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ORIGINAL RESEARCH PAPER

Exchange rate volatility and its effect on stock market volatility

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ABSTRACT:This paper investigates empirically the effect of volatility of the exchange rate of the U.S. dollar vis-à-vis the euro on U.S. stock market volatility while controlling for a number of drivers of stock return volatility. Using a GARCH(1, 1) model and using weekly data covering the period from the week of January 1, 1999 through the week of January 25, 2010, it is found that the 9/11 terrorist attack, bear markets, fluctuations in jobless claims, and negative equity market returns increase financial volatility. On the other hand, no conclusive results are found regarding the effect of fluctuations in M2, or incorrect expectations of changes in the federal funds target rate. Finally, it is found that when major drivers of financial volatility are controlled for, increased exchange rate volatility exerts a positive and statistically significant effect on the volatility of stock returns. Monetary policymakers need to take this effect into account when formulating exchange rate actions within the prevailing managed float.

KEYWORDS: *Exchange rates, GARCH, Stock market, Volatility*

INTRODUCTION

Volatile financial markets are a sign of widespread uncertainty about both the near and distant future. As a result, firms reduce their investment spending (Chen and Funke, 2009) and become cautious to hire new workers. Similarly, countries experiencing high volatility attract less foreign investment (Erdal, 2001). Lower stock returns have been associated with higher volatility reflecting the market's poor appetite for such conditions (Bae *et al.,* 2007). In recent times, high volatility and uncertainty caused banks to stop lending, even as the Federal Reserve continued to increase liquidity, causing a breakdown in the Fed's ability to manipulate the market. Understanding the consequences of financial volatility is important.

What actually causes financial volatility? The research on this topic is abundant. The effect of variables from both the monetary and real sectors as well as such random events as terrorist attacks has been explored. Incorrect market expectations bear markets, and negative stock returns have all been linked to financial volatility. Increased globalization of financial markets is another factor that has been blamed for increased financial volatility. This latter issue is the main concern of the present paper.

We examine the effect of a number of factors, including exchange rate volatility, on financial volatility using weekly data for the U.S. covering the period from the first week of 1999 through the third week of 2010. This study finds that when major drivers of financial volatility are controlled for, increased exchange rate

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volatility exerts a positive and statistically significant effect on the volatility of stock returns. It is found that bear markets are the largest driver of financial volatility followed by fluctuations in the money supply. Incorrect expectations about changes in the federal funds rate also play a significant role, as do negative returns in the previous time period. Perhaps most interesting, fluctuations in the monetary sector have a much stronger impact on financial volatility than fluctuations in the real sector. It is also noted that asymmetry exists in the effects of positive and negative changes in jobless claims and federal funds rate expectations when explaining financial volatility.

The paper is structured as follows. Section 2 provides a review of previous work on the topic and how it shapes our research. Section 3 presents our model and a description of the data. Section 4 describes alternative measurements of volatility. Section 5 discusses the empirical results and their implications and Section 6 concludes.

Exchange rate volatility and monetary policy

Recent work on exchange rate volatility and monetary policy include Arratibel and Michaelis (2014), arvalho and Nechio (2015), Muellery *et al.*, (2015), and Syarifuddin *et al.* (2014).

Exchange rate volatility can affect monetary policy through its impact on the demand for money. McGibany and Nourzad (1995) argue that "faced with increased volatility of the domestic currency *vis-à-vis* foreign currencies, domestic investors are inclined to substitute assets they deem safer for the riskier currency so that domestic demand for money declines."
Their empirical results indicate that increased volatility of the exchange value of U.S. dollar reduces the demand for real **M2** balances. A consequence of this is that the Fed would be forced to pursue defensive monetary policy to offset the effect of excess volatility on the output and inflation gaps.

