Quantitative Analysis of Macroeconomic Shocks and the Euro Currency in High Frequency Perspective*

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Abstract

Using new datasets of high frequency Dollar-Euro foreign exchange rates, Surveyed expectations and Actual realizations of macroeconomic indicators in the US and the EMU, this paper characterizes a new type of the high frequency Dollar-Euro foreign exchange rate data after 1999 when the Euro currency was first introduced in foreign exchange markets. The FIGARCH model is found to be the preferred specification for the Dollar-Euro returns data, with similar values of the long memory volatility parameter across different frequencies, which is indicative of returns being generated by a self similar process.

This paper also examines whether the Euro currency reacts to macroeconomic shocks in different ways depending on whether the shocks come form the US or the EMU region and whether the shocks are positive or negative. By quantifying the duration of the intraday impacts of the macroeconomic shocks on the high frequency Dollar-Euro returns, this paper finds that the macroeconomic shocks of the US and the EMU are found to have statistically significant impacts on both the conditional mean and the conditional variance but their impacts appear to be asymmetric depending on the regions (US and EMU area) and the signs (positive and negative) of the shocks.

JEL classifications: C13, C22, F31, G14

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1. Introduction

On January 1, 1999, European Monetary Union (EMU) introduced a new currency, *the Euro*, in foreign exchange markets. The introduction of the Euro appears to be the most salient change in the international monetary system since the breakdown of the Bretton Woods system. With the inception of the Euro, the Dollar-Euro foreign exchange market has finally included the previous foreign exchange markets of eleven member countries for the respective domestic currency against the US dollar. It has become the world's second largest currency after the US dollar and the Dollar-Euro has become the largest pair of currencies in the trading volume of spot transactions in foreign exchange markets around the world.[1)]

It is argued that the Euro currency may significantly affect the international means of payment, unit of account and store of value in international financial transactions and that the Euro currency may challenge to the hegemonic status of the US dollar. And, the adoption of Euro currency as an international vehicle currency may be pertinent to the expansion of the European Union. Many studies have analyzed the international role and the importance of the Euro and the EMU (European Monetary Union) in international finance (see e.g., Cohen, 1997; Benassy-Quere et al. 1997, 1998; Mundell, 1998; Corsetti and Pesenti, 1999; Mussa, 2000).

The aim of this paper is twofold. First, this paper characterizes the features of the high frequency Dollar-Euro exchange rates focusing on long memory property and temporal aggregation, and it also investigates whether the returns are a self similar process. Second this paper quantitatively investigates whether the Dollar-Euro exchange rates react to macroeconomic shocks in different ways depending on whether the shocks come form the US or the EMU region and whether the shocks are positive or negative.

This paper first focuses on the intriguing features of the Euro currency by using a new high frequency dataset of 15-minute Dollar-Euro exchange rates sampled from 00:00 (Greenwich Mean Time: GMT), January 4, 1999 to 00:00 (GMT), January 1, 2003. And, this paper is concerned with the stochastic properties of the high frequency Dollar-Euro exchange rate returns data and applies a relatively recent development in volatility modeling to the returns, the Fractionally Integrated Generalized Auto Regressive Conditional Hetroskedastistic (FIGARCH) long memory volatility model of Baillie et al. (1996).[2)] The high frequency returns are found to be dominated by strong intraday periodicity resulting from repeated institutionalized trading day behavior, and which is removed by a deterministic Flexible Fourier Form (FFF) filter of Gallant (1981, 1982). The subsequently filtered high frequency returns are remarkably well described by the FIGARCH process.

This paper also wishes to see if the FIGARCH model is consistent with the theory that returns are a self similar process, which implies the long memory parameter is invariant to the sampling frequency; see Beran (1994). The relatively similar estimates of the long memory parameter from the FIGARCH model across different sampling frequencies suggest that the long memory property is an intrinsic feature of the system rather than being due to exogenous shocks which lead to regime shifts. And, the conditional means of the high frequency returns are close to being uncorrelated with small departures from martingale behavior being represented by MA (1) models. The results of the paper have important implications for our understanding of the stochastic properties of the high frequency Dollar-Euro exchange rates, and hence for the asset pricing and risk management applications in the Euro currency market.

Then, this paper quantifies the duration of the intraday impacts of the US and the EMU macroeconomic shocks on the conditional means and the conditional variances of the high frequency Dollar-Euro exchange rates during the first four years of the Euro. For this investigation, this paper uses ten US major macroeconomic indicators and seven EMU indicators to construct the macroeconomic shocks in the two regions. The new datasets of the macroeconomic indicators contain the information of surveyed macroeconomic expectations and actual macroeconomic realizations in the US and the EMU area which are provided by Economic Release Screen in Bloomberg News (BN). Furthermore and to highlight the effects of the shocks contained in the important macroeconomic news, this paper distinguishes positive from negative shocks by computing the difference the expected surveys and the realizations.

Even though this paper relates to the earlier papers such as Galati and Ho (2003), Fatum and Hutchison (2003), Omrane et al. (2003) and Omrane and Heinen (2004) who have investigated the impacts of macroeconomic shocks on the Euro currency in intriguing ways, three features can differentiate this paper from the previous papers. First, this paper uses more recent and larger high frequency data sets of foreign exchange rates of the Euro currency and macroeconomic indicators of the US and the EMU with the sample periods of four years, from January 4, 1999 to December 31, 2002. Second, this paper focuses on the application of a FIGARCH volatility model to the high frequency returns of the Dollar-Euro exchange rates. Several papers such as Baillie et al. (2000, 2004), Beine et al. (2002, 2003), Baillie and Han (2002) and Han (2003, 2004) have found that the FIGARCH model appears to be more effective to describe foreign exchange returns than regular GARCH model. Finally, this paper focuses the impacts of macroeconomic shocks of the US and the EMU on both the conditional mean and the conditional variance of the Dollar-Euro exchange rates since the volatility process can not be extracted accurately if the conditional mean is modeled adequately. In particular this paper distinguishes positive shocks from negative shocks by computing the difference between the surveyed forecasts and the actual realized values in order to highlight the effects of the possible "shocks" contained in the macroeconomic indicators

The quantitative analysis in this paper shows that both US and the EMU macroeconomic shocks are found to have statistically significant effects both on the Euro spot rate and on market volatility but their impacts appear to be different depending on the regions, the US and the EMU. The details of the linkage are pursed by the analysis of sign effects of the macroeconomic shocks. The sign effect analysis shows that the high frequency Dollar-Euro exchange returns react to the shocks asymmetrically to different extent at different signs just like the asymmetric responses to different regions of the shocks. Thus, the high frequency exchange rate dynamics appears to be closely linked to macroeconomic shocks but the responses to the shocks seem to be asymmetric to different extents at different regions and signs of the shocks.

The plan of the rest of this paper is as follows; section 2 describes the basic properties of the high frequency Dollar-Euro exchange rate data and the presence of long memory and intraday periodicity in the autocorrelation functions of the squared and absolute returns over various temporally aggregated returns. The application of the Flexible Fourier Form (FFF) filter proposed by Gallant (1981, 1982) to remove deterministic intra-day periodicity is then discussed. This section also discusses the application of the long memory volatility, FIGARCH model for the filtered high frequency data. Section 3 of the paper then provides the definition of macroeconomic shocks of the US and the EMU and presents the econometric models in order to quantify the intraday impacts of the macroeconomic shocks and the estimation results. In particular, the dynamic distributed lag model is used together with the MA(1)-FIGARCH model to measure the impacts of the macroeconomic shocks on the both conditional mean and the conditional variance. Section 4 briefly concludes.

2. High Frequency Dollar-Euro Returns

This section is concerned with the set of 15 minute Dollar-Euro spot exchange rate data provided by Olsen & Associates of Zurich, in which Reuter FXFX quotes are taken every 15 minutes for the complete calendar years of 1999 through 2002. The sample period is 00:00 GMT, January 4, 1999 through 00:00 GMT, January 1, 2003. Each quotation consists of a bid and an ask price and is recorded in time to the nearest second. Following the procedures of Müller et al. (1990), Dacorogna et al. (1993), Baillie et al. (2000, 2004) and Han (2004), the spot exchange rate for each 15 minute interval is determined as the linearly interpolated average between the preceding and the following quotes.

