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Do Macro News Surprises of the US Affect Forex Implied Volatility? The Evidence of Japanese Yen in 1997-2015

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Abstract

This paper investigates the effect of nine scheduled macro news announcements of the US on Japanese Yen's implied volatility and returns. The findings show that most significant effects of macro news surprises on implied volatility are concentrated in 1997-2006. These effects become weaker or insignificant in subsequent periods, namely 2005-2012 and 2012-2015. Such results suggest that earlier results on modelling the effect of macro news surprise on forex market volatility may be invalid today. The paper also identifies that negative surprises on GDP consistently result in increase in implied volatility. When there is a severely negative surprise on GDP announcement, implied volatility displays a pattern of overreaction at the announcement date and reversal in the next subsequent date.

Keywords: Implied volatility; Forex trading; Japanese yen; News surprises; Option market

Introduction

This paper aims to provide an updated research on how macroeconomic news announcements affect forex option implied volatility (IV). Forex options are actively traded and used by corporations and financial institutions for risk management, arbitrage and speculation. According to Bank of International Settlement, forex options make up the second largest segment of the global OTC option market [1]. At the end of 2014, the notional amount of outstanding foreign exchange option contracts is totaled at US$15 trillion. Given the important role of IV in options pricing, risk management, trading, investment and forex transaction services, it is worthwhile to explore how IV is affected by macroeconomic news.

Implied volatility (IV) as important market information

Many previous studies analyze how a realized volatility can be predicted by news surprises, information embedded in forex options IV and econometrics models. For instance, Andersen conclude that historical volatility in the forex market is more powerful than predicted volatility obtained from GARCH-related models in forecasting future realized volatility [2-5]. Bush applies heterogeneous autoregressive (HAR) model suggested by Corsi and demonstrates that IV remains to be useful to predict future volatility if it is considered with together jump components in the forex market [6,7]. However, in the crude oil futures market, Agnolucci finds that GARCH-type models seem to outperform IV in predicting realized volatility [8]. These studies focus mainly on realized volatility and ignore a fact that IV itself is a collective perception on risk and a fundamental input for derivatives pricing. As information on risk, IV itself can affect how market makers manage their quotes. For instance, studies on bid-ask spreads, such as Bollerslev and Melvin and King, find that spreads tend to be higher when IV increases [9,10]. Traders may consider IV as a pre-condition of specific hedge fund strategies. Studies on currency carry trades, such as Egbers and Swinkels, suggest that carry-trade strategies tend to suffer serious lose when IV turns sharply higher [11]. This may explain why traders tend to reverse their carry-trade positions after increased IV see, Menkhoff [12]. All these indicate that IV, regardless of its association with realized volatility, is important market information for asset pricing and trading. How market participants form their risk perception and determine the IV is an interesting research area.

Macro news and options IV

One external factor on IV is macroeconomic news, including their announcement schedules and news surprises. There is enormous research on macro new announcements on foreign exchange return and realized volatility. Neely provides a detailed survey on literature relating to announcement effects on foreign exchange volatility and exchange rate returns [13,14]. Some focus on how news announcements affect volatility of both spot and futures exchange rate (see, for instance, Andersen, Bauwens, and Ederington and Lee [2,3,15,16]).

Only a few papers study their impacts on IV of forex options. Marshall finds that forex option IV drops after macroeconomic new announcements as market participants get less uncertain about macroeconomic fundamentals [17].

For stock index IV, Konstantinidi finds weak effects of macroeconomic fundamentals on changes of IV [18]. Dubinsky and Johannes and Barth and so document that implied volatility of related stocks tends to be high before earnings announcement and then to drop after the announcement [19,20].

How market participants react to macro news and news surprises can follow different behavioral patterns. Previous studies on exchange rates, such as Baillie and Bollerslev, and Laakkonen and Lanne, Pearce and Solakogl, Evans, Evans and Lyons, argue that business cycles,

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information quality of announcements (no revision of economic figures), conflicting information from multiple sources of news, and order flows, can affect market reactions to scheduled macro news. These findings suggest no consistent effects of macro news announcements on the FX market, in term of return, realized volatility and IV [21-26].

To investigate how macro new surprises affect IV, this paper selects 9 mostly-watched scheduled macroeconomic announcements and measures their forecast errors as a proxy to news surprises. Forecasted errors are the difference between actual and forecasted values, with respect to forecasted values. The effects of absolute forecast errors (absolute size of surprises), positive forecast errors (positive surprises) and negative forecast errors (negative surprises) are examined respectively. The paper studies the effects of these forecast error on IV of Japanese Yen (Dollar/Yen). We choose Japanese Yen because it offers a longer data history for subsample comparison. Our findings show that most significant effects of macro news surprises on IV are concentrated in the sample period between 1997 and 2006. For a sample period between 2005 and 2012, the news surprises mostly have no effect on IV. For a sample period between 2012 and 2015, only forecast errors of several macro news announcements have effect on IV. In addition, this paper finds that negative surprises on GDP at chained volume consistently result in increase in IV. When there is a severe negative surprise on this announcement, IV overreacts remarkably at the announcement date and reverts remarkably in the next day. The remaining of the paper proceeds as follows. Section 2 introduces the data and the equations to be used. Section 3 discusses the empirical findings. Section 4 concludes the paper.