Exchange rate volatility can also affect monetary policy through its effect on the domestic equity market. Subair and Salihu (2004) find that exchange rate volatility depresses the Nigerian stock market. Lawal and Ijirshar (2015) also examine the relationship between exchange rate volatility and stock market performance in Nigeria and find one-way causal relation from exchange rate volatility the stock market in which increased volatility in the currency market exerts a negative effect on equity market performance.

Lim and Sek (2014) examine the relationship between exchange rate volatility and stock return in emerging Asian countries and find two-way causality between exchange rate volatility and stock returns in Indonesia, Korea and Thailand. Moreover, they find that interest rate, money supply, international reserves, lagged exchange rate volatility of and lagged stock returns volatility affect stock returns volatility in these countries.

Adjasi *et al.* (2008) also find such a negative relationship between exchange rate volatility and stock market return. If increased volatility of the exchange value of domestic currency leads to financial volatility, lending institutions might take this as a sign of increased uncertainty and reduce lending thus leading to credit crunch similar to that which was witnessed in the aftermath of bursting of the housing bubble in the U.S. This would make monetary authority's effort to close inflation and output gaps more difficult.

Other determinants of financial volatility

As indicated earlier, our goal is to investigate the effect of exchange rate volatility on financial volatility empirically. This requires controlling for other factors that can influence financial volatility. Many authors have studied financial volatility using one of two paths; examining the effect volatility has on the market or assessing the drivers of volatility. Engle's (2003) not only offers an approach for measuring volatility, he also attempts to explain it. It is his belief that "volatility clustering is simply clustering of information arrivals" and for this reason, he states that volatility will be highest when news intensity is strongest. He cites events such as wars, economic distress, "global summits, congressional or regulatory hearings, or central bank meetings" as triggers of information, resulting in financial volatility. However, using announcements as a driver of volatility, Engle (2003) finds "difficulty in finding important explanatory power." This study follows Engle's groundwork, and build upon it by considering other causes of volatility found in the literature.

Kim and Nguyen (2007) have similar thoughts on the value of monetary announcements in explaining volatility. Studying the Australian economy, they model stock return volatility as a function of interest rate announcements from both the Australian Central Bank and the United States Federal Reserve. They find volatility is significantly higher following announcements, and the market's response is stronger when the news is unexpected. Using federal funds futures data, Kim and Nguyen (2007) determine which announcements are expected and which are surprises to the market. While this study does not follow their methodology exactly, their finding -that unexpected changes in interest rates cause higher volatility - is of relevance to the present study and attempt to control for this effect in our model.

Bernanke and Kuttner (2004) also study the impact of unanticipated changes in the target rate on equity prices using federal funds futures data to identify expected and unexpected changes in the target rate. They measure the change in the implied rate between the day before the announcement and the day after, while adjusting for the fact the settlement price is based on the monthly average federal funds rate. They find that an unexpected cut in the target rate of 25 basis points leads to "a 1 percent increase in broad stock indexes." While the nature of their work is more of a collection of event studies, their findings support the proposition that unexpected changes in the target rate can have significant impacts on returns and financial volatility.

A recent paper by Calhoun *et al* . (2009) provides an important method for measuring expectations. Their focus is on predicting the actions of the Federal Reserve using federal funds futures data. While our study diverges from this line of work, Calhoun *et al*. (2009) method for extracting an implied/expected federal funds rate from the data on futures contracts has strong implications for assessing whether changes in the target rate are a surprise to the market. The method couples nicely with Kim and Nguyen's work in 2007 will be explained in later on. Francesco (2008) uses an EGARCH model that relates returns variance to past variance and announcement days. He uses data from the Mibtel Stock Market in Italy and finds that announcements from the European Central Bank have a larger effect than announcements from the Federal Reserve. The use of an EGARCH model suggests that volatility does not react the same way to positive and negative news. And as Bomfim (2003) finds, increases in the federal funds rate have a more severe impact on the market and volatility than a decrease in the rate. Also considering that positive and negative news may not impact the market with equal magnitudes.

