the closeness between the evolution of the Swiss franc and German mark. The variance of returns on British pounds is also increased by news originating in the market for Japanese yen (β_{31}) whereas volatility in the yen market is significantly lowered by news from Switzerland (β_{12}).

Volatility dynamics

In Figures 2 to 4, we show the evolution of conditional volatility of exchange rate returns, and the conditional covariance and correlation coefficients between foreign exchange markets from 1971 to mid 2005. Establishing return dynamics and comovements are important issues for traders, international investors and other managers of international financial risks. One issue is whether financial integration has resulted in an increase in the correlation between foreign exchange markets over time. If correlations are increasing, portfolio risk may also be increasing as it is becoming more difficult to optimally allocate assets because diversification is less efficient. These issues are discussed in detail by Forbes and Rigobon (2002), Longin and Solnik (2001), Goetzmann et al (2001), and Boyer et al (1999). For present purposes, we note that it is important to estimate more precise, or conditional, measures of association between markets or asset returns that account for heteroskedasticity in the data.

Figure 2 here

The conditional variances are shown in Figure 2. The annualised mean volatilities of the three exchange rates lie within 1.5 percentage points of each other: 12.31% for yen, 13.12% for franc, and 11.64% for pound, respectively. The standard deviation of volatility is lower for the franc at 2.20% and equivalent for the yen and pound at 2.32%. The Figures show conditional volatility is time-varying. Generally speaking, volatility trends upwards from the 1970s to the early 1980s; thereafter, volatility appears relatively stable until the mid 1990s. Following the Asian crisis of 1997-98, volatilities exhibit further stability to the mid-2000s. Figure 3 shows the evolution of conditional covariance between exchange rates. Covariances are time varying and increase with episodes of crisis; for instance, the 1973 oil shock, 1987 stock market crash, and 1997-98 Asian crisis. On an annualised basis, the mean conditional covariance is of similar magnitude for the franc and pound and yen and franc, at 11.60% and 11.36%, respectively, compared with 10.22% for the yen and pound.

Figure 3 here

It is possible that the time variation observed in the covariances is due to the variance of volatility. If this is the case, correlation between exchange rate returns will be constant. This is not the case since Figure 4 shows conditional correlations are highly variable over time. Generally speaking, correlations between exchange rates increase until the end of the 1980s where they appear to be at their highest. Over the first half of the 1990s, correlations tend to weaken before strengthening again from around the time of the Asian crisis. The mean correlation is highest for the franc and pound at 0.5894, followed by the yen and franc and yen and pound at 0.5049 and 0.3754, respectively. The level of annualised standard deviation in the correlation coefficients is largest for the yen and pound at 11.26%, followed by the franc and pound and yen and franc at 11.04% and 10.89%, respectively.

Figure 4 here

5. Conclusion

In this paper, we employed a multivariate asymmetric BEKK GARCH model to estimate the conditional volatility and volatility dynamics of exchange rate returns between 1971 and 2005. The asymmetric model was found to be superior to the symmetric model. Therefore, we investigate volatility transmission under conditions where the variance of returns is allowed to respond asymmetrically to the arrival of good and bad news. We consider bad news to be a depreciation of a currency against the US dollar. Whereas foreign exchange markets react more to news originating in their own markets, we find empirical evidence of significant cross-market spillover effects. Thus, we find evidence that supports the heat wave and meteor shower effects hypotheses.

We establish the dynamics of foreign exchange market returns. The conditional volatility of exchange rate returns, the covariance of returns, and the correlation coefficient between returns are all time-varying. Generally speaking, there is a sharp upward trend in conditional volatility and correlation from 1971 to the mid-to-late 1980s which probably reflects increasing integration in financial markets. Although there is variability in the 1990s, the trend is slightly downwards. It is increasing, however, in the early-to-mid 2000s though the patterns show far less dispersion compared with the 1970s and 1980s. We find that the time variation observed in the conditional covariances are not caused by the variance of volatility.

