A study of effects of order-flow on return in FX market

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Abstract: In this project, The Portfolio Shifts Model is adopted to analyze The relationship between order flow and exchange rate fluctuations. The theoretical hypothesis is verified by using multi-country exchange rate and foreign exchange Order flow data. The empirical results show that there is a significant positive correlation between order flow and Exchange Rate fluctuation, and a higher Order flow means the possibility of currency appreciation in the short term. In addition, we found that the relationship between Order Flow and Exchange Rate Fluctuation was not stable. During the international financial crisis and European debt crisis with high market risks, Order Flow had a greater influence on Exchange Rate fluctuation, and the R2 of the model fluctuated more sharply during this period. In addition, the regression results show that there is a significant negative relationship between R2 and the fear index VIX. When the market panic rises, the explanatory power of the model tends to decline.

1. Introduction

Since the 1970s, the macro exchange rate determination model, which has been dominant in the exchange rate determination theory, has been blocked in the demonstration of empirical research. It cannot explain the excessive volatility of short-term exchange rates, nor the problem that exchange rate volatility has nothing to do with macro fundamentals in empirical studies. Therefore, some researchers began to pay attention to the study of the microstructure of the foreign exchange market.

Order flow is the core variable of market microstructure theory. It is defined as the difference between transactions initiated by buyers and sellers and is a measure of excess demand in the market. Regardless of the motivations of market participants and their expectations of price changes, changes in their portfolio need to be realized through the submission of orders. Therefore, order flow is the most important information medium in the price discovery process. Love & Payne (2003), Rime & Sojli (2006), Evans & Lyons (2008) etc. analyzed two ways of integrating information into price, namely the direct way of public information and the indirect way of private information. The results show that the order flow brings together scattered private information and has significant explanatory power for exchange rate fluctuations.

In this essay, we will analyze the possible impact of Order Flow on exchange rate fluctuations by using the combined drift model after studying the relationship between order flow and exchange rate fluctuations. Firstly, it is theoretically analyzed why order Flow data has explanatory power to exchange rate fluctuations under heterogeneous information environment. Second, multiple exchange rates and corresponding Order flow data are used to test the relationship between Order Flow and exchange rate changes. Third, empirically, it tests how market panic affects order Flow's explanation of exchange rate changes.

2. Literature review

2.1 Micro theory and exchange rate fluctuations

Empirical research results show that traditional macro models often fail to explain the fluctuation of exchange rate in the short and medium term during economic operation (Rogoff, 2009; Engel et al., 2015). Therefore, the reasons for short-term exchange rate fluctuations should be analyzed from the perspective of the microstructure of the foreign exchange market (Evans & Lyons, 2002, 2004). Relevant studies believe that the special transaction structure of foreign exchange market determines that foreign exchange order flow can be used as an explanation of exchange rate fluctuations.

Order Flow refers to the difference between the volume of transactions initiated by buyers and sellers in the foreign exchange market. This variable measures the excess demand (excess supply) for a particular foreign exchange. According to this theory, transaction behavior reflects the expectation of transaction subjects on price changes, and Order Flow is the embodiment of transaction subjects' behavior of adjusting asset portfolio, and is the most important information medium in the process of price discovery. The research of Evans & Lyons (2008) also verifies this view from municipal level.

Based on this idea, this paper will discuss the possible impact of Order Flow on exchange rate fluctuations on the basis of further combing relevant studies.

2.2 The Portfolio shifts model

First, we refer to the research of Evans and Lyons (2002) and use the Portfolio shifts model to analyze why order flow helps to predict the change of exchange rate. Suppose there are two assets in period T, one is a risk-free asset and the other is a randomly profitable asset, the exchange rate. The profit of the exchange rate in time T is denoted by F, which is determined by a series of increments, $F = \sum_{t=1}^{T} r_t$. Where, increment R follows independent co-distribution, nominal exchange rate is the observed value before each period, and these increments represent the macroeconomic information available to the public in period T.

Assume that the foreign exchange market is a decentralized agent market (denoted by i) consisting of N dealers, and a continuous non-dealer's customer, namely the public, denoted by $Z \in [0,1]$. There are three rounds of trading in each day: The first round is between public traders; The second is between dealers, who share the risk of their foreign exchange positions; The third round, which is still open to the public, is designed to allow traders to take more risk out of their positions.