A topic that has received much attention after the September 11, 2001 World Trade Center attacks is terrorism's effect on financial markets. While attacks can lead to a period of low returns, they are also a possible driver of volatility. Chulia *et al*. (2009) use a binary variable to recognize what they call "crisis periods." They set this variable to unity from the day of the terrorist attack until the market has its first positive return, a total of six days. Using a variant of a vector auto-regression (VAR) model with a GARCH process, Chulia *et al*. (2009) find "S&P 500 volatility is directly affected by its own volatility" as well as by the September 11 terrorist attacks. Other terrorist attacks that did not take place in the United States did not affect the S&P 500, which is not a surprise since the United States has seldom had a strong worldly focus. This work leads us to account for the 9/11 terrorist attacks in our model.

Throughout the financial literature, asymmetric volatility is frequently mentioned. Cunado *et al*. (2009) explore stock market volatility in bull versus bear markets. They theorize that investors behave differently during bear markets because they react to bad news more quickly in periods of high uncertainty. They state that this behavior "add[s] even more volatility to the market." Bae *et al*. (2007) hypothesize that this could be due to increases in leverage ratios as the market value of equity decreases. This line of thinking is in agreement with Engle's models of autoregressive volatility. Bae *et al*. (2007) also find that negative returns in the previous time period lead to higher volatility levels in the next period. However, their study uses daily data and there is no evidence to suggest that the same relationship exists in weekly data. This study controls for bear and bull markets in our volatility model using the dates identified by Cunado *et al*. (2009) and include negative returns in the previous period.

In *A Monetary History of the United States*, Friedman and Anna Schwartz argue how important money supply is in the performance of the economy. They believed that the Federal Reserve's constant shifting of the money supply was creating volatility in the economy. While this argument has come under criticism by Paul Samuelson, James Tobin and most recently Paul Krugman, the model used in this study accounts for changes in the money supply as a potential driver of financial volatility.

Another factor related to recent increase in market volatility is volatility index (VIX) instrument, analyzed by Dawson and Staikouras(2009). Volatility derivatives can be used as a hedge against excessive volatility. Thus, when markets become unstable, hedged investors may be less likely to react and add to the commotion because they are protected from uncertainty. According to Dawson and Staikouras (2009) volatility derivatives started being widely used in May 2004. Afterward, they note a significant decrease in S&P 500 return volatility. They also note through impulse response functions that unexpected shocks in the market disappear much faster after May 2004.

Day-of-the-week effects have commonly been studied from the perspective of equity returns. Kamaly and Tooma (2009) look at relation of volatility in Arab stock exchanges to the day of the week. They use a GARCH approach to allow for the time-varying volatility present in stock markets. In eight of the 12 markets they consider, Kamaly and Tooma (2009) find significant day-of-the-week effects on volatility. All significant days are either at the beginning or end of the week. While their research is relevant, because weekly data are used in this paper, it will be impossible to control for day-of-the-week effects.

Ahn and Lee (2006) study the relationship between stock performance volatility and real output volatility. Like Kamaly and Tooma (2009), they use a GARCH process to measure volatility, looking at five countries, including the United States. Their research suggests high stock market volatility is "likely to be followed by increased volatility in the output sector." However, they also conclude that high volatility in output will be followed by high market volatility. While circular, the relationship may explain why an initial shock can result in a long period of financial volatility.

Chowdury and Rahman (2004) explore how market volatility and macroeconomic variables in Bangladesh affect each other using a vector auto-regression approach. They view "macroeconomic risk as a source of systemic risk of a firm and so on, such risk is supposed to have an impact on stock market volatility." They find macroeconomic volatility strongly causes stock market volatility, but not the other way around, suggesting that the causality only flows one way. It must be recognized that their study is not conducted on United States data. This is an improvement upon Ahn and Lee's (2006) circular logic of the two variables causing each other. They include money supply (M2), industrial production and inflation as macroeconomic factors.