The Data and the Model

Macroeconomic news, news surprises and hypotheses

We select 9 US macro news announcements mostly monitored by traders and analysts, including announcements relating to GDP, initial jobless claims, durable goods new orders, industries, consumer sentiment, existing homes sales, manufacturing PMI, new one family houses sold and nonfarm payrolls. Before news announcements, forex traders generally build their long/short positions on exchange rates and derivatives on volatility. When news surprises occur, traders tend to quickly adjust their positions. That will usually lead to remarkable changes in exchange rate and sharp increase in implied volatility. Effects of such news surprises may be related to their absolute news surprises (i.e. absolute forecast errors), positive news surprises (actual better than forecasts), or negative news surprises (actual worse than forecast). Our three hypotheses include:

- H1: Higher the absolute news surprise, higher the implied volatility
- H2: Higher the positive news surprise, higher the implied volatility
- H3: Higher the negative news surprise, higher the implied volatility

Table 1 shows the details of these macro news announcements, such as their history and their reporting frequency. We compare the forecasted values and realized values and apply relative percentage difference between the two values to measure forecast errors (i.e. news surprises). The forecast is the median forecasts on a new announcement. Bloomberg surveys a number of economists and provide the data of median forecasts before announcement dates. Some previous studies measure forecast errors with normalized values. This method is not applicable to our data because Bloomberg solely provides median forecasts without the information on distribution. Therefore, this paper applies "percentage error" as a guiding principle to measure forecast errors. A standard equation on "percentage error" is , in which an actual value is the denominator. For most traders in the forex market, their reactions to a macro announcement mainly focus on an error relative to its forecasted value because they may have built their long/short positions with the forecasted value. Therefore, the paper considers forecast as the denominator. This means, forecast errors (or macro news surprises) are generally defined by , which is same as . As mentioned by Hyndman and Koehler and Kim and Kim, "percentage error" has its limitations [27-29]. For instance, it may generate biases with forecasts which are zero values, negative values or very small values. Therefore, the paper adds a common base to both Actual and Forecast for calculating "percentage error" in order to mitigate such biases, with the guiding rules below to measure forecast errors:

If a forecasted value is a growth rate estimate in percentage, the equation for forecast error (FE) will be either or

If a forecasted value is a number estimate (either a change value or a total value), the equation for forecast error (FE) will be

.

We set the "Base" at either 100 (for values between 0 and 100) or 1000 (for values mostly between 100 ad 1000), aiming to make both the denominator and numerator to be positive.

Macro announcement	Start Date	End Date	Frequency	Source
GDP US Chained 2009 Dollars QoQ SAAR	30-06-1947	31-12-2014	quarterly	Bureau of Economic Analysis
US Initial Jobless Claims SA	06-01-1967	13-03-2015	weekly	Department of Labor
US Durable Goods New Orders Industries MoM SA	29-02-1992	28-02-2015	monthly	US Census Bureau
US GDP Price Index QoQ SAAR	30-06-1947	31-12-2014	quarterly	Bureau of Economic Analysis
University of Michigan Consumer Sentiment Index	31-01-1978	31-03-2015	monthly	University of Michigan
US Existing Homes Sales SAAR	31-01-1999	31-01-2015	monthly	National Associate of Realtors
Markit US Manufacturing PMI SA	31-03-2012	28-02-2015	monthly	Markit

US New One Family Houses Sold Annual Total SAAR	31-01-1963	31-01-2015	monthly	US Census Bureau
US Employees on Nonfarm Payrolls Total SA	28-02-1939	28-02-2015	monthly	Bureau of Labor Statistics
Note: Seasonally adjusted annual rate (SAAR) data have been adjusted for the effects of seasonal patterns. These effects can include things such as increased retail spending around Christmas or decreased construction activity during winter months in colder climates. Seasonal adjustment also removes the effects of calendar variations (e.g. differing number of working days per month). These seasonally adjusted data have been annualized, meaning the monthly (or quarterly) values have been multiplied by 12 (or 4 for quarterly data) to give an estimate of what the annual total would be if conditions remained the same throughout the year. Seasonally adjusted (SA) data means that data is seasonally adjusted but not annualized. Analysts generally prefer to use seasonally adjusted data, as it is easier to observe the underlying trend in the data series. GDP at chained volume measure is a series of GDP statistics adjusted for the effect of inflation to give a measure of 'real GDP'. Chained volume GDP statistics are calculated by measuring output using the price level of the preceding year and then linking the statistics to give a reflection of actual output changes and excluding any monetary (inflationary) change. Chained dollars is a method of adjusting real dollar amounts for inflation over time, so as to allow comparison of figures from different years. The U.S. Department of Commerce introduced the chained-dollar measure in 1996. Chained dollars generally reflect dollar figures computed with 2009 as the base year.				