Figure 1 plots the Dollar-Euro exchange rate series and shows that Euro currency appeared to be weak relative to US Dollar so that the exchange rate declined from \$1.18 to \$0.83 during the first three years since the currency was introduced. Many analysts blamed the Euro’s weakness on the Euro area’s sluggish rate of growth compared with the American economy. But, the Euro currency stared to gain against the US Dollar from the beginning of 2002 and finally approached to \$ 1.05 at the end of 2002. Since the growth rate in Euro area was still lag behind that in US in 2002, the Euro's bounce seemed to come from the weak dollar which has been hit by worries about US huge current account deficit and uncertainties in a war with Iraq.

2.1. Intraday Features of the High Frequency Dollar-Euro Exchange Returns

Then the n-th 15 minute spot return for day t is,

$$R_{t,n} = 100*[\ln(S_{t,n}) - \ln(S_{t,n-1})] \tag{1}$$

As provided by Goodhart et al. (1993) and Danielsson and Payne (2002), the basic characteristics of the 15 minute exchange rate returns constructed from the quotes are quite similar to those from calculated from actual transaction prices which are not generally available in the foreign exchange markets. It has become fairly standard in this literature to remove atypical data associated with slower trading patterns during weekends; see Műller et al. (1990) and Bollerslev and Domowitz (1993). Hence returns from Friday 21:15 GMT through Sunday 20:10 GMT are excluded. However, returns for holidays occurring during the sample are retained in order to preserve the number of returns associated with one week. In particular, the eventual sample used in subsequent analysis contains 1042 trading days, each with 96 intervals of 15 minute duration; which realizes a total of 100,032 observations for the Dollar-Euro returns for the 1042 days. Figure 2 which represent the returns series of the Dollar-Euro exchange rate shows that the returns are centered on zero but there exists obvious volatility clustering in the series.

The sample mean of the 15 minute exchange return is found to be -0.0001 (Euro depreciation of 0.0001% during the sample period) which is very close to zero and indistinguishable at the standard significance level given the sample deviation of 0.0724%. However, the return is not normally distributed since the sample skewness of 0.9722 and the sample kurtosis of 56.9485 are found to be both statistically significant based on the fact that the standard errors of the statistics are 0.003 and 0.015 respectively[3)]. Similar features can be found in the return series obtained at a range of different intraday frequencies.

Table 1 provides the descriptive statistics for all 12 possible intraday returns sampled at different frequencies over a 24-hour periodicity. The returns are continuously compounded so that the *n* th return on day *t* for the series at (*k**15) minute interval is defined by $R^{k}_{t,n} = \Sigma_{i=(n-1)k+1,nk} (R_{t,i})$, t = 1,2,…1042, n = 1,2,..,K where K = 96/k is the number of returns per day. In particular, the standard deviations increase proportionally to the square root of the sampling frequency, implying that the returns are approximately uncorrelated (see, e.g. Andersen and Bollerslev, 1997). And, there are small but significant, negative autocorrelations at the first lag in the returns across various frequencies, which can be attributed to a combination of a small time varying risk premium, bid-ask bounce, and/or non-synchronous trading phenomena; see Goodhart and O'Hara (1997) for a description of this issue in high frequency currency markets.

Figure 3 plots the first 480 autocorrelation coefficients for the returns, squared returns and absolute returns of the unadjusted (raw) 15 minute Dollar-Euro exchange rates. The usual $T^{-1/2}$ asymptotic standard errors for the sample autocorrelations are not strictly valid for a process with ARCH effects and are no more than useful guidelines. As mentioned, there is a small, negative but very significant first order autocorrelation in returns. The weak negative correlation may be attributed to a combination of a small time varying risk premium, bid-ask bounce, and/or non-synchronous trading phenomena while higher order autocorrelations are not significant at conventional levels.

However, the autocorrelation functions of the squared and absolute returns exhibit a pronounced U-shape pattern, associated with substantial intraday periodicity. The general pattern is consistent with the studies of Wasserfallen (1989), Müller et al. (1990), Baillie and Bollerslev (1991), Dacorogna et al. (1993), Andersen and Bollerslev (1998), Baillie et al. (2000, 2004) and Andersen et al. (2003). The pattern is generally attributed to being due to the opening of the European, Asian and North American markets superimposed on each other. A further representation of this phenomenon in the Euro market is provided by figure 4, which shows the average absolute returns for each of the 96 intervals over all the days in the years. It represents a pronounced difference in the volatility over the 24-hour periodicity. The highest average absolute return occurs around 15:00 GMT (interval 60) when the two largest FX markets, the Europe market and the US market just start to trade together while the return is the lowest around 04:00 GMT (interval 16) when the FX market in Japan is trading alone and is at a lunch time (Lunch time effect).

2.2. Analysis of the High Frequency Dollar-Euro Exchange Returns

In order to remove the strong intra day periodicity, this study follows a similar approach as Andersen and Bollerslev (1997, 1998), Baillie et al. (2000, 2004), Baillie and Han (2002), and uses a two step estimation method. First, the intraday periodicity is removed by applying Gallant's (1981, 1982) FFF (Flexible Fourier Form) approach. See Appendixes of Andersen and Bollerslev (1997) and Baillie et al. (2002) for the details. The 15 minute returns are then filtered by the estimated intraday seasonality series from FFF method, $s_{t,n}$, to generate the filtered returns, which are defined as[4)]

$$\check{R}_{t,n} = R_{t,n} / \hat{s}_{t,n}. \qquad (2)$$

Figure 5 presents the autocorrelations of the raw, squared and absolute filtered 15 minute Dollar-Euro exchange returns. While the filtered high frequency returns have virtually found small autocorrelation at the first lag, which is quite similar to the raw returns, it is clear that the autocorrelations of the squared and absolute filtered returns have dramatically reduced intraday periodicity. But, the plots reveal the marked persistence of squared and absolute returns that was first noticed by Ding et al. (1993) for the case of stock market returns.

In particular, the autocorrelation function for the squared and absolute returns does not display the usual exponential decay associated with the stationary and invertible class of ARMA models, but rather appears to be generated by a long memory process with hyperbolic decay. More formally, the theoretical autocorrelation at lag *k*, ρ_k, tends to satisfy $\rho_k \approx ck^{2d-1}$ as *k* gets large, where *d* is known as the long memory parameter. This type of persistence is consistent with the notion of hyperbolic decay, sometimes called the Hurst phenomenon, where the Hurst coefficient *H* is simply defined as $H = d +0.5$. While many stochastic processes could potentially have the long memory property, the most widely used is the ARFIMA(p,d,q) process of Granger and Joyeux (1980), Granger (1980) and Hosking (1981).

In the ARFIMA process a time series y_t is modeled as

$\phi(L)(1-L)^d y_t = \theta(L)\varepsilon_t$ with $\phi(L)$ and $\theta(L)$ being p'th and q'th order polynomials in the lag operator L respectively, with all their roots lying outside the unit circle, while ε_t is a white noise process. The ARFIMA process is stationary and invertible in the region of $-\frac{1}{2} < d < \frac{1}{2}$. At high lags the ARFIMA(p,d,q) process is known for to have an autocorrelation function that satisfies $\rho_k \approx ck^{2d-1}$, so that the autocorrelations decay at a slow hyperbolic rate as opposed to the exponential rate associated with the stationary and invertible class of ARMA models. The sample autocorrelation function of the squared and absolute returns of the filtered Dollar-Euro exchange rate appears to be very consistent with the above properties. Thus, volatility has been found to be very persistently autocorrelated with long memory hyperbolic decay.

A model that is consistent with these stylized facts is the MA(1)-FIGARCH(1,δ,1) process,

$$\check{R}_{t,n} = \mu + \varepsilon_{t,n} + \theta\varepsilon_{t,n-1}, \tag{3}$$

$$\varepsilon_{t,n} = z_{t,n}\, \sigma_{t,n}, \tag{4}$$

$$\sigma^2_{t,n} = \omega + \beta\sigma^2_{t,n-1} + [1 - \beta L - (1 - \varphi L)(1 - L)^{\delta}]\varepsilon_{t,n}^{2}, \tag{5}$$

where $z_{t,n}$ is an i.i.d.(0,1) process, and where the two time indices are t = 1,.. 1042 days, and n = 1,.. K, intra day periods, so that K = 96/k, for k = 1, 2, 3, 4, 6, 8, 12, 16, 24, 32, 48 and 96.