Table 1: Autocorrelations of Returns & Squared Returns

	Returns			Squared Returns		
Lag (days)	**¥ / $**	**SF / $**	**£ / $**	**¥ / $**	**SF / $**	**£ / $**
1	0.0274	0.0172	0.0498	0.0919*	0.1556*	0.1251*
2	0.0230	-0.0041	0.0099	0.0744*	0.1454*	0.1281*
3	0.0012	-0.0009	-0.0118	0.0446*	0.0969*	0.1137*
4	-0.0005	0.0067	0.0040	0.0301*	0.0737*	0.1298*
5	0.0141	0.0067	0.0380	0.0429*	0.0960*	0.1111*
6	-0.0072	-0.0050	-0.0105	0.0450*	0.0743*	0.1281*
7	0.0066	0.0034	-0.0098	0.0280	0.0903*	0.0929*
8	0.0148	0.0168	0.0059	0.0288	0.0730*	0.0848*
9	0.0155	0.0072	0.0198	0.0462*	0.0469*	0.0734*
10	0.0444	0.0172	0.0086	0.0304*	0.0587*	0.1086*
11	0.0060	0.0072	-0.0051	0.0332*	0.0933*	0.1430*
12	0.0060	-0.0081	-0.0121	0.0238	0.0669*	0.0896*
13	0.0052	-0.0079	-0.0112	0.0292	0.0535*	0.0761*
14	0.0133	0.0105	0.0051	0.0409*	0.0739*	0.0959*
15	0.0076	0.0266	0.0314	0.0278	0.0339*	0.0950*
16	0.0042	-0.0001	-0.0056	0.0139	0.0388*	0.0949*
17	-0.0120	-0.0030	0.0092	0.0212	0.0373*	0.0820*
18	0.0159	-0.0097	-0.0102	0.0393*	0.0464*	0.0780*
19	0.0001	0.0031	-0.0055	0.0449*	0.0602*	0.1126*
20	0.0193	0.0122	0.0194	0.0424*	0.0689*	0.1286*
21	0.0069	0.0272	0.0097	0.0330*	0.0465*	0.0572*
22	-0.0018	-0.0072	0.0064	0.0286	0.0413*	0.0766*
23	0.0021	0.0136	0.0148	0.0420*	0.0501*	0.0711*
24	-0.0079	0.0212	0.0016	0.0337*	0.0345*	0.0562*
25	0.0202	0.0082	0.0204	0.0265	0.0508*	0.0879*
26	0.0018	-0.0201	-0.0118	0.0333*	0.0275	0.0866*
27	0.0023	-0.0029	0.0124	0.0273	0.0357*	0.0513*
28	0.0077	0.0083	0.0163	0.0332*	0.0414*	0.0749*
29	-0.0031	-0.0007	0.0081	0.0261	0.0535*	0.0712*
30	-0.0134	0.0018	0.0082	0.0143	0.0730*	0.0660*

Note: * , statistically significant at the 5 percent level.

Table 2: Descriptive Statistics: Exchange Rate Returns

	¥ / $	**SF / $**	**£ / $**
Sample Mean	-0.0129*	-0.0134*	0.0034
Standard Error	0.6306	0.7170	0.5744
Variance	0.3977	0.5140	0.3300
Standard Error of the Mean	0.0066	0.0076	0.0061
t-Statistic (Mean = 0)	-1.9462	-1.7691	0.1594***
Skewness	-0.7798***	0.0006	0.2142***
Kurtosis (excess)	11.7957***	3.8519***	4.4027***
Jarque-Bera	53118.87***	5562.21***	7304.60***
Observations	8997	8997	8997

Note: ***, **, * statistically significant at 1%, 5% and 10%.

Table 3: Ljung -Box Q Statistics (6 to 30 lags) for Returns & Squared Returns

	Returns	**Squared returns**
¥ / $		
Q (6 lags)	13.79***	186.68***
Q (12 lags)	36.74***	243.81***
Q (18 lags)	42.84***	293.26***
Q (24 lags)	47.26***	371.04***
Q (30 lags)	53.27***	412.01***
SF / $		
Q (6 lags)	3.88**	674.36***
Q (12 lags)	10.67	965.27***
Q (18 lags)	19.54	1096.10***
Q (24 lags)	33.82**	1239.86***
Q (30 lags)	38.82**	1370.86***
£ / $		
Q (6 lags)	38.58***	815.89***
Q (12 lags)	45.51***	1369.68***
Q (18 lags)	57.72***	1782.79***
Q (24 lags)	64.62***	2202.99***
Q (30 lags)	74.61***	2500.02***

Note: ***, **, * statistically significant at 1%, 5% and 10%.