Table 1: The 9 selected macroeconomic news announcements.

Name	Period		Equation for forecast error (FE)	Mean Forecast	Mean Actual
	Start	End			
GDP US Chained 2009 Dollars QoQ SAAR	01-06-1997	12/31/2014	FE=(100+Actual)/(100+Forecast) –1	2.704	2.403
US Initial Jobless Claims SA	3/21/1997	3/20/2015	FE=(1000+Actual)/(1000+Forecast) – 1	365.724	368.304
US Durable Goods New Orders Industries MoM SA	10/31/1997	2/28/2015	FE = (100+Actual)/(100+Forecast) – 1	0.159	0.233
US GDP Price Index QoQ SAAR	3/31/2005	12/31/2014	FE=(100+Actual)/(100+Forecast) – 1	1.875	1.825
University of Michigan Consumer Sentiment Index	5/31/1999	3/31/2015	FE=Actual/Forecast – 1	83.506	83.827
US Existing Homes Sales SAAR	2/28/2005	2/28/2015	FE=(100+Actual)/(100+Forecast) – 1	5.357	4.998
Markit US Manufacturing PMI SA	6/30/2012	3/31/2015	FE=Actual/Forecast – 1	54.229	54.174
US New One Family Houses Sold Annual Total SAAR	4/30/1998	2/28/2015	FE=(1000+Actual)/(1000+Forecast) – 1	746.465	739.739
US Employees on Nonfarm Payrolls Total SA	01/06/1997	2/28/2015	FE=(1000+Actual)/(1000+Forecast) – 1	95.553	92.014
Note: The table summarizes the equations to measure macro news surprises and summary statistics of those news surprises. In the table, only dates with related news announcements are included. The forecast of each macro announcement is the median of all economists surveyed before the release of an economic announcement. The data on median forecasts is provided by Bloomberg.					

Table 2: The equations of forecast error (FEj) and summary statistics of the actual and forecasted numbers.

Table 2 summarizes the equations of the 9 forecast errors (FEj) and the summary statistics of forecasted and actual numbers in our sample. Table 3 summarizes the distribution of 9 news surprises (FEj). FEj carries both positive and negative values. With FEj, we develop three additional sets of variables on news surprises: (i) Absolute news surprises (AFEj) (NB: It is the absolute value of FEj); (ii) Positive news surprises (PFEj) (NB: It treats all negative FEj to be zero); and (iii) Negative news surprise (NFEj) (NB: It treats all positive FEj to be zero). Their effects on Japanese Yen IV will be studied respectively.

Macroeconomic News Announcement	FEj	Obs	Mean	SD	Min	Max
GDP US Chained 2009 Dollars QoQ SAAR	FE01	51	-0.32%	1.49%	-3.99%	2.41%
US Initial Jobless Claims SA	FE02	937	0.19%	1.19%	-4.92%	7.17%
US Durable Goods New Orders Industries MoM SA	FE03	146	0.07%	3.38%	-8.42%	16.95%
US GDP Price Index QoQ SAAR	FE04	28	-0.11%	0.79%	-2.17%	1.80%
University of Michigan Consumer Sentiment Index	FE05	135	0.46%	1.87%	-4.25%	8.51%

US Existing Homes Sales SAAR	FE06	86	-0.32%	0.39%	-1.42%	0.32%
Markit US Manufacturing PMI SA	FE07	86	-0.32%	0.39%	-1.42%	0.32%
US New One Family Houses Sold Annual Total SAAR	FE08	144	-0.97%	7.69%	-31.71%	19.21%
US Employees on Nonfarm Payrolls Total SA	FE09	153	-1.25%	11.31%	-48.24%	25.41%

Table 3: Summary statistics on macro news surprises (FEj).