The FIGARCH process is described by Baillie et al. (1996), and has impulse response weights of

$$\sigma^2_{t,n} = \omega/(1 - \beta) + \lambda(L)\varepsilon^2_{t,n}, \tag{6}$$

where $\lambda_k \approx k^{d-1}$. Hence, d characterizes the long memory property, or "Hurst effect" of hyperbolic decay and indicates that for high lags the impulse response weights decay at a very slow hyperbolic rate. The attraction of the FIGARCH process is that for $0 < \delta < 1$, it is sufficiently flexible to allow for intermediate ranges of persistence, between complete integrated persistence associated with $\delta = 1$ and the sharp rates of decay associated with $\delta = 0$. The above equations (3) through (5) are estimated by using non-linear optimization procedures to maximize the Gaussian log likelihood function,

$$\log(\zeta) = -(T/2)\ln(2\pi) - (1/2)\Sigma_{t=1,..,1042,\ n=1,..96}[\ln(\sigma^2_{t,n} + \varepsilon^2_{t,n}\sigma^{-2}_{t,n})] \tag{7}$$

However, it has long been recognized that most asset price returns are not well represented by assuming $z_{t,n}$ in equation (4) is normally distributed; for example see McFarland et al. (1987), Boothe and Glassman (1987), etc. Consequently, inference is usually based on the QMLE of Bollerslev and Wooldridge (1992), which is valid for $z_{t,n}$ being non Gaussian. On denoting the vector of parameter estimates from a sample of T observations by $\hat{\theta}_T$, the limiting distribution is given by,

$$T^{1/2}(\hat{\theta}_T - \theta_0) \rightarrow N[0, A(\theta_0)^{-1} B(\theta_0) A(\theta_0)^{-1}], \quad (8)$$

where A(.) and B(.) represent the Hessian and outer product gradient respectively; and θ_0 denotes the vector of true parameter values. Equation (6) is used to calculate all the robust standard errors that are reported in the subsequent tables, with the Hessian and outer product gradient matrices being evaluated at the point $\hat{\theta}_T$ for practical implementation.

Table 2 presents the estimation results of applying the above model to the filtered high frequency Dollar-Euro exchange returns across different frequencies over k, within the day. The long memory volatility parameters (δ) are estimated to be within the range of 0.20 to 0.29 for the twelve different sampling frequencies and they appear to be quite consistent regardless of the sampling frequencies.[5)] The estimated long memory parameters are strongly statistically significant for the return series across different sampling frequencies and the hypotheses that $\delta = 0$ (stationary GARCH) and also $\delta = 1$ (integrated GARCH) can be comprehensively rejected for all returns using standard significance levels.

Table 2 also reports Robust Wald test statistics denoted by $W_{\delta=0}$ for testing the null hypothesis of GARCH(1,1) versus a FIGARCH(1, δ,1) data generating process. Under the null, W will have an asymptotic χ_1^2 distribution and, from Table 2, the GARCH(1,1) model is rejected for every return across various frequencies at standard significance levels. This formal statistical test supports the conclusion that FIGARCH is superior to GARCH for modeling the conditional variances of exchange returns.

Furthermore, a sequence of diagnostic tests for higher order MA structures and higher order FIGARCH models failed to find evidence in favor of expanding the model further. Several tests for mis-specification do not reveal any obvious deficiencies with the model, and the standardized residuals from the MA (1)-FIGARCH (1,δ,1) model for the 15 minute returns appear to be uncorrelated.[6)]

In particular, the general similarity in the estimated long memory parameters from the FIGARCH model across different sampling frequencies presents that the FIGARCH models are consistent with the theory that the exchange returns are self similar processes, and hence have long memory parameters that are invariant with sampling frequency; see Beran (1994). The robustness of the estimates of the long memory volatility parameter across relatively short spans of high frequency data strongly suggests that the long memory property is an intrinsic feature of the system rather than being due to exogenous shocks which lead to regime shifts, as suggested by Andersen and Bollerslev (1997, 1998), Baillie et al. (2000, 2004) and Han (2004).

3. High Frequency Dollar-Euro Exchange Rates and Macroeconomic Shocks

Many previous studies have theoretically and empirically investigated the impacts of macroeconomic news or shocks on foreign exchange returns. They have been generally based on the idea that if foreign exchange markets are efficient, only unexpected news (shocks) can cause unanticipated movements in foreign exchange rates while expected news (shocks) would be incorporated in current exchange rates. In particular, they have provided evidence that macroeconomic news (shocks) have statistically significant effects on foreign exchange rates; e.g. Engel and Frankel (1984), Hakkio and Pearce (1985), Hogan and Melvin (1994) etc.

Even though macroeconomic news (shocks) influence foreign exchange rates significantly, the influence can be dissemble only within intraday data sampled at high frequencies. Hence many papers in recent years have increasingly used intraday high frequency data, which provides more precise information for the announcement times of macroeconomic variables. While some papers like Goodhart et al. (1993) and Almeida et al. (1998) have focused mainly on the impacts of macroeconomic news on the level of high frequency exchange rates, the papers of Ederington and Lee (1993), Payne (1996), Degennaro and Shrieves (1997), Andersen and Bollerslev (1998), Melvin and Yin (2000) and Cai et al. (2001) have investigated the news effects in the volatility of high frequency exchange rates.[7)] Recently, Andersen et al. (2003) have analyzed the impacts of macroeconomic announcement surprises on both the conditional means and the conditional variances of several high frequency foreign exchange rates including Euro-Dollar exchange rates sampled from the periods before 1999. They have presented that the macroeconomic announcement surprises produce conditional mean jumps and the foreign exchange markets react to the surprises in an asymmetric fashion: bad news has greater impact than good news.

However, little empirical work has yet been done on measuring the impacts of macroeconomic shocks (news) in particular on the Euro currency after 1999 when the Euro currency was introduced. Recent studies investigating the effects of macroeconomic news on the relatively new Euro exchange rate are Galati and Ho (2003), Fatum and Hutchison (2003), Omrane et al. (2003) and Omrane and Heinen (2004). Similar to the previous studies, this paper also investigates the impacts of macroeconomic shocks on the

Euro-Dollar exchange rates on the high frequency perspectives but it is different from the previous papers in the following ways; i) this paper uses more recent and larger high frequency data sets of foreign exchange rates of the Euro currency and macroeconomic indicators of the US and the EMU, ii) this paper focuses on the application of a FIGARCH volatility model with a distributed lag dummy variable to quantify the impacts of macroeconomic shocks, and iii) this paper focuses the impacts of macroeconomic shocks of the US and the EMU on the conditional mean and the conditional variance of the Dollar-Euro exchange rates at the same time.

3.1. Descriptions of Bloomberg Macroeconomic Data and Macroeconomic Shocks

In order to investigate and compare the impacts of the US and the EMU macroeconomic shocks on both conditional mean and the conditional variance of the high frequency Dollar-Euro exchange rates, this paper uses the Bloomberg News (BN) Surveys Data and Actual Realizations Data for macroeconomic indicators of the US and the EMU displayed on Bloomberg Economic Release Screen from January 4, 1999 to December 31, 2002.[8)] In particular, the BN survey data includes the forecasts for economic indicators complied from participating financial firms by Bloomberg in the weeks prior to the release date for actual indicator data.

For the analysis, this paper select ten major economic indicators of the US and seven indicators of the EMU area which are typically used in the literature. Some indicators such as Consumer Confidence, PPI and Unemployment are available in the two regions (the US and the EMU) at the same time and their release times are not overlapped so that it is possible to make a direct comparison. More detailed descriptions of the selected data from Bloomberg (both the surveyed data and the actual released data) are presented in Appendix A and B. In order to highlight the effects of the possible "macroeconomic shocks" contained in the macroeconomic indicators, this paper distinguishes positive shocks from negative shocks by computing the difference between the surveyed forecasts and the actual realized values. If the actual realization value is larger than the surveyed forecast value, the shock is classified as positive, which contributes to the growth of the economy. But, if the actual value is less than the expected value, it is regarded as negative shocks which mean the slowdown of the economy.