Table 4: Diagnostic Tests: Standardised, Standardised Squared, and Cross-Products of Residuals

	e_1	e_2	e_3	e^2_1	e^2_2	e^2_3	e_1e_2	e_1e_3	e_2e_3
Mean	-0.0192*	-0.0225**	-0.0013	0.9705	0.9908	0.9793	0.9205	1.5864	0.9199
Variance	0.9702	0.9904	0.9794	25.6466	7.7617	10.8849	351.2042	1342.5645	612.4854
Skewness	-1.3486	-0.1376	0.0874	51.3591	23.8182	32.7231	6.4641	12.9784	46.1464
Kurtosis	25.1553	5.9026	9.3556	3499.1316	1034.3638	1747.0120	1867.9727	885.4611	3928.6675
LM ARCH test[(a)]				4.9992	13.7064**	1.3954			
t-stat for H_0: $\varepsilon_{it} = 0$	-1.8450	-2.1480	-0.1248	-	-	-	-	-	-
t-stat for H_0: $\varepsilon_{it}\varepsilon_{it} = 1$	-	-	-	-0.5506	-0.3083	-0.5958	-0.4017	1.5179	-0.3069
Ljung-Box Q Statistics[(b)]									
Q (6)	25.4155***	13.8258**	23.1483***	5.8343	13.4041**	1.5333	0.8200	5.9611	5.8203
Q (12)	53.3159***	32.8148***	40.6188***	7.7341	17.0968	3.0625	4.5540	8.6028	6.7462
Q (18)	59.7407***	39.4955***	49.6153***	8.8968	21.0088	5.8675	14.8011	26.6037	7.2854
Q (24)	65.0801***	54.9892***	58.3460***	9.2792	51.0905***	10.0191	16.1200	31.8276	8.3943
Q (30)	69.2726***	59.4527***	70.4648***	10.0204	56.0204***	12.1387	18.0893	57.3348***	9.4972

Notes:

(a) The LM ARCH test is the Lagrange multiplier test of Engle (1982) for the presence of ARCH effects in residuals. The 95% and 99% critical values from the χ^2 distribution with *df* = 5 are 11.1 and 16.7, respectively.

(b) The 95% critical values for Q(6), Q(12), Q(18), Q(24), and Q(30) are 12.6, 21.0, 28.9, 36.4 and 43.8, respectively. The 99% critical values for Q(6), Q(12), Q(18), Q(24), and Q(30) are 18.5, 28.3, 37.2, 45.6 and 53.7, respectively.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Parameter Estimates: Standard & Asymmetric BEKK GARCH(1,1)