Data on return and implied volatility of Japanese Yen

As most news announcements in our data set starts in 1997, we trace back the data of Japanese Yen (Dollar/Yen) and its implied volatility in the period between January of 1997 and March. We select Japanese Yen for detailed analysis because this currency is actively traded in the sample period, providing a longer data history. We do not consider Euro as it comes to existence in 1999. We obtain data of Japanese Yen spot rate from Bloomberg BGN (Bloomberg Generic Pricing) source. It is the average of the last bid and ask price (i.e. the mid-price). BGN is a pricing algorithm that produces highly accurate bid and ask FX quotes in real-time. BGN quotes are designed to represent market-consensus executable prices and are derived from hundreds of quote providers, including top tier money-center and regional banks, broker-dealers, and inter-dealer brokers, as well as FX electronic trading platforms. Our sample includes three sets of IV, including 1-month IV, 3-month IV and 6-month IV. This IV data is derived from Black Scholes option pricing model, downloaded from the same source, Bloomberg BGN.

We denote the three IV with Vk, where k=1M, 3M and 6M. To facilitate application of regression analysis, we take natural logarithm on Vk and name the new variables in log as LNVk. LNVk tends to less skewed in their distribution[1]. For Japanese Yen (YEN), we consider its daily return (YRET) with the following equation:. Table 4 summarizes the distribution of LNV1M, LNV3M, LNV6M and YRET and their Augmented Dickey-Fuller (ADF) test results. The ADF test considers the AIC method to select the maximum number of lags for hypothesis testing. The ADF statistics show that these four dependent variables are stationary and suitable for ARIMA modelling.

Variable	Obs	Mean	SD	Min	Max	ADF	
LNV1M	4732	2.355	0.279	1.493	3.649	-4.859	***
LNV3M	4732	2.362	0.25	1.639	3.31	-3.798	***
LNV6M	4732	2.377	0.234	1.791	3.097	-3.152	**
YRET	4731	0	0.007	-0.069	0.055	-69.275	***
FE01	4732	0	0.002	-0.04	0.024	-68.801	***
FE02	4732	0	0.005	-0.049	0.072	-23.362	***
FE03	4732	0	0.006	-0.084	0.17	-68.769	***
FE04	4732	0	0.001	-0.022	0.018	-68.776	***
FE05	4732	0	0.003	-0.042	0.085	-68.88	***
FE06	4732	0	0.001	-0.014	0.002	-69.322	***
FE07	4732	0	0	-0.012	0.014	-68.777	***
FE08	4732	0	0.013	-0.317	0.192	-68.801	***
FE09	4732	0	0.02	-0.482	0.254	-68.795	***
AFE01	4732	0	0.002	0	0.04	-69.24	***
AFE02	4732	0.002	0.005	0	0.072	-21.926	***
AFE03	4732	0.001	0.006	0	0.17	-69.971	***
AFE04	4732	0	0.001	0	0.022	-68.954	***
AFE05	4732	0	0.003	0	0.085	-69.874	***
AFE06	4732	0	0.001	0	0.014	-69.451	***
AFE07	4732	0	0	0	0.014	-68.89	***
AFE08	4732	0.002	0.013	0	0.317	-70.042	***
AFE09	4732	0.003	0.02	0	0.482	-69.944	***
PFE01	4733	0	0.001	0	0.024	-68.977	***
PFE02	4733	0.001	0.004	0	0.072	-22.371	***
PFE03	4733	0	0.004	0	0.17	-69.323	***
PFE04	4733	0	0	0	0.018	-68.864	***
PFE05	4733	0	0.003	0	0.085	-69.425	***
PFE06	4733	0	0	0	0.002	-68.95	***
PFE07	4733	0	0	0	0.014	-68.812	***
PFE08	4733	0.001	0.008	0	0.192	-69.372	***
PFE09	4733	0.001	0.011	0	0.254	-69.489	***
NFE01	4733	0	0.001	-0.04	0	-69.049	***
NFE02	4733	-0.001	0.003	-0.049	0	-22.572	***
NFE03	4733	0	0.004	-0.084	0	-69.432	***
NFE04	4733	0	0	-0.022	0	-68.876	***
NFE05	4733	0	0.002	-0.042	0	-69.251	***
NFE06	4733	0	0.001	-0.014	0	-69.398	***
NFE07	4733	0	0	-0.012	0	-68.862	***
NFE08	4733	-0.001	0.011	-0.317	0	-69.449	***
NFE09	4733	-0.002	0.017	-0.482	0	-69.32	***

Note 1: The table summarizes the variables to be used in this paper. LNVk, where k = 1M, 3M and 6M is the natural logarithm of implied volatility. YRET is daily return of Japanese Yen. FEj, where j=1 to 9, is the forecast error (news surprise) of news j. Dates with no related news announcement are inserted with 0. FEj can be positive or negative. AFEj is the absolute value of FEj, which measures the size of the news surprises. PFEj counts positive FEj only, in which non-positive FEj are all replaced by 0. NFEj counts negative FEj only, in which non-negative FEj are all replaced by 0. In addition, dates without related news announcements are inserted with zero to represent zero surprises. Skewness (S) and Excess Kurtosis (EK) of LNV1M, LNV3M and LNV3M are (S=0.416, EK=0.831), (S=0.294, EK=0.152), and (S=0.211, EK=-0.318) respectively. This suggests that LNVk are symmetric and close to normal distribution. YRET has S=-0.340 and EK=5.533, meaning a symmetric but clustered distribution.