3.2. Modeling the Impacts of the Macroeconomic Shocks

Using the high frequency 15 minute Dollar-Euro exchange rates of more recent and larger sample period, this paper takes account into the specific impacts of the macroeconomic shocks calculated from important economic indicators of the US and the EMU and quantifies them. Furthermore, this paper distinguishes positive and negative shocks by differencing the surveyed values and the actual values of the macroeconomic indicators provided by Bloomberg News (BN) to check whether the impacts vary with the sign of the shocks. On the high frequency perspectives, this paper quantitatively examines what extent changes in the Dollar-Euro exchange rate are driven by macroeconomic shocks in different ways depending on whether the shocks come from the US or the EMU region, and whether the shocks are positive or negative.

This paper specifies and estimates a model of high frequency Dollar-Euro exchange rate dynamics which allows for the possibility of macroeconomic shocks, both positive and negative, affecting both the conditional mean and the conditional variance process. In order to assess the direct quantitative effect of the macroeconomic shocks of the US and the EMU on the Dollar-Euro spot foreign exchange market, this paper generalizes the model of equations (6) through (8) by allowing a dummy variable with distributed lags.

It is convenient to estimate the generalized model,

$$\check{R}_{t,n} = \mu + [\alpha_0 /(1 - \lambda_0 L)]D_{t,n} + \varepsilon_{t,n} + \theta\varepsilon_{t,n-1} , \tag{9}$$

$$\varepsilon_{t,n} = z_{t,n}\, \sigma_{t,n}, \tag{10}$$

$$\sigma^2_{t,n} = \omega + \beta\sigma^2_{t,n-1} + [\alpha_1/(1 - \lambda_1 L)]D_{t,n} + [1 - \beta L - (1 - L)^{\delta}]\varepsilon^2_{t,n} , \tag{11}$$

where $\check{R}_{t,n}$ is the filtered exchange returns and $D_{t,n}$ is defined to be unity when there exists the macroeconomic shock and is zero otherwise. The model is again estimated by QMLE as discussed in Section 2. The advantage of this specification is that this model can provide more detail information for the impacts of the shocks, contemporaneous impact, total impact and persistence. The contemporaneous impact multiplier is α_i,, the total impact multiplier is $\alpha_i/(1 - \lambda_i)$ and the persistence (mean lag) is $\lambda_i/(1 - \lambda_i)$, where i = 1 and 2 for the conditional mean and the conditional variance process.

The generalized model is estimated to quantify the impacts of the positive and the negative shocks from the two regions of the US and the EMU on the Euro currency exchange market. The estimation results show that the estimated parameters of the generalized model are generally quite similar to the parameters estimated from the basic

MA-FIGARCH model for the 15 minute returns as in Section 2.[9)] In particular, the estimated values of the long memory parameters are found to be around 0.24 regardless of the sign (positive and negative) and the region (the US and the EMU) of the macroeconomic shocks, which is almost the same as the value estimated from the basic MA-FIGARCH model for the 15 minute returns in Table 2. These results suggest that the macroeconomic shocks of the US and the EMU appear not to affect the long memory property in the volatility process of the exchange rate returns and support the result that the long memory property seems to be intrinsic rather that caused by outside shocks as presented in the previous section.

3.2.1. Contemporaneous Impact of the US Macroeconomic Shocks

This paper first considers the contemporaneous impacts of the US macroeconomic shocks. The estimated contemporaneous impacts on the conditional mean and the conditional variance of the Dollar-Euro returns are represented in the Table 3 (a) and (b) respectively. Many US macroeconomic shocks have statistically significant impacts on the conditional mean and/or the conditional variance of the Euro currency, including Consumer Confidence, NAPM, PPI, Retail Sales, Trade Balance and Unemployment. Thus, the unexpected shocks (positive and negative) to the US macroeconomic fundamentals could affect the Euro exchange returns, in accordance with the predictions of rational expectation theory.

For the impacts on the conditional mean, i) generally the estimated values of α_0 are negative for the positive shocks, and conversely, implying that the US positive (negative) macroeconomic shocks generally tend to appreciate (depreciate) US Dollar against Euro currency. For example, the positive shock from Consumer Confidence indicator is statistically significant and tends to produce the US Dollar appreciation against Euro currency by 0.28% while the negative shock is also statistically significant and produces the depreciation of US Dollar by 0.29%, ii) On average, the estimated α_0 and λ_0 of the negative shocks are found to be larger than those of the positive shocks. Hence, the impact of the negative shocks seems to be greater and more persistent than that of the positive shocks, which is in consistent with the findings of Andersen et al. (2003).[10] For the impacts on the conditional variance, i) the estimated α_1 for both the positive and the negative shocks are generally positive providing that the US macroeconomic shocks tend to increase the volatility. In particular, negative Consumer Confidence shock, negative Unemployment shock and positive PPI shocks are statistically significant and increase the volatility by 0.73%, 0.39% and 0.09% respectively. ii) On average, the impacts of the positive shocks appear to be smaller but more persistent than the negative shocks.

Thus, the US macroeconomic shocks appear to have contemporaneous impacts on both the conditional mean and the conditional variance dynamics of the Dollar-Euro exchange rates significantly. In particular, the sign effect is generally maintained even though there is some variation across shocks. The impacts of the positive shocks on the conditional mean seem to be greater but less persistent than the negative shocks, while the impacts on the conditional variance seem to be smaller but more persistent. These estimation results indicate that there exist asymmetric responses of the high frequency Dollar-Euro returns to different extent at different signs of the US macroeconomic shocks.

3.2.2. Contemporaneous Impact of the EMU Macroeconomic Shocks

Now, consider the contemporaneous impacts of the EMU macroeconomic shocks on the Dollar-Euro exchange returns. Table 4 (a) and (b) represent the contemporaneous impacts of the EMU shocks on the conditional mean and the conditional variance of the Dollar-Euro returns. Similar to the US shocks, several EMU macroeconomic shocks such as Consumer confidence, CPI, PPI, Retail Trade and Unemployment have statistically significant impacts on either the conditional mean or the conditional variance dynamics.

For the impacts on the conditional mean, i) as expected, favorable EMU positive macroeconomic shocks appreciate Euro currency against US Dollar, and vice versa. The positive shock from EMU-zone PPI indicator is statistically significant and appreciates the Euro currency against US Dollar by 0.44% while the negative shock from EMU-zone CPI indicator is also statistically significant and depreciate the Euro by 0.52%. ii) The negative shocks are on average found to affect greater but less persistent than the positive shocks. And, for the impacts on the conditional variance, i) both the positive and the negative shocks are generally decrease the volatility. For instance, the positive shock from Consumer Confidence and the negative shock from CPI significantly produce the volatility declines by 0.03% and 0.04% respectively. ii) The impacts of the positive shocks on average appear to be greater and more persistent than the negative shocks. There exist asymmetric responses of the high frequency Dollar-Euro returns to different extent at different signs of the EMU shocks.

The EMU macroeconomic shocks significantly affect the conditional mean and the conditional variance dynamics of the Dollar-Euro exchange rates. But the general pattern of the impacts of the EMU shocks on the conditional mean and the conditional variance seems to be in contrast to that of the US shocks implying the existence of the asymmetric responses to different regions. And, the positive EMU shocks seem to affect the conditional mean more greatly and more persistently than the negative shocks, while its impacts on the conditional variance seem to be greater but less persistent. The results also indicate the asymmetric responses to different signs of the shocks.

Hence the estimation results provide some evidence that i) both the US and the EMU macroeconomic shocks, defined as the differences between the surveyed and realized macroeconomic data, do have statistically significant impact on intraday movements including both the conditional mean and the conditional variance of the Euro currency against Dollar. This is in line with the findings of Andersen et al. (2003), Galati and Ho (2003), Omrane et al. (2003) and Ormane and Heinen (2004) who presented evidence of significant impacts of surprises about macroeconomic announcements on the Euro/Dollar exchange rates. ii) Euro currency market reacts to the macroeconomic shocks in different ways depending on the whether the shocks came from the US or from the EMU region and whether the shocks are positive or negative, indicating the asymmetric responses to different extent at different signs and regions.