Beltratti and Morana (2004) address the same issue as Chowdhury and Rahman but use a Markov switching model. Like Ahn and Lee (2006), they find the causal relationship between macroeconomic factors and stock market volatility to flow both ways. However, they also determine the causality of macroeconomic factors on market volatility is much stronger. Their variables include volatility in the growth of the money supply (M1), volatility in the federal funds rate and volatility in the S&P 500.

The above review reveals that there is a wealth of information about financial volatility and its drivers. These include monetary announcements, terrorist attacks, money supply fluctuations, negative returns, bear markets and derivatives, and exchange rate volatility. The next section specifies a model that includes these factors in addition to exchange rate volatility.

MODEL AND DATA

Using the framework proposed by Francesco (2008) and the review presented in the previous section, the following model is specified that is a syndicate of many factors considered by others as the major determinants of volatility:

$$\begin{aligned} VOL_t = {} & \beta_0 + \beta_1 VOL_{t-1} + \beta_2 BEAR\_MARKET_t + \\ & \beta_3 NEGATIVE\_RETURNS_{t-1} + \\ & \beta_4 NINE\_ELEVEN_t + \beta_5 CRISIS + \\ & \beta_6 REAL\_SECTOR_t + \beta_7 VIX_t + \\ & \beta_8 M2\_GROWTH_t + \beta_9 FED\_SURPRISE_t + \\ & \beta_{10} EXR\_VOL_t \end{aligned} \tag{1}$$

The dependent variable is volatility of S&P 500 return measured as a GARCH(1, 1) process. The result is shown in Fig. 1. This study uses the same process for measuring the volatility of the dollar-Euro exchange rate whose graph in shown in Fig. 2. The GARCH specification of volatility assumes that present volatility is determined by all past values of volatility. As Engle (2003) states, "if the true causes of volatility were included in the specification, then the lags would not be needed." Even though Eq. 1 includes several determinants of volatility, lagged financial volatility, $\mathbf{VOL}_{t-1}$, is also included in order to capture the combined effect of any relevant regressors that might be missing from the model.