Note 2: ***, **: sig at 1% and 5% respectively for the Augmented Dickey-Fuller (ADF) test

Table 4: Summary statistics of the variables to be used for regression analysis.

Dates with no macro news announcement

Macro news announcements have their regular schedules. This means, many dates do have no observation. To facilitate regression analysis, we insert "0" on the dates with no related announcement to represent a zero surprise in FEj, AFEj, PFEj and NFEj respectively. With the insertion of zero, all these variables have their number of observation increased to 4732. Their summary statistics are also displayed in Table 4.

The regression model

We apply the following regression model to study effects of the macro news announcements:

Yt = a0 + a1 Yt-1 + a2 Forecast_Errort + et

Yt denotes either LNVk or YRET at t. Forecast_Errort denotes one of the FEj, AFEj, PFEj and NFEj observed at t. Neely summarizes that previous studies on forex volatility are mostly based on ARIMA-type or GARCH-type models. The above model is a typical AR(1) model with an additional explanatory variable, Forecast_Errort. If Yt is represented by return of exchange rate, i.e. YRET, the equation will be similar to the model mentioned by Neely and Dey [18,22]. The equation aims to evaluate how news surprises (i.e. Forecast_Errort) affect implied volatility. Yt-1 is a lagged variable, capturing effects of all information of the implied volatility on t-1. According to GARCH models, higher volatility at t-1 tends to result in higher volatility at t.

We have done some preliminary analysis before confirming the use of this model. First, we analyze partial autocorrelation on LNVk and YRET. LNVk have their partial autocorrelation dropping to be very small at lag 2. YRET has its partial autocorrelation dropping to be very small at lag 1. Thus, Yt-1 may well capture possible lagged effects of Yt. Second, we analyze effects of individual years and individual months in a year on the LNVk. LNVk are much lower in the period between 2002 and 2007 and much higher in 1998, 1999, 2008 and 2009. On the other hand, LNVk are similar in their values for all individual months in a year. Thus, we do not include month-of-year effect in the regression analysis. The Yt-1, which is the data of the last trading day, may have sufficiently reflected all public and private information before a news announcement (see, for instance, Bauwens et al. [15]). If it is true, news surprises at t will not surprise the market at t.

Only one of the FEj, AFEj, PFEj and NFEj is included as an independent variable in the regression model. We run model repeatedly to get the estimate on each of these variables. As multiple announcements may happen at the same time and at the same date, a multiple regression analysis with combinations of the FEj, AFEj, PFEj and NFEj may not easily produce statistically meaningful results.

Table 5 shows the release time of the news announcements. Most are released at 2030 New York time. Table 6 summarizes the number of announcements in a day and their corresponding averages of LNVk and YRET. More than 75% of the dates do not have the selected news announcements. There are 911 dates containing only one of our selected news announcements (mostly the weekly announcement of US Initial Jobless Claims). Most of the dates contain 4 to 8 announcements. YRET are generally negative in the sample period, reflecting the depreciation of US dollar against Japanese Yen.

Code	Item	Release Time (New York Time)
1	GDP US Chained 2009 Dollars Qo	20:30:00
2	US Initial Jobless Claims SA	20:30:00
3	US Durable Goods New Orders In	20:30:00
4	US GDP Price Index QoQ SAAR	20:30:00
5	University of Michigan Consume	22:00:00
6	US Existing Homes Sales SAAR	22:00:00
7	Markit US Manufacturing PMI SA	21:45:00
8	US New One Family Houses Sold	22:00:00
9	US Employees on Nonfarm Payroll	20:30:00

Table 5: Release time of the selected macro news announcements.

Number of announcements in a day	Frequency	LNV3M	LNV3M	YRET

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0	3672	2.363	2.377	-0.01%
1	911	2.36	2.377	0.04%
2	3	2.404	2.427	-0.13%
3	5	2.667	2.674	-0.01%
4	33	2.444	2.467	-0.08%
5	19	2.321	2.312	0.00%
6	49	2.258	2.285	-0.02%
7	12	2.403	2.393	0.00%
8	23	2.417	2.428	0.29%
9	5	2.262	2.288	0.00%
Total	4732	2.362	2.377	0.00%

Note: The table summarizes the LNVk and YRET associated with the number of announcements in a day. There are 911 dates with only one macro news announcement, which is mostly the weekly announcement of US Initial Jobless Claims. Many dates provide with 3 announcements or more. This situation suggests macro news surprises would interact among themselves in some announcement dates. In other words, multiple regression analysis with several announcements included as independent variables may provide statistically misleading results. The dates with both 3 and 7 announcements provide the highest average volatility. However, both the two cases have small sample size for statistically reliable conclusions. YRET are generally negative, reflecting depreciation of US dollar in the sample period.