3.2.3. Total Impact and Persistence of major US and EMU Macroeconomic Shocks

More details for the asymmetric behavior of the Euro currency are presented in Table 5(a) and (b). The tables show the total impacts and the persistence (mean lags) of the top five major macroeconomic shocks which affect the conditional mean and the conditional variance most significantly. The total impacts of the negative US Retail Sales shock is the greatest and the most persistent on the conditional mean, implying that the shock tends to depreciate the US Dollar against Euro totally by 12.5% and the impact appears to last 74.2 lags (about 18 hours). And, the positive EMU Consumer Confidence shock has the greatest total impact on the conditional variance and the most persistent. The shock seems to decrease the volatility by 7.1% and the impact could last 73 lags (about 18 hours).

As presented in Table 5, the total impacts and the persistence are quite different depending on the regions and signs of the shocks even in the case that they are the same shocks resulted from the same macroeconomic fundamentals. For example, the shock from Consumer Confidence appears to be different in the total impacts and the persistence depending on the region and the sign. Only the positive EMU shock affects the conditional mean significantly by appreciating Euro against Dollar by 3.6% for 31 lags (about 8 hours) but negative EMU shock and US shock (both positive and negative) has no impact. And, the shocks from both the positive US and EMU Consumer Confidence have significant impacts on the conditional variance at different extent and persistence while the negative US and EMU shocks do not have any significant impacts. Positive shock from the EMU Consumer Confidence tends to decrease the volatility by 7% for 73 lags (about 18hours) while the same positive shocks but from the US Consumer Confidence increases the volatility by 0.5% for 0.37 lag (less than 15 minute).

4. Conclusions

This paper investigates the intriguing intraday features of the Euro currency by using a new high frequency dataset of 15-minute Dollar-Euro exchange rates after 1999 when the Euro currency was officially introduced in foreign exchange market. In particular, this paper is concerned with the stochastic properties of the high frequency Dollar-Euro exchange rate returns data by using FIGARCH model of Baillie et al. (1996).

The estimation results present i) that the high frequency returns are found to be dominated by strong intraday periodicity resulting from repeated institutionalized trading day behavior, and which is removed by a deterministic Flexible Fourier Form (FFF) filter. The subsequently filtered high frequency returns are remarkably well described by the FIGARCH process and ii) that the estimates of the long memory parameters from the FIGARCH model are found to be generally consistent across different sampling frequencies implying that the long memory property is an intrinsic feature of the system rather than being due to exogenous shocks which lead to regime shifts. These results of the paper have important implications for our understanding of the stochastic properties of the high frequency Dollar-Euro exchange rates, and hence for the asset pricing and risk management applications in the Euro currency market.

And, this paper quantitatively analyzes the intraday duration of the US and the EMU macroeconomic shocks effects on both the conditional means and the conditional variances of the Dollar-Euro high frequency exchange rates. In particular, this paper investigates how the Euro currency market reacts to macroeconomic shocks in different ways depending on whether the shocks come from the US or from the EMU region, and whether the shock is positive or negative. For the analysis, this paper generalizes the basic MA(1)-FIGARCH model by combining the distributed lag dummy variable. Thus, the main focus of the asymmetric responses of the Euro exchange rates to macroeconomic shocks constitutes the key element of interest in this study of the Euro's intraday behavior since 1999.

This study shows several important results. First, macroeconomic shocks of the US and the EMU have statistically significant impacts on the intraday movements of the Dollar-Euro exchange rates with some exceptions. This result provides some supports that the macroeconomic data can be used as a factor relevant to the intraday changes of the Dollar-Euro exchange rates and is generally in accordance with the finding of previous studies on the macroeconomic news (shocks) effects and foreign exchange rates. Second, the high frequency Dollar-Euro exchange rates responds to the macroeconomic shocks asymmetrically depending on the geographical regions (US and EMU) and the signs (positive and negative) of the shocks. This finding supports the claims by earlier studies that the Euro currency responds asymmetric to macroeconomic news (shocks). Third, the total impact of the macroeconomic shocks on the Euro-Dollar exchange rates seems to last for relatively a short term, which is an intraday effect. This result may be useful to explain why many studies in recent years are increasingly using intraday high frequency data to figure out the relationship between macroeconomic news (shocks) and foreign exchange rates and why previous studies which used low frequency data like daily foreign exchange rate data could not find significant results.

End notes

1) For the details, see Bank for International settlements (BIS), Central Bank Survey of Foreign Exchange and Derivatives Market Activity, Basle.

2) The FIGARCH model has already been applied gainfully to improve our understanding of the stochastic properties of foreign exchange rates, stock returns, inflation rates, and commodity prices; for example, see Baillie et al. (2000, 2004), Beine et al. (2002, 2003), Han (2003, 2004) for foreign exchange rates, Bollerslev and Mikkelsen (1996) for stock prices, Baillie et al. (2001) for inflation rates and Jin and Frechette (2004) and Song et al. (2004) for commodity prices.

3) According to Jarque and Bera (1987), the standard errors of the sample skewness and the sample kurtosis in their corresponding normal distributions are $(6/T)^{1/2}$ and $(24/T)^{1/2}$.

4) There are several alternative methods for seasonal adjustment; i) using seasonal dummy variable to allow the effects of each hour of the day (Baillie and Bollerslev, 1991), ii) adopting an intraday time scale to deseasonalize the volatility (Dacorogna et al., 1993), iii) modeling the seasonality by a set of multiplicative factors (Taylor and Xu, 1997;Chang and Taylor ;1998, 2003) and iv) dividing returns by their cross sectional average(Melvin and Yin, 2000).

5) The estimated values of the long memory parameters are also quite similar to the value of 0.26 estimated from daily Dollar-Euro exchange rates samples from January 4, 1999 to December 31, 2002. More detailed results for the analysis of the daily data are available from the requests on the author.

6) Specification tests are performed by applying the Box-Pierce portmanteau statistic on the standardized residuals. The standard portmanteau test statistic, $Q_m = T\sum_{j=1}^{m} r_j^2$, where r_j is the j'th order sample autocorrelation from the residuals, is known to have an asymptotic χ^2_{m-k} distribution, where k is the number of parameters estimated in the conditional mean. Similar degrees of freedom adjustments are used for the portmanteau test statistic based on the squared standardized residuals when testing for omitted ARCH effects. This adjustment is in the spirit of the suggestions by Diebold (1988) and others. The standardized residuals from the model exhibit the usual features of excess kurtosis of the return. And, the correlograms for the standardized residuals from the MA (1)-FIGARCH (1,δ,1) model for the 15 minute returns are not reported to reserve the space, but they are available by the request on the author.
7) Similarly, there has been empirical literature on the effects of macroeconomic public news on stock and bonds markets. Samples of this literature can be seen in Admati and Pfleiderer (1989), Glosten and Millgrom (1985), Balduzzi et al. (2001) and Fleming, Remolona (1999).
8) Actually, EMU area indicators of macroeconomic activity are published since 1999 but the BN survey data on market forecasts are available only from 2001. This may be because foreign traders did not consider announcements of the Euro region macroeconomic indicators during the first two years of EMU as Galati and Ho (2003) pointed out.
9) The detailed results are not reported in the paper to save the space, but they are available from the authors on request.

10) Similarly, Conrad et al. (2002) found that stock prices respond asymmetrically to macroeconomic news: their responses on negative news are much stronger.