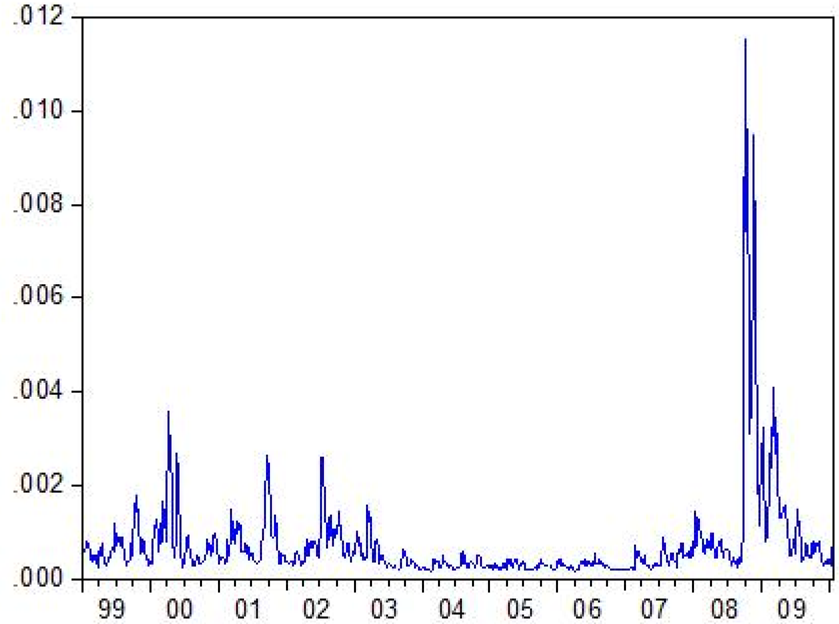

Fig. 1: GARCH(1,1) estimate of the variance of S&P500 return

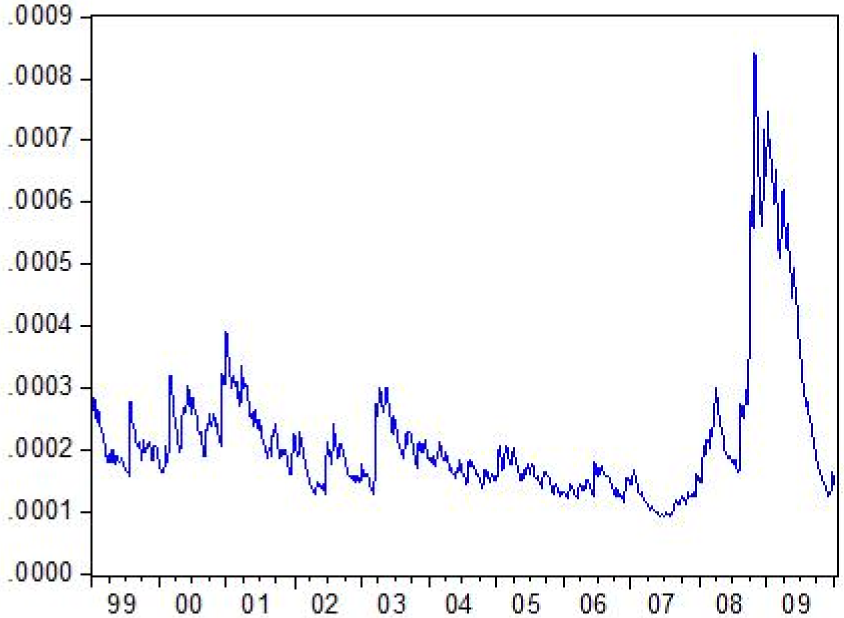

Fig. 2: GARCH(1,1) estimate of the variance of the dollar-Euro exchange rate

The **FED SURPRISE** variable is expressed as the absolute value of the unexpected change in the Federal Funds Rate (FFR). Using federal funds futures data gathered from the Chicago Board of Trade, the implied FFR on the day before each scheduled and unscheduled meeting of the Federal Open Market Committee (FOMC) is derives. From this, the expected rate from the target rate after the meeting is subtracted and the absolute value of this difference is used as a measure of unexpected changes in the target rate. Because the federal funds futures contracts expire on the third Friday of every month, if the FOMC met after the expiration date, the contract expiring in the next month contains the relevant information. It is expected that there to be a positive relationship between the Fed Surprise variable and volatility as found by Kim and Nguyen (2007) and Bernanke and Kuttner (2004).

The next independent variable in , **BEAR**, is a binary variable that captures presence of a bear market. It is set to unity for observations that coincide with a bear market and is equal zero for bull markets. These periods are determined by Cunado *et al.* (2008) using a turning point method. Using this method, the dates are updated to 1/25/2010 to suit the sample period. It should be noted that during our sample period, the periods of a bear market are 1/4/1999 - 9/25/2000 and 4/7/2003-10/29/2007, while those of a bull markets are 10/2/2000 – 3/31/2003 and 11/8/2007 – 1/25/2010. Given investors' tendencies to react quickly in bear markets, it is expected bear markets to cause higher volatility and thus the coefficient on this variable to be positive, which is the result reported by Cunado *et al.* (2008).

As was mentioned in the previous section, in May 2004 volatility instruments were introduced allowing firms to hedge their exposure to market volatility and not have to react in volatile times. To control for this, a binary variable, **DRIVATIVE**, that equals one in May 2004 and thereafter and equals zero otherwise is included in the model. Consistent with Dawson and Staikouras (2009), it is expected that the coefficient on this variable to be negative as the derivatives should hedge away risk caused by volatility.

TERROR is a binary variable to control for the 9/11 terrorist attack and the anthrax mailing attacks that followed. Such terrorist attacks in the U.S. as the Oklahoma City Bombing on April 19, 1995 and the Centennial Olympic Park Bombing on July 27, 1996 do not fall in our sample period. Following Chulia *et al.* (2009), this variable is set equal to one as long as the S&P 500 index continues to decrease after these events. This variable is expected to have a positive impact on volatility.