Table 6: Implied volatility, exchange rate returns and number of macro news announcements in a day.

Subsamples for comparison

Our selected news announcements do not have the same data length. Thus, we consider several subsamples that match approximately their data length and help evaluate robustness of the effects of the news surprises over different time periods. These subsamples include:

- Subsample 1 (January 6, 1997 to December 29, 2006): This period covers the years before the global crisis in 2008. Many previous studies on macro news announcements mostly include data in this period. Results in this period can be easily compared with those of related studies
- Subsample 2: (January 2, 2006 to December 31, 2012): This covers 2-year period before and 4-year period after the 2008 crisis. Also, European sovereign debt crisis happens in 2010-2012. Macroeconomic forecasts and their effects may be less stable in this crisis period
- Subsample 3 (January 2, 2012 to Mar 27, 2015): This period covers the data in most recent 27 months until the end of our time series. The data of Markit US Manufacturing PMI begins to be available in this period

		Whole Sample			Subsample 1			Subsample 2			Subsample 3		
		Coeff		Adj RSQ	Coeff		Adj RSQ	Coeff		Adj RSQ	Coeff		Adj RSQ
Forecast Error	FE01	-1.296		0.972	-2.078		0.966	-0.351		0.976	2.052		0.978
	FE02	-0.036		0.972	-0.015		0.966	0.071		0.976	0.068		0.978
	FE03	-0.034		0.972	-0.001		0.966	-0.165		0.976	-0.069		0.978
	FE04	-1.068		0.972	-1.969	***	0.966	-0.832		0.976	-7.655		0.978
	FE05	-0.021		0.972	-0.341		0.966	0.178		0.976	0.133		0.978
	FE06	-0.699		0.972	-10.122		0.966	-0.661		0.976	-6.259		0.978
	FE07	-3.031		0.972	n/a		0.966	n/a		0.976	-3.136		0.978
	FE08	0.011		0.972	0.049		0.966	0.008		0.976	-0.009		0.978
	FE09	0.011		0.972	0.023		0.966	0.016		0.976	-0.01		0.978

Absolute Forecast Error	AFE01	1.516	**	0.972	2.418	**	0.966	0.245		0.976	3.289		0.978
	AFE02	-0.392	***	0.972	-0.323		0.966	-0.306		0.976	-0.711	**	0.978
	AFE03	0.134		0.972	0.222		0.966	0.095		0.976	0.004		0.978
	AFE04	0.898		0.972	-2.548	***	0.966	0.949		0.976	10.461		0.978
	AFE05	0.367	**	0.972	0.734	**	0.966	0.143		0.976	0.435		0.978
	AFE06	0.677		0.972	1.965		0.966	0.631		0.976	11.389		0.978
	AFE07	1.471		0.972	n/a		0.966	n/a		0.976	1.775		0.978
	AFE08	0.097	***	0.972	0.223	***	0.966	0.037		0.976	0.108		0.978
	AFE09	0.019		0.972	0.03		0.966	0.015		0.976	0.091		0.978
Positive Forecast Error	PFE01	0.334		0.972	0.414		0.966	-0.308		0.976	3.096		0.978
	PFE02	-0.316	**	0.972	-0.273		0.966	-0.147		0.976	-0.435		0.978
	PFE03	0.086		0.972	0.19		0.966	-0.081		0.976	-0.051		0.978
	PFE04	-0.266		0.972	-2.337	***	0.966	0.201		0.976	2.239	***	0.978
	PFE05	0.233		0.972	0.373		0.966	0.185		0.976	0.391		0.978
	PFE06	-1.218		0.972	-7.136		0.966	-2.624		0.976	4.425		0.978
	PFE07	-1.836	**	0.972	n/a		0.966	n/a		0.976	-1.619	**	0.978
	PFE08	0.146	**	0.972	0.263	**	0.966	0.103		0.976	0.104		0.978
	PFE09	0.05		0.972	0.061		0.966	0.095		0.976	0.044		0.978
Negative Forecast Error	NFE01	-2.047	**	0.972	-3.681	***	0.966	-0.362		0.976	-4.437	**	0.978
	NFE02	0.472	**	0.972	0.351		0.966	0.689	**	0.976	1.207		0.978
	NFE03	-0.197		0.972	-0.261		0.966	-0.235		0.976	-0.103		0.978
	NFE04	-1.453		0.972	8.565	***	0.966	-1.237		0.976	-23.869	***	0.978
	NFE05	-0.731		0.972	-1.099	**	0.966	0.144		0.976	-0.539		0.978
	NFE06	-0.694		0.972	-14.182	***	0.966	-0.65		0.976	-20.163		0.978
	NFE07	-3.928		0.972	n/a		0.966	n/a		0.976	-4.297		0.978
	NFE08	-0.067		0.972	-0.175	**	0.966	-0.018		0.976	-0.11		0.978
	NFE09	-0.006		0.972	-0.006		0.966	0.001		0.976	-0.608		0.978