		Standard BEKK		Asymmetric BEKK	
Variable		**Coefficient**	**Standard error**	**Coefficient**	**Standard error**
C11	ω_{11}	0.0952***	0.0172	0.0935***	0.0137
C12	ω_{12}	0.0282**	0.0121	0.0300***	0.0061
C13	ω_{13}	-0.0101	0.0098	-0.0114	0.0076
C22	ω_{22}	0.0669***	0.0102	0.0670***	0.0095
C23	ω_{23}	-0.0146	0.0093	-0.0126**	0.0049
C33	ω_{33}	0.0508***	0.0108	0.0518***	0.0040
A11	α_{11}	0.3576***	0.0469	0.3605***	0.0332
A12	α_{12}	0.0689	0.0472	0.0719**	0.0290
A13	α_{13}	0.0419	0.0296	0.0482**	0.0231
A21	α_{21}	-0.0282**	0.0138	-0.0303	0.0191
A22	α_{22}	0.2263***	0.0175	0.2214***	0.0164
A23	α_{23}	-0.0267**	0.0128	-0.0236**	0.0101
A31	α_{31}	-0.0193	0.0191	-0.0287**	0.0128
A32	α_{32}	-0.0013	0.0230	0.0017	0.0123
A33	α_{33}	0.2646***	0.0227	0.2420***	0.0086
B11	β_{11}	0.9301***	0.0151	0.9274***	0.0119
B12	β_{12}	-0.0165	0.0153	-0.0165*	0.0097
B13	β_{13}	-0.0072	0.0090	-0.0080	0.0078
B21	β_{21}	0.0056	0.0049	0.0062	0.0058
B22	β_{22}	0.9655***	0.0047	0.9634***	0.0058
B23	β_{23}	0.0134***	0.0047	0.0135***	0.0026
B31	β_{31}	0.0127*	0.0069	0.0129***	0.0035
B32	β_{32}	0.0090	0.0068	0.0085***	0.0021
B33	β_{33}	0.9555***	0.0068	0.9521***	0.0016
D11	δ_{11}	-	-	-0.0560	0.0586
D12	δ_{12}	-	-	0.0855**	0.0428
D13	δ_{13}	-	-	0.0399*	0.0235
D21	δ_{21}	-	-	0.1041**	0.0422
D22	δ_{22}	-	-	0.0470	0.0301
D23	δ_{23}	-	-	-0.0175	0.0155
D31	δ_{31}	-	-	0.0095	0.0277
D32	δ_{32}	-	-	-0.0216	0.0137
D33	δ_{33}	-	-	0.1606***	0.0200

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Figure 1 – Exchange Rate Index and Returns, January 1971 – June 2005