Following of the literature that focuses on monetary variables, the growth rate of **M2** is included in the model to account for changes in the money supply. Because the magnitude of the change is most likely to lead to higher financial volatility rather than its direction of change, this variable is expressed as the absolute value of the growth rate of **M2** and is expected to have a positive coefficient.

Bae *et al.* (2007) observe that declining returns in the previous period generally lead to higher volatility in the next period. In order to account for this effect, a binary variable, **DECLINING RETURNS**, which equals one unity in weeks when the change in stock return is negative, lagged one period is added to the model. A positive coefficient for the variable is to be expected.

Ahn and Lee (2006) suggest that a fluctuation in real variables leads to higher volatility in financial markets. This study uses jobless claims as a measure of the real sector. Because it is expected that both increases and decreases in jobless claims to positively affect financial volatility, the variable, **REAL SECTOR**, is expressed as the absolute value of the growth rate of jobless claims.

CRISIS is a binary variable that controls for the increased volatility of the market when the housing bubble burst. It takes on a unit value for the period from July 2007 to October 2008 and is zero otherwise. The housing crisis could not be controlled for using such indicators as the Case-Shiller Index because they are not available in weekly frequency used in this paper.

ESTIMATION RESULTS

This empirical study carries out using weekly data covering the period from the week of January 1, 1999 through the week of January 25, 2010 for a total of 578 observations. The choice of the sample period is dictated by the fact that our measure of exchange rates is the dollar-Euro rates, which is available only since the introduction of Euro in January 1999. The study begins by testing the unit root tests in the non-binary variables entering Eq. 1. Two different tests are used to accommodate different characteristics of the data, the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) tests. In the Augmented Dickey-Fuller unit root tests, the lag length is chosen to be the shortest interval that renders the error term white noise. The PP test uses Newey-West automatic bandwidth selection method. The results, which are not reported to conserve space, indicate that all variables are integrated to order zero, I(0), meaning that they are stationary in their present from and there is no need for differencing them.

Table 1 reports the results from the model estimated using OLS that serves as a benchmark. The point estimates in this table are standardized so they can be compared with one another to determine which explanatory variable has the largest impact on volatility. Observe that only four of the ten estimates are statistically significant at the 10% level of one-tailed tests or better. These include lagged financial volatility, **M2** growth negative returns and exchange rate volatility. What is more, they all have the expected positive sign indicating that as they increase, so does financial volatility.

However, not much should be made of these results in view of the fact that the residuals from this model suffer from first-order ARCH effect. Moreover, exchange rate volatility fails the Hausman test of endogeneity. This issue is handled by using the once-lagged value of this variable as an instrument.

Given the presence of ARCH effect in the residuals, Eq. 1 is estimated as an ARCH (1) process using Generalized Error Distribution instead of the normal distribution. The residuals from the OLS model fail the Jarque-Bera test ($\chi^2(2) = 313{,}079$). This is not surprising as most financial time series are known to suffer from excess kurtosis. In the present case, the kurtosis coefficient equals 116.2 and the skewness equals 8. The results are found in Table 2. The adjusted R^2 of 63.9% suggests that the model captures a fairly large portion of the change in financial volatility. The F-statistic for overall significance of the model reveals that the estimated coefficients are jointly significantly different from zero. The LM test of ARCH effect shows that the estimated model is free of this effect.