Note 1: This table summarizes the coefficient of announcement effects (a2) in the following regression model: Yt = a0 + a1 Yt-1 + a2 Forecast_Errort + et, where Yt denotes LNV1M and Forecast_Error denotes one of the FEj, AFEj, PFEj and NFEj. There are a total of 4 samples: the whole sample and three subsamples. The subsamples include: Subsample 1 (Jan 6, 1997 – Dec 29, 2006), Subsample 2 (Jan 2, 2006 – Dec 31, 2012) and Subsample 3 (Jan 2, 2012 – Mar 27) 2015. Subsample 3 starts with data available in 2012 because Markit US Manufacturing PMI data begins to be included in 2012. Also, it can represent a recent 27-month sample period. Subsample 2 includes data in the crisis period, covering a 2-year period before and 4-year-period after the crisis. Subsample 1 is the pre-crisis period. The results in the subsamples help evaluate robustness of the effect of the forecast errors. "n/a" is shown for those forecast errors relating to FE07 because it does not have any observation in our Subsamples 1 and 2.

Note 2: ***, **: sig at 1% and 5% respectively.

Table 7: Regression results of forecast errors on implied volatility.

Results and Discussion

Inconsistent effects on implied volatility over time

Table 7 exhibits the regression coefficients of all the forecast errors on LNV1M. They are the coefficient a2 of the regression equation in Section 2.4. To mitigate possible bias on hypothesis testing, we apply White heteroscedasticity-consistent standard errors to test the coefficients. Firstly we look at the results for the whole sample. Only coefficients significant at 1% or 5% level are marked with"***" or ** respectively [30]. We expect higher forecast errors leading to stronger increase in LNV1M as the market should react quickly to unexpected information. Obviously those FEj in the table do not have any significant effect on LNV1M. The results of absolute forecast errors, AFEj, show four significant coefficients. Three of them, including AFE01, AFE05 and AFE08, have significantly positive impact on LNV1M. AFE02 shows a significantly negative effect and this effect does not match our expectation. Both PFEj and NFEj show 2 to 3 significant coefficients. Positive and negative surprises can differ in their impacts. For instance, NFE01, a negative value indicating less-than-expected GDP, has significantly negative impact on LNV1M. This means, more severe the NFE01, the higher the LNV1M. In contrast, PFE01 has insignificant impact.

When we compare the results among all the three subsamples, it is obvious that most significant coefficients are concentrated in Subsample 1, in which 12 out of the 20 coefficients in the table are significant. Previous findings covering data before 2008 usually conclude that macro new surprises do have impacts on IV. Subsample 2 has only one significant coefficient. This subsample covers an eight-year period around the global crisis in 2008. This matches our expectation that the coefficients tend to be less stable in such a turbulent period. Subsample 3 shows 5 significant coefficients out of the 20 coefficients in the table. Only 3 of the 5 significant coefficients in this subsample are also significant in Subsample 1. Only two significant coefficients share the same sign in both Subsamples 1 and 3. The findings from the three subsamples seem to suggest that macro news surprises have weaker influence on IV after 2007. There is only one forecast error, NFE01, demonstrating consistently significant coefficient 3 out of our four sample periods in the table. This suggests that IV increases when an announced GDP is less than its forecast.

We apply the same regression model on LNV3M and LNV6M as the Yt respectively. Their results are close to those from LNV1M but provide less number of significant coefficients. This may be due to the fact that 1-month options contracts are more popular for trading and hedging in the FX market.