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Appendix A: Examples of Bloomberg News (BN) Survey Data for the US and the EMU Macroeconomic Indicators

1) The US data (January, 2002)

Date/Time (GMT)[1]		Indicator		BN[2] Survey	Actua[3]	Prior[4]	Revised
1/ 4 13:30	US	Unemployment Rate	(DEC)	5.8%	5.8%	5.7%	5.6%
1/11 13:30	US	Producer Price Index	(DEC)	-0.1%	-0.7%	-0.6%	--
1/15 13:30	US	Advance Retail Sales	(DEC)	-1.2%	-0.1%	-3.7%	-3.0%
1/16 13:30	US	Consumer Price Index	(DEC)	0.0%	-0.2%	0.0%	--
1/16 14:15	US	Industrial Production	(DEC)	0.0%	-0.1%	-0.3%	-0.4%
1/30 13:30	US	Gross Domestic Product	(4Q A)	-1.1%	0.2%	-1.3%	- -

2) The EMU data (January, 2002)

Date/Time (GMT)		Indicator		BN Survey	Actual	Prior	Revised
1/ 4 18:45	EC	Euro-Zone Unemployment Rate	(NOV)	8.5%	8.5%	8.4%	8.5%
1/ 8 19:00	EC	Euro-Zone PPI	(NOV)	-0.4%	-0.4%	-0.6%	-0.7%
1/ 8 19:00	EC	Euro-Zone Retail Trade	(OCT)	-0.2%	-1.1%	0.3%	- -
1/ 8 19:00	EC	Euro-Zone Consumer Confidence	(DEC)	-13.0	-10.0	-12.0	- -
1/10 19:00	EC	Euro-Zone GDP s.a.	(3Q 2)	0.1%	0.1%	0.1%	- -
1/21 19:00	EC	Euro-Zone Ind. Prod. sa	(NOV)	-1 .0%	-0.8%	-1.4%	- -
1/22 19:00	EC	Euro-Zone CPI	(DEC F)	0.1%	0.2%	-0.1%	- -
1/31 19:00	EC	Euro-Zone Retail Trade	(NOV)	0.7%	1.2%	-1.1%	-1.0%

Notes: 1.The dates and times are the current dates and times that the economic indicators are released.

2. The BN survey is an estimate of the release figures. The number of survey responses on which the release figures are based varies depending on the number of forecasts available from participating firms.

3. The actual figure is the released figure.

4. Prior figure is the last actual release figure for the indicator. In cases where the release figure is a revision to an earlier estimate, the prior figures refer to the preliminary estimate for the same period.

Appendix B: Summaries of the US and the EMU Macroeconomic Shocks

1) The US Macroeconomic Indicators

Macroeconomic Indicator	Total Observations	Dates[1]	Release Time(GMT)[1]	Positive shocks[2]	Negative shocks[2]
Consumer Confidence	47	1/26/99 - 12/31/02	15:00	24	23
Durable Goods	47	1/26/99 - 12/24/02	13:30	28	19
GDP	48	1/29/99 - 12/20/02	13:30	27	18
Government Budget Statement	48	1/25/99 - 12/19/02	19:00	20	22
Leading Indicators	47	3/2/99 - 12/19/02	15:00	16	12
NAPM	47	1/4 /99 - 12/4/02	15:00	19	28
New Home Sales	49	1/6/99 - 12/27/02	15:00	30	19
PPI	48	2/18/99 - 12/13/02	13:30	14	25
Retail Sales	48	1/14/99 - 12/12/02	13:30	22	19
Trade Balance	47	1/21/99 - 12/18/02	13:30	19	28
Unemployment	48	1/08/99 - 12/06/02	13:30	16	19

2) The EMU Macroeconomic Indicators

Macroeconomic Indicator	Total Observations	Dates[1]	Release Time(GMT)[1]	Positive shocks[2]	Negative shocks[2]
Consumer Confidence	19	3/4/01 - 11/29/02	11:00	8	5
CPI	21	3/16/01- 12/18/02	11:00	9	2
GDP	18	5/3/01 - 12/04/02	11:00	7	1
Industrial Production	22	3/21/01- 12/19/02	10:00/11:00	11	11
PPI	18	4/4/01 - 12/02/02	11:00	1	5
Retail Sales	17	4/5/01- 12/02/02	10:00/11:00	10	7
Unemployment	18	3/4/01 - 12/3/02	11:00	1	7

Notes: 1. Starting and ending dates of the indicators. The EMU indicators are available only from 2001 to 2002. The release dates and times for US indictors are known in advance whereas the dates and times for the EMU indicators are not known in advance and are variable. They usually release around 10:00 GMT or 11:00 GMT.
2. If the actual realization value is larger than the surveyed forecast value, the shock is classified as positive, which contributes to the growth of the economy. But, if the actual value is less than the expected value, it is regarded as negative shocks which mean the slowdown of the economy.

Table 1: Descriptive statistics for Intraday $-Euro Exchange Returns

Frequencies (k)	Observations (T/k)	Means	Standard Deviations	Skewness	Kurtosis	ρ_1
1	100,032	-0.0001	0.0724	0.9722	56.9485	-0.0535
2	50,016	-0.0002	0.0993	0.3023	17.8209	-0.0214
3	33,344	-0.0003	0.1215	0.7991	33.3348	-0.0125
4	25,008	-0.0004	0.1386	0.0698	11.8596	0.0024
6	16,672	-0.0007	0.1698	0.2138	11.6039	0.0029
8	12,504	-0.0009	0.1973	0.2004	12.1782	-0.0155
12	8,336	-0.0014	0.2379	0.2472	8.7989	-0.0123
16	6,252	-0.0018	0.2800	0.0115	8.8779	-0.0405
24	4,168	-0.0027	0.3402	0.2076	7.1132	-0.0398
32	3,126	-0.0036	0.3813	-0.1186	5.5504	-0.0183
48	2,084	-0.0054	0.4795	0.1628	4.7521	-0.0175
96	1,042	-0.0108	0.6611	-0.0081	3.5826	-0.0686

Table 2: Estimated models for the filtered 15 minute Dollar-Euro spot returns

$$y_{t,n} = \Sigma_{i=(n-1)k+1,nk} (R_{t,i}) = \mu + \varepsilon_{t,n} + \theta\varepsilon_{t,n-1},$$
$$\varepsilon_{t,n} = z_{t,n}\,\sigma_{t,n},$$
$$\sigma^2_{t,n} = \omega + \beta\sigma^2_{t,n-1} + [1 - \beta L - (1 - \varphi L)(1 - L)^{\delta}]\varepsilon_{t,n}^2,$$

where $z_{t,n}$ is an i.i.d.(0,1) process, and where the two time indices are t = 1,.. 1042 days, and n = 1,.. K, intra day periods, so that K = 96/k, for k = 1, 2, 3, 4, 6, 8, 12, 16, 24, 32, 48 and 96.

	15 minutes	30 minutes	45 minutes	1 hours	11/2 hours	2 hours
k	1	2	3	4	6	8
Obs	100,032	50,016	33,344	25,008	16,672	12,504
μ	0.0004	0.0018	0.0011	0.0053	0.0056	0.0138
	(0.0021)	(0.0037)	(0.0059)	(0.0083)	(0.0111)	(0.0137)
θ	-0.0914	-0.0647	-0.0422	-0.0369	-0.0398	-0.0482
	(0.0053)	(0.0064)	(0.0075)	(0.0096)	(0.0134)	(0.0142)
δ	0.2462	0.1981	0.2339	0.2574	0.2587	0.2914
	(0.0253)	(0.0137)	(0.0254)	(0.0464)	(0.0427)	(0.0876)
ω	0.0486	0.0210	0.0285	0.0481	0.0840	0.1571
	(0.0057)	(0.0051)	(0.0056)	(0.0143)	(0.0237)	(0.0533)
β	0.4950	0.9146	0.9152	0.8799	0.8614	0.7797
	(0.0464)	(0.0208)	(0.0152)	(0.0273)	(0.0290)	(0.0385)
φ	0.4040	0.8941	0.8711	0.8056	0.7680	0.6181
	(0.0561)	(0.0261)	(0.0210)	(0.0327)	(0.0388)	(0.0626)
ln (L)	-99064.97	-65895.61	-50268.32	-41338.55	-30943.25	-25147.02
m3	-0.118	-0.161	-0.010	-0.371	-0.200	-0.394
m4	16.906	11.380	10.995	11.865	10.294	19.422
Q(50)	87.387	88.810	83.618	72.959	80.306	60.318
Q2(50)	48.398	51.469	34.712	47.869	29.802	10.613
$W_{\delta=0}$	94.493	89.729	84.714	30.792	36.676	11.070

(continued)