With the exceptions of the two monetary policy variables, **FED SURPRISE** and **M2 GROWTH**, all other variables have point estimates that are statistically significant at the 5% level of one-tailed tests. The results indicate that the change in market volatility in one week is followed by a change in volatility in the same direction in the following week. Similarly, a bear market in any given week leads to increased volatility in the following week, a finding that is consistent with the result reported by Cunado *et al.* (2009). This result has a practical implication. Option traders may be more inclined to purchase straddles during bear markets, as straddles are bullish on volatility. A straddle consists of purchasing an option as well as a put on the same underlying security with identical expiration dates and

Table 1: OLS estimates of volatility of S&P 500 return

Regressors	Standardized coefficients	t-Stat.	Prob.
VOL(-1)	0.713	22.7400	0.0000
FED_SURPRISE	-0.009	-0.3725	0.7096
BEAR_MARKET	0.035	1.2085	0.2274
VIX	0.017	0.6645	0.5067
NINE_ELEVEN	0.020	0.7177	0.4794
M2_GROWTH	0.065	2.2073	0.0277
NEG_RETURN	0.040	1.6192	0.1060
REAL_SECTOR	0.011	0.4777	0.6330
CRISIS	-0.009	-0.3342	0.4382
EXR_VOL	0.116	3.5035	0.0000
Adjusted R-squared	0.6664		
S.E. of regression	0.0006		
F-statistic	115.8618		
Prob(F-statistic)	*0.00000*		
AR(1)	1.1738		
Prob(Chi-Sqr)	*0.2786*		
ARCH(1)	5.1140		
Prob(Chi-Sqr)	*0.0237*		

strike prices. They could also profit from purchasing straddles in a week of negative returns, expecting higher volatility to follow. The positive coefficient on **NEGATIVE RETURN** suggests that negative returns in the previous week lead to higher financial volatility in the following week, which is the same result as that reported by Bae *et al.* (2007). It should be pointed out that Bae *et al.* (2007) use daily returns in their work while this study uses weekly data. Consistent with Chulia *et al.* (2009), it is found that the 9/11 terrorist attack increased financial volatility. As expected, the estimated coefficient on the **CRISIS** variable is also positive capturing increased market volatility that followed bursting of the housing bubble. Observe that changes in initial jobless claims lead to higher volatility leading to conclude, although rather narrowly, that greater fluctuation in the real sector leads to greater volatility in the financial sector, a result that is in agreement with the findings of Lee (2006).

The **DERIVATIVE** variable, which controls for the introduction of volatility derivatives, has a positive coefficient, which goes against *a priori* expectation of this study that introduction of the volatility derivative would lower stock market volatility. As such, the finding contradicts that of Dawson and Staikouras (2009). An interaction term between the derivative variable and a binary variable denoting the recent financial crisis was used but did not affect the earlier result markedly. Additionally, the sample was reduced to July 2007 to exclude the financial crisis and still it was found that the derivative variable had a positive and statistically significant coefficient. Table 2 also contains two other unexpected results both dealing with the effect of monetary policy. The results indicate that **M2** growth does not have a discernable impact on volatility of stock returns, a result that contradicts the finding by Beltratti and Morana (2004) that the growth of money supply leads to higher financial volatility. It is also found that that unanticipated changes in the target federal funds rate have no statistically significant effect on financial volatility. This goes against the findings by Bernanke and Kuttner (2004) as well as Kim and Nguyen (2007).

Bae *et al.* (2007) suggest that expect changes which signal a contraction in the economy would have a larger impact on financial volatility than changes signaling an expansion. In order to examine the possibility of asymmetric response of volatility to negative versus positive shocks, **M2** growth and the change in initial jobless claims are interacted with separate binary

Table 2: GARCH estimates of volatility of S&P 500 return

Regressors	Standardized coefficient	z-Stat.	Prob.
VOL(-1)	0.685	68.1532	0.0000
FED_SURPRISE	-0.002	-0.6902	0.4900
BEAR_MARKET	0.039	11.1106	0.0000
VIX	0.004	1.9130	0.0558
NINE_ELEVEN	0.071	6.0649	0.0000
M2_GROWTH	-0.002	-0.8490	0.3959
NEG_RETURN	0.006	2.6333	0.0085
REAL_SECTOR	0.006	2.6692	0.0076
CRISIS	0.007	2.1045	0.0353
EXR_VOL(-1)	0.036	7.1931	0.0000
Adjusted R-squared	0.639425		
S.E. of regression	0.000610		
F-statistic	79.30020		
Prob(F-statistic)	*0.00000*		
ARCH(1)	0.022602		
Prob(Chi-Sqr)	0.022602		