Overreactions and reversals of implied volatility after negative surprises

Marshall finds that IV tends to drop on the news announcement dates and larger news surprises have stronger impact on the IV than smaller surprises [17]. To investigate whether this is the same for our samples, we identify the top 10 NFE01 and observe LNV1M on t-1, t and t+1 and their changes at t and t+1. NEF01 is chosen because it is the only forecast error with consistently significant effect in the whole sample and two of our three subsamples. Table 8 shows the top 10 negative forecast errors, NFE01, ranging between -3.985% and -1.459% in the sample period. They are the most negative surprises on GDP figures. LNV1Mt-1, LNV1Mt and LNV1Mt+1 in Table 8 are the LV1M before the announcement date (t-1), at the announcement date (t) and at the next date after the announcement date (t+1) respectively. Their changes at t and t+1 are shown in the last two columns of the table. To make the results easily readable, we define absolute change of 0.03 or higher for LNV1M as "remarkable change" and define "overreaction and price reversal" if LMV1M has positive remarkable change at t and negative remarkable change at t+1. Such a remarkable change is approximately a change by 3% on the IV. 4 out of the 10 cases in the table show the above-mentioned pattern of "overreaction and reversal". The size of those overreaction cases is pronounced, with "LNV1Mt - LNV1Mt-1" ranging between 0.039 and 0.252. Their size of those reversal cases is also pronounced, with "LNV1Mt+1 - LNV1Mt" ranging between -0.044 and -0.090. These sizable changes in LNV1M at t and t+1 could have serious impact the prices of relevant derivatives and provide traders profit-making opportunities. These results contradict to the findings of Marshall that IV drops at announcement date and the conclusion of Ederington and Lee that IV has no reversion after the announcement date. Our findings are slightly consistent with Huskaj and Larsson that IV demonstrates some forms of mean reversion [17,31,32].

No consistent effect on Japanese Yen return (YRET)

The same regression model is also applied on YRET. Only one out of the 20 coefficients is significant in the whole sample. Significant coefficients in the three subsamples are very inconsistent. As the results do not give any insight about the FX market, we do not display the table of the results here. Probably business cycles do have effect on the linkage between news surprises and exchange rate movements.

Date	NFE01	LNV1Mt-1	LNV1Mt	LNV1Mt+1	LNV1Mt-LNV1Mt-1	LNV1Mt+1 - LNV1Mt
3/31/2000	-3.99%	2.635	2.888	2.797	0.252	-0.09
3/31/2008	-3.66%	2.796	2.835	2.749	0.039	-0.086
3/31/2011	-3.34%	2.393	2.355	2.351	-0.038	-0.004
3/31/1997	-2.55%	2.272	2.327	2.313	0.055	-0.015
3/31/2004	-2.01%	2.466	2.52	2.427	0.054	-0.093
9/30/2002	-1.92%	2.344	2.402	2.358	0.058	-0.044
12/31/2009	-1.89%	2.62	2.61	2.613	-0.011	0.003
12/31/2008	-1.71%	2.872	2.889	2.886	0.017	-0.003
6/30/2006	-1.65%	2.186	2.194	2.197	0.008	0.003
9/30/2009	-1.46%	2.642	2.653	2.623	0.011	-0.03

Note: The NFE01 in the regression analysis demonstrates its robust negative effect on implied volatility across different sample periods. This table identifies the top 10 negative FE01, which are the most severe negative surprises on GDP announcements in the sample, and investigates their impacts on implied volatility. We apply a change by 0.03 on LV1M as a remarkable change. If LV1M increases by more than 0.03 at t and decreases by more than 0.03, we classify it as a phenomenon of overreaction and reversal. Among the 10 selected cases, four cases demonstrate the pattern of overreaction and reversal (see the cells in grey colors). These remarkable changes in implied volatility can have serious impact on forex derivatives prices. All these top 10 negative surprises are concentrated in Subsamples 1 and 2. In Subsample 3, there are only 3 negative GDP surprises, which are not severe.

Table 8: Impacts of severe negative surprises of GDP announcements on implied volatility.

Conclusion

Most previous research on macro news announcements and exchange rate volatility focus on actual volatility and seldom investigate how news surprises affect implied volatility. This paper has investigated the effect of nine scheduled macro news announcements on Japanese Yen IV. These macro news announcements are commonly followed by traders in the forex market. Our findings show that most significant effects of macro news surprises on implied volatility are concentrated in 1997-2006. These effects become insignificant and less significant in the sample period for 2005-2012 and 2012-2015 respectively. The paper identifies that negative surprises on GDP consistently result in increase in IV. When there is a severe negative surprise on this GDP announcement, IV displays a pattern of overreaction at the announcement date and reversal in the subsequent date. There is no consistent effect of the news surprises on Japanese Yen return in the period between 1997 and 2015.

In one single day, there can be more than 3 different news announcements with very close schedules. Therefore, researchers would find it hard to differentiate individual effect of the news announcement on IV with daily data. We are not sure whether high-frequency data would provide more interesting results because some of the announcements occur almost at the same time. This is definitely another research project worth to explore.

In sum, our study does not convincingly support the hypotheses that macro news surprises affect implied volatility of Japanese Yen. Such effect becomes less significant in recent years than the years in the late 1990s and the early 2000s. This hints that earlier findings on the association between macro news and forex volatility may need to be re-examined. It is believed that, with gradual changes in market dynamics, including market players, products and strategies, determinants on exchange rate return and volatility change over time. Although our results show some mean reversion after severe negative surprises of GDP figures, such conclusion is based on small sample of observations. Researchers or traders may need to find out more evidence on such price patterns.

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