	3 hours	4 hours	6 hours	8 hours	12 hours	24 hours
k	12	16	24	32	48	96
Obs	8336	6252	4168	3126	2084	1042
μ	0.0070	0.0325	0.0256	0.0350	0.0235	0.0544
	(0.0172)	(0.0327)	(0.0444)	(0.0577)	(0.0954)	(0.1646)
θ	-0.0492	-0.0568	-0.0442	-0.0282	-0.0282	-0.0770
	(0.0130)	(0.0186)	(0.0178)	(0.0180)	(0.0252)	(0.0330)
δ	0.2655	0.2679	0.2305	0.2359	0.2325	0.2142
	(0.0450)	(0.0739)	(0.0454)	(0.0663)	(0.0684)	(0.1161)
ω	0.2365	0.5263	0.9738	1.2106	1.6821	3.2637
	(0.0709)	(0.2053)	(0.5452)	(0.8352)	(1.0858)	(3.2159)
β	0.7872	0.6484	0.5860	0.6070	0.6363	0.6613
	(0.0388)	(0.1029)	(0.1654)	(0.1658)	(0.1398)	(0.1832)
φ	0.6302	0.4451	0.4019	0.3904	0.4539	0.5242
	(0.0563)	(0.1557)	(0.1699)	(0.1368)	(0.1314)	(0.1845)
ln (L)	-18324.20	-14749.77	-10586.38	-8333.01	-5998.85	-3346.03
m3	0.057	-0.592	0.059	-0.062	0.078	-0.001
m4	7.754	18.228	7.061	7.044	5.098	4.067
Q(50)	74.292	52.783	72.590	56.783	48.504	61.507
Q2(50)	35.144	10.132	23.697	40.285	46.178	49.882
$W_{\delta=0}$	34.766	13.151	28.716	12.668	11.547	3.401

Keys; The model is estimated by maximizing the Gaussian likelihood and robust standard errors from QMLE are reported in parentheses below corresponding parameter estimates. The quantity ln(L) is the value of the maximized log likelihood, m_3 and m_4 are the sample skewness and kurtosis of the standardized residuals, and Q(50) and Q2(50) are the Ljung-Box statistics with 50 degrees of freedom based on the standardized residuals and squared standardized residuals.

Table 3: Contemporaneous Impacts of the US Macroeconomic Shocks on the Filtered 15 minute Dollar-Euro spot returns

(a) Impacts on the Conditional Means

Macroeconomic Indicators	Positive Shocks α_0	Positive Shocks λ_0	Negative Shocks α_0	Negative Shocks λ_0
Consumer Confidence	-0.2809*	0.5346*	0.2202*	0.6235*
Durable Goods	-0.0058	0.9948*	0.1047	0.8344*
Government Budget Statement	-0.0361	0.9953*	0.0342	0.9395*
Leading Indicators	-0.1089	0.5799*	0.0378	0.9436*
NAPM	-0.1699*	0.7707*	0.0765	0.9246*
New Home Sales	-0.0267	0.5103	0.0141	0.9660*
PPI	0.0361	0.9849*	0.1004*	0.9852*
Retail Sales	-0.1766*	0.5625*	0.0438*	0.9867*
Trade Balance	0.0288	0.9753*	0.1016*	0.4495*
Unemployment	-0.1184	0.8378*	0.6316	0.3296*

(b) Impacts on the Conditional Variances

Macroeconomic Indicators	Positive Shocks α_1	Positive Shocks λ_1	Negative Shocks α_1	Negative Shocks λ_1
Consumer Confidence	0.0299	0.8996*	0.3909*	0.2706
Durable Goods	-0.0161	0.9941*	0.0603	0.7897*
Government Budget Statement	0.1795	0.8975*	0.0588	0.8870*
Leading Indicators	-0.0039	0.9989*	-0.0203	0.9879*
NAPM	-0.0141	0.9988*	0.2836	0.4019
New Home Sales	0.0110	0.9574*	-0.0182	0.9299*
PPI	0.0906*	0.9732*	0.0307	0.9858*
Retail Sales	0.1970	0.9703*	0.0156	0.9666*
Trade Balance	0.0318	0.9031*	0.0109	0.9843*
Unemployment	0.0223	0.9815*	0.7299*	0.5643*

Keys: 1) The values of α_0 and λ_0 are estimated from the model, $\check{R}_{t,n} = \mu + [\alpha_0 /(1 - \lambda_0 L)]D_{t,n} + \varepsilon_{t,n} + \theta\varepsilon_{t,n-1}$, $\varepsilon_{t,n} = z_{t,n}\,\sigma_{t,n}$, $\sigma^2_{t,n} = \omega + \beta\sigma^2_{t,n-1} + [\alpha_1/(1 - \lambda_1 L)]D_{t,n} + [1 - \beta L - (1 - L)^{\delta}]\varepsilon^2_{t,n}$ where $\check{R}_{t,n}$ is the filtered exchange returns and $D_{t,n}$ is defined to be unity when there exists the macroeconomic indicators or the shock and is zero otherwise. The model is again estimated by QMLE. 2) An asterisk (*) represents the coefficients are statistically significant at the conventional level (10%, 5% or 1%).

Table 4: Contemporaneous Impacts of the EMU Macroeconomic Indicators on the Filtered 15 minute Dollar-Euro spot returns

(a) Impacts on the Conditional Means

	Positive	Shocks	Negative	Shocks
Macroeconomic Indicators	α_0	λ_0	α_0	λ_0
Consumer Confidence	0.1135*	0.9692*	-0.1017	0.7522*
CPI	0.0177	0.9862*	-0.5213*	0.6522*
GDP	0.1049	0.8985*	-0.0612	0.6622
Industrial Production	0.0186	0.9672*	-0.0541	0.9262*
PPI	0.4418*	0.9592*	-0.1826	0.7690*
Retail Trade	0.0125	0.9868*	-0.0909*	0.9820*
Unemployment	0.0823	0.9930*	-0.0088	0.9188*

(b) Impacts on the Conditional Variances

	Positive	Shocks	Negative	Shocks
Macroeconomic Indicators	α_1	λ_1	α_1	λ_1
Consumer Confidence	-0.0305*	0.9865*	-0.0246	0.9825*
CPI	-0.0168	0.9258*	-0.0409*	0.9863*
GDP	-0.0148	0.9987*	-0.0452	0.5561*
Industrial Production	-0.0219	0.9835*	-0.0394	0.9477*
PPI	0.1218	0.9443*	-0.0327	0.9844*
Retail Trade	0.5297	0.8337*	0.0573	0.9798*
Unemployment	-0.0130	0.9989*	0.0241	0.9656*

Key: 1) The values of α_0 and λ_0 are estimated from the model, $\check{R}_{t,n} = \mu + [\alpha_0/(1 - \lambda_0 L)]D_{t,n} + \varepsilon_{t,n} + \theta\varepsilon_{t,n-1}$, $\varepsilon_{t,n} = z_{t,n}\,\sigma_{t,n}$, $\sigma^2_{t,n} = \omega + \beta\sigma^2_{t,n-1} + [\alpha_1/(1 - \lambda_1 L)]D_{t,n} + [1 - \beta L - (1 - L)^{\delta}]\varepsilon^2_{t,n}$ where $\check{R}_{t,n}$ is the filtered exchange returns and $D_{t,n}$ is defined to be unity when there exists the macroeconomic indicators or the shock and is zero otherwise. The model is again estimated by QMLE. 2) An asterisk (*) represents the coefficients are statistically significant at the conventional level.