variables, one representing negative changes in the corresponding variable and the other identifying positive changes in these two variables. The results indicate that decreases in initial jobless claims have a negative effect on financial volatility while increases in this variable have a positive effect although neither effect is statistically significant. Decreases in **M2** growth do not impact volatility in a statistically significant manner but increases in this variable increases stock market volatility and the effect is significant at high levels of confidence.

Having discussed our findings regarding the effects of a number of determinants of stock market volatility, consider next the effect of exchange rate volatility. As with Table 1, standardized estimates are reported in Table 2. The results in Table 2 indicate that this variable has a positive and highly statistically significant coefficient. What is more, the standardized coefficient is just slightly smaller than that associated with bear markets, which has the second largest standardized coefficient after that lagged financial volatility.

SUMMARY AND CONCLUSION

This study took a first step towards an investigation of what financial globalization means for the U.S. domestic monetary policy. It noted that this issue can be approached from several directions. This study looked at the effect of volatility of the exchange rate of the U.S. dollar *vis-à-vis* the euro on stock market volatility. The study investigated the relationship between these two forms of financial volatility while controlling for of other drivers of stock return volatility. Consistent with previous research, it is found that the 9/11 terrorist attack, bear markets, fluctuations in jobless claims, and negative equity market returns increase financial volatility. No conclusive results were found regarding the effect of fluctuations in M2, or incorrect expectations of changes in the federal funds target rate find that when major drivers of financial volatility are controlled for, increased exchange rate volatility exerts a positive and statistically significant effect on the volatility of stock returns.

The following asymmetric relationships was observed: increases in jobless claims have a larger impact on financial volatility than do decreases and a higher than expected federal funds rate has a larger impact than a lower than expected rate. The results do not indicate that the introduction of volatility derivatives has had any effect on financial volatility, which is the one inconsistency with previous research.

Note that after accounting for persistence in volatility, bear markets have the largest impact on volatility, followed by fluctuations in M2. of the two proxies for the real and monetary sectors, it is found that the monetary proxy has the greater impact on financial volatility. Arguably, no research has incorporated so many explanatory variables when explaining volatility. That this study finds nearly all proposed relationships which strengthen previous findings as multicollinearity has not decayed any significance.

Further research is needed on this topic. The real sector and financial volatility are likely endogenous, as output and weekly jobless claims could both be caused by uncertainty. An approach utilizing vector auto-regression or two-stage least-squares would explore this relationship. Additionally, this study market volatility at a time when volatility was especially high due to the financial crisis. As volatility takes on more moderate levels in the future, these relationships should again be tested for a loss in significance. Different measures of volatility such as a rolling measure or the VIX could be substituted for the dependent variable in our model. VIX is a measure of market variance created by the Chicago Board Options Exchange. It is also referred to as the *fear* index. It would be interesting to see if the same relationships exist with different measures of volatility as does with the GARCH derived measure. The binary variable used to identify volatility derivatives is too simplistic of an approach. Replacing this variable with the volume of volatility derivatives traded in the week would give a much stronger indication of investors' exposure to volatility. Finally, it may be a good idea to employ an approach using lower frequency data which would allow more macro variables to enter the model. While the loss of frequency might not allow for volatility to be properly represented, it would be interesting to look at variables such as output, housing prices and inflation.

This research provides strong implications for the financial sector. The Federal Reserve could use these findings and try to meet market expectations and also change the money supply in smaller increments. While this would result in a loss of some discretionary policy, it would also reduce volatility and uncertainty in the market. Traders could also use this information and take positions that are bullish on market volatility following a weekly negative return. They could also profit from observing the strong positive relationship of current volatility and volatility in the past week.

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

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