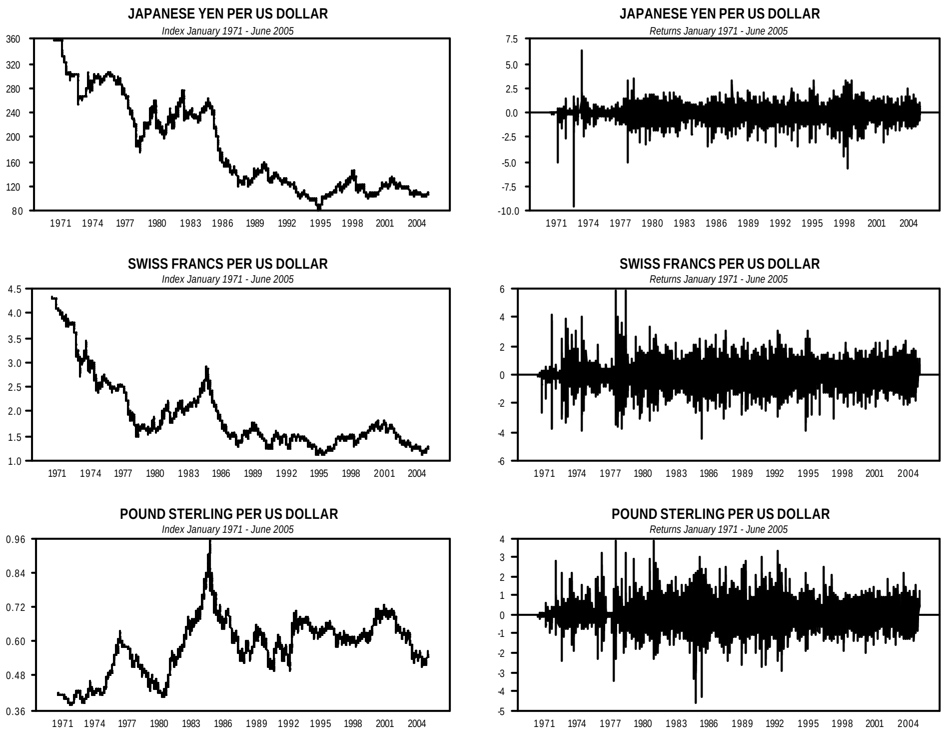


Figure 2: Conditional Volatility

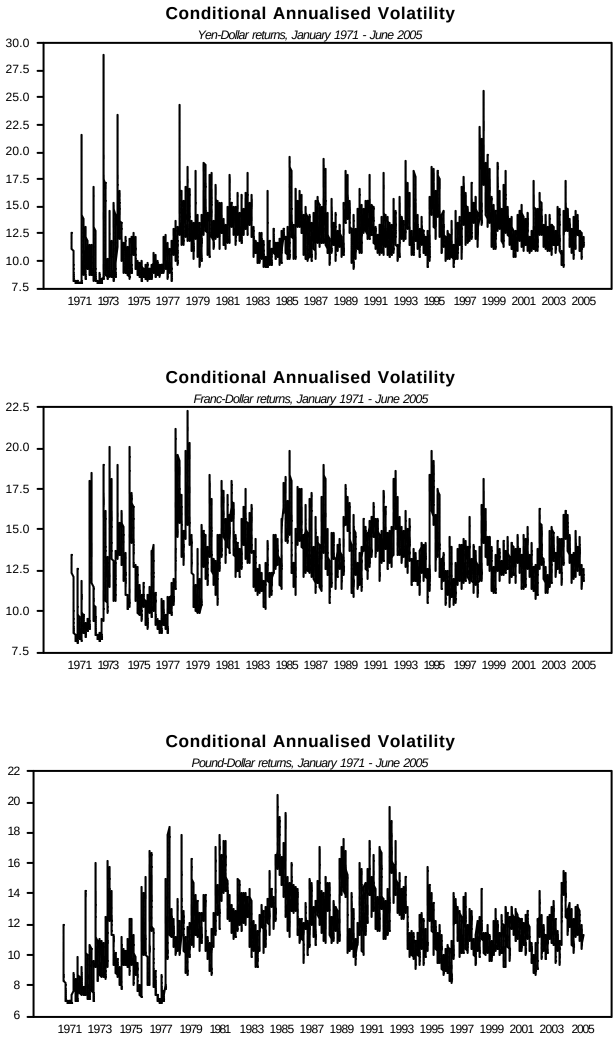
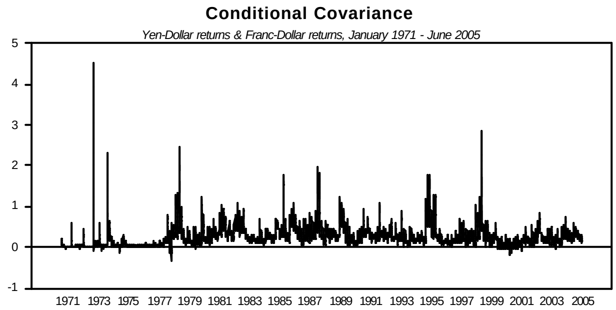
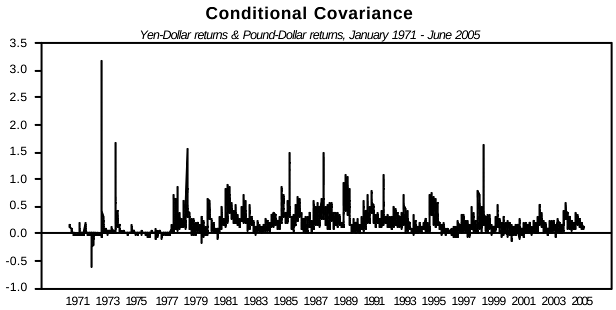


Figure 3: Conditional Covariance





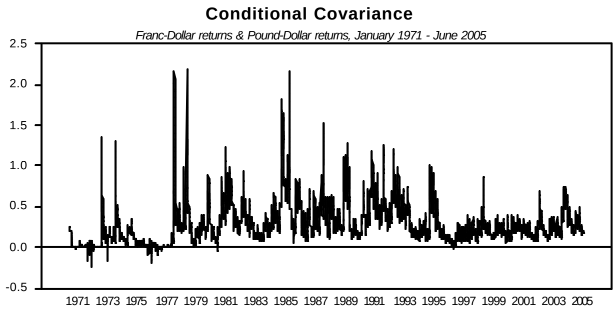


Figure 4: Conditional Correlation