Table 5: Total Impacts and Mean Lags of the Major US and EMU Macroeconomic Shocks on the Filtered 15 minute Dollar-Euro spot returns

a) Impacts on the Conditional Mean

Macroeconomic Indicators	Region of the Shocks	Sign of the Shocks	Total Impacts	Mean Lags
Retail Sales	US	Negative	12.5143	74.1880
Retail Trade	EMU	Positive	10.8284	23.5098
PPI	US	Negative	6.7838	66.5676
Retail Trade	EMU	Negative	-5.0500	54.5556
Consumer Confidence	EMU	Positive	3.6851	31.4675

b) Impacts on the Conditional Variance

Macroeconomic Indicators	Region of the Shocks	Sign of the Shocks	Total Impacts	Mean Lags
Consumer Confidence	EMU	Positive	-7.0930	73.0741
CPI	EMU	Negative	-6.5968	71.9927
PPI	US	Positive	3.3806	36.3134
Unemployment	US	Negative	1.6752	1.2952
Consumer Confidence	US	Positive	0.5359	0.3710

Figure 1: 15 minute Dollar-Euro Exchange Rate (S_t)

Figure 2: 15 minute Dollar-Euro Exchange Returns [100*(ln(S_t)-ln(S_{t-1}))]

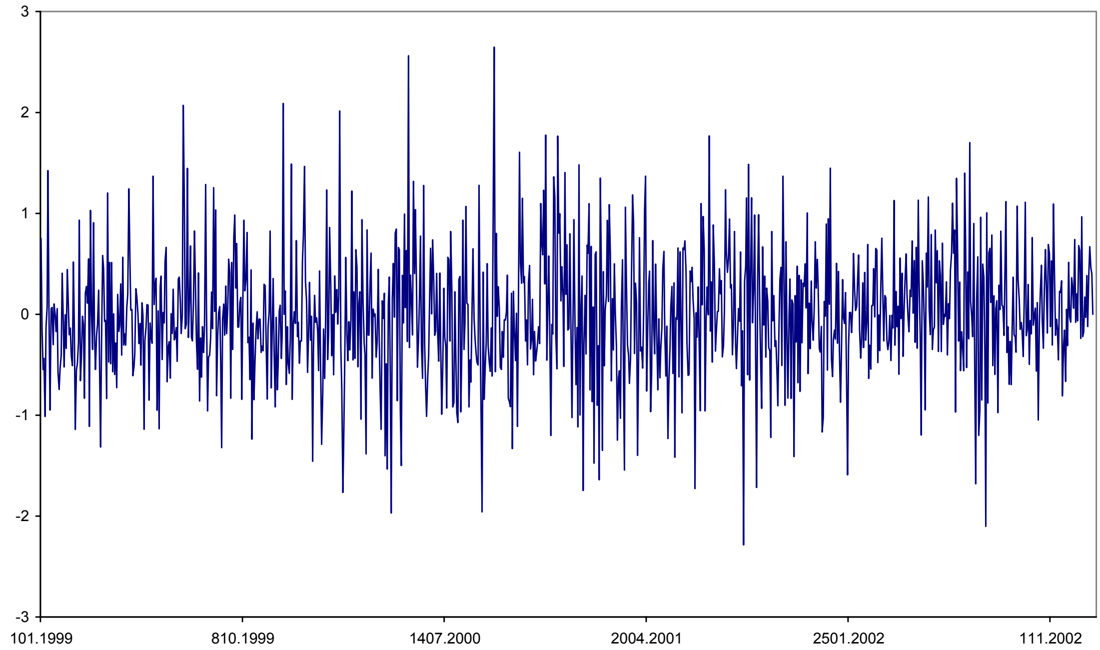

Figure 3: Correlograms for 15 minute Dollar-Euro Spot Returns

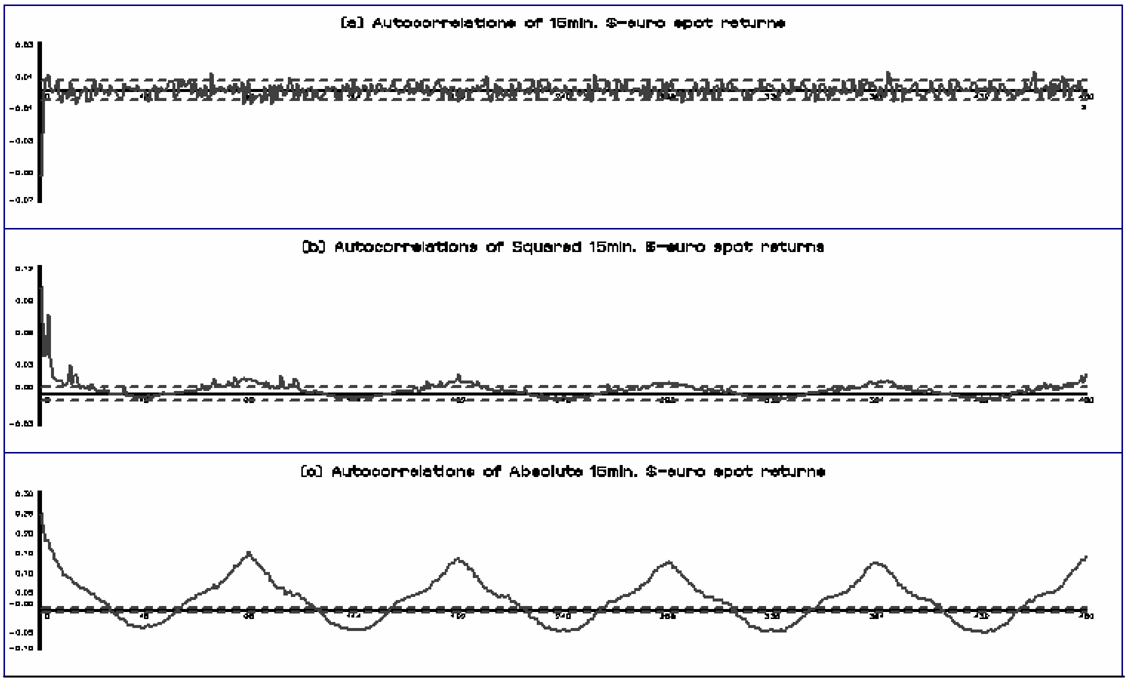

Figure 4: Intraday Average Absolute Returns of the 15 minute Dollar-Euro Exchange Rate

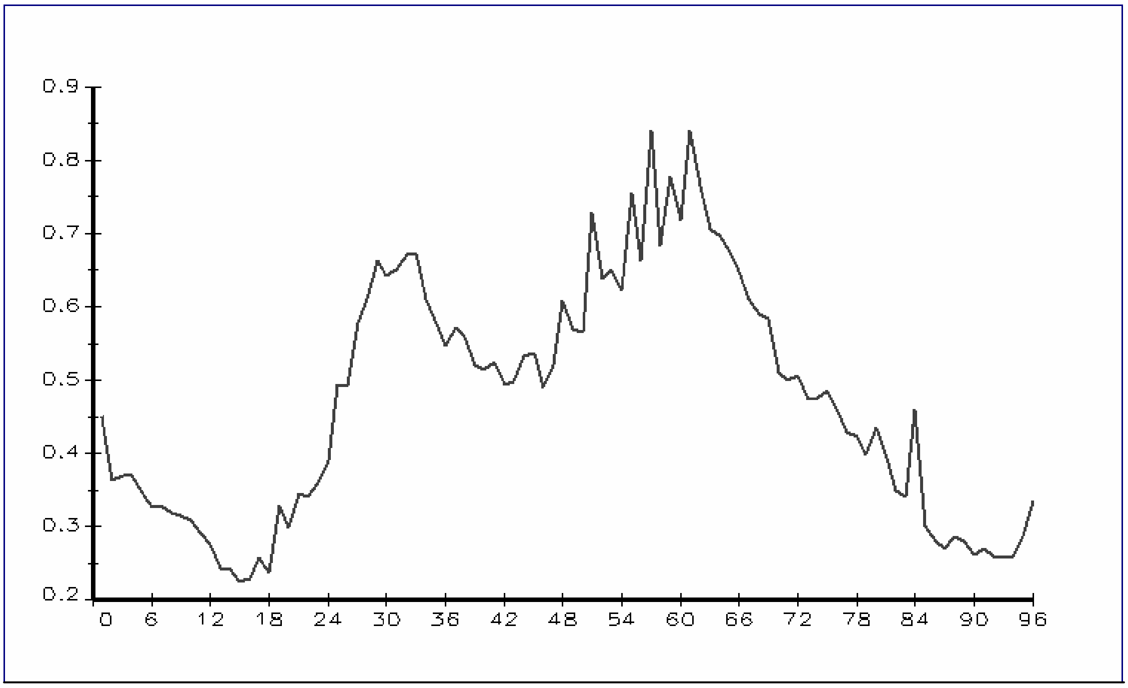

Figure 5: Correlograms for 15 minute Filtered Dollar-Euro Spot Returns