The first round of trading begins at the beginning of each period t, and all market participants can observe the incremental contribution of rt to F during that period. Based on this increment and other publicly available information, each trader simultaneously and independently quotes different levels of Bid and Ask to his customers. The transaction price of this round is usually called Pi, each dealer receives his customer's net order c (executed at his previous price p).If $c \leq 0$, it means that the customer sells a certain foreign exchange net, that is, the dealer buys a certain foreign exchange. After the second round of trading begins, each trader simultaneously and independently quotes to other traders a price at which they are willing to buy or sell a certain foreign exchange asset. All traders can get these quotation information in the market, and then each trader trades on the basis of other traders' quotations. Orders are separated at a given price due to the different quotes from each dealer. Assuming that T_{i2} represents the net internal trading of trader i in round 2, at the end of the round, the order flow observed by all traders $\Delta x = \sum_{i=1}^{N} T_{i2}$. In the third round of trading, first define 4 variables that appear in the trading process, p_{i1}, p_{i2}, p_{i3} and T_{i2}. Assuming that there is no triangular arbitrage between the three quotations, in a given cycle, all traders quote the same price, then the foreign exchange price is only determined by public information. Although r is public information in period 1, the order flow Δx is not observed until the end of period 2. The price p_{i3} in period 3 is affected by both r and Δx.

The extent to which Δx affects the price depends on its price-related information. First, in round 2 each transaction is determined by the transaction rules. Each dealer's transactions in round 2 are proportional to the customer orders received in round 1. This means that when traders observe the order flow of insiders at the end of round 2, they can infer the aggregate change in the public's portfolio movement during round 1. Traders also know that the public will need to reduce or absorb portfolio changes in round 3. In other words, Δx has a predictive effect on the final change in the exchange rate during the current period.

2.3 Does Order flow have explanatory power for exchange rate fluctuations?

Evans and Lyons (2002) designed a simple model of exchange rate determination based on an instruction stream containing information. According to this model, daily exchange rate changes are determined by the difference in interest rates and the flow of orders. Therefore, as for $\Delta S_{t+1} = \beta_i \Delta(\mathrm{i_t} - i_t^*) + \beta_z z_t$, ΔS_{t+1} refers to the first-order difference of the logarithm of the foreign exchange price within t days, that is $S_{t+1} - S_t$; $\Delta(\mathrm{i_t} - i_t^*)$ refers to the first-order difference of the interest rate differentials $(\mathrm{i_t} - i_t^*) - (\mathrm{i_{t-1}} - i_{t-1}^*)$; z_t is the difference (order flow) between buyer and seller-originated volumes during t days. In other words, a positive z_t within t days means that the number of buy orders exceeds the number of sell orders.

The data used by Evans and Lyons are data on all bilateral transactions in the DM/USD and JPY/USD spot markets through the Reuters 2000-1 electronic trading system from May 1 to August 31, 1996. Their data set shows that for any exchange rate transaction, the two parties to the transaction, or more importantly, the party initiating the transaction, determines the corresponding transaction direction (ie, a buy or sell order). This dataset does not indicate the size of the transaction or the identity of the counterparty. Evans and Lyons found that positive order flow signified an appreciation of FX. Their research estimates that buying an extra $1,000 in a day would increase the price of the Deutsche Mark by 2.1%.

There are three reasons to explain this positive correlation. The first reason is that the customer order flow may contain private information (and reflected in the order flow within the dealer), and the impact of this private information on the value of the currency is not short-term. The second reason is that there is a short-term liquidity effect of the exchange rate, which may be caused by the consideration of inventories by foreign exchange dealers when pricing. The last explanation reverses causality, arguing that changes in exchange rates lead to changes in the flow of orders—so-called feedback transactions. This positive correlation may be triggered by a customer buying (selling) a currency that has just appreciated (depreciated).

Marsh and O'Rourke (2005) attempted to identify the plausibility of these three explanations through empirical testing. The dataset used is a two-year daily dataset of customer order flows provided by Royal Bank of England (RBS), one of the top ten FX trading banks in the world. RBS Bank provides customers with foreign exchange trading services 24 hours a day. Client order flow data is the accumulated data for 24 hours from the opening of the Sydney foreign exchange market to the closing of the US foreign exchange market. This data set is from August 1, 2002 to June 29, 2004 and includes nearly 460 trading days (excluding holidays) with detailed currency varieties. In that essay, they used customer order flow data in 4 currencies: USD, EUR, JPY and GBP. This means that there are 6 bilateral exchange rates, and they have order flow data for all these bilateral exchange rates. Of course, out of the confidentiality of the bank data, they did not disclose the data in detail, but provided the results of the regression. They built a simple regression equation for the relationship between order flow and exchange rate:

$$\Delta S_t = \beta_0 + \beta_1 X_t + \mu_t$$

The dependent variable is the change in the logarithm of the spot exchange rate, and the single independent variable is the total customer order flow (customer buy value minus customer sell value). A positive β_1 coefficient indicates that a positive flow of orders for a currency means that the currency appreciates. The main conclusions they reached are: Confirmed that the order flow is related to the daily (or weekly) exchange rate fluctuations of the same period; Different components of the order flow have different effects on exchange rate fluctuations; In particular, the flow of orders from customers of non-financial firms is negatively correlated with exchange rate changes, and the flow of orders from financial firms is positively correlated with exchange rate fluctuations. This shows that if there is a liquidity effect, it will not be the reason for the positive correlation between customer order flow and exchange rate fluctuations, otherwise the impact of different customers' order flow on exchange rate should be the same. They argue that this further proves that the information contained in the customer order stream is relevant to the determination of the exchange rate.

We propose theoretical hypothesis 1: order flow has a positive impact on exchange rates.

2.4 Is the prediction effect of Order Flow on exchange rate changes stable?

We must clearly recognize that order flows in different economic circumstances are different. It is a medium for transmitting information, so when the instruction stream is decomposed into different parts, the information intensity contained in each part of the instruction stream is different from each other. Therefore, the influence of the order flow of each part on the price formation is also different.

Andrew Carpenter (2003) conducted an empirical test on the impact of different foreign exchange market participants on prices. He argues that prices reflect the content of information traded by different groups of investors, and thus the source of private information about foreign exchange transactions. Andrew Carpenter used high-frequency data to conduct an empirical test on "the relationship between dealer pricing and previous (including present) transactions". At the same time, he made a more detailed classification of customer transactions and interbank transactions, which is an important supplement to the research contents of the former two. Carpenter used data from a major Australian bank's AUD/USD and EUR/USD spot FX market for 45 days in 2002. Customers are divided into central banks, non-bank financial institutions and non-financial corporations. Andrew Carpenter's research led to the following two important conclusions: First, the central bank's instruction flow has the greatest impact on prices, followed by non-bank financial institutions (such as hedge funds, mutual funds), and non-financial companies have the least impact on traders' pricing; Besides, in the interbank market, traders with more private information will choose direct transactions with low transparency. Indirect transactions through brokers are partially disclosed to the market and have little effect on prices. Empirical studies by Marsh and O'Rourke (2005) also show that different components of the order flow have different effects on exchange rate volatility. In particular, the order flow from non-financial corporate clients is negatively correlated with exchange rate changes, and the order flow from financial corporations is positively correlated with exchange rate fluctuations.

Based on this, we propose theoretical hypothesis 2: Under different market environments, there are differences in the impact of order flow on exchange rate changes and the interpretation of interest rates.

3. Empirical Research Design

3.1 Basic model and data

Referring to the research ideas of Marsh and O 'Rourke (2005), this paper takes domestic currency changes under the indirect quotation method as the explained variable and domestic currency order flow (i.e. the net purchase order volume of domestic currency) as the explanatory variable to construct the following empirical model:

$$\Delta S_t = \beta_0 + \beta_1 X_t + \mu_t \tag{1}$$

Among them, ΔS_t is the exchange rate change, X_t is the order flow variable. Daily closing price data of GBP/USD, EUR/GBP, AUD/USD, EUR/USD, CAD/USD, NZD/USD, EUR/JPY and JPY/USD were adopted from 2004 to 2014. And during the corresponding time period, Order flow for buying GBP with USD, order flow for buying EUR with GBP, order flow for buying AUD with USD, order flow for buying EUR with USD, order flow for buying CAD with USD, order flow for buying NZD with USD, order flow for buying EUR with JPY, and order flow for buying JPY with USD. The above indicators were used as explanatory variables respectively to estimate the empirical model. When the model is estimated, we get β_1, which reflects the effect of order flow (non-public information) on exchange rate changes. The R2 estimated by the model represents the explanation strength of the order flow (non-public information) to exchange rate changes.

3.2 The time-series changes in the impact of Order flow on exchange rate changes and the explanatory power.

As mentioned earlier, the instruction flow is different from the requirement, it is a medium for conveying information. Therefore, the information intensity represented by the order flow in different time intervals may also be different from each other, so the influence of the order flow in each time period on the price formation is also different. In particular, in the early stage of the economic crisis, market uncertainty increases, non-public information may be more, and its impact on the exchange rate will be greater. Therefore, we extend the empirical model (1).

We use rolling regression to estimate the model. Taking January 6, 2004 as the first trading day, the data of 100 consecutive trading days are used for regression to obtain a set of regression results. After that, take January 7 as the first trading day, and perform regression with the data of 100 consecutive trading days, so as to obtain the second set of regression results. By analogy, we can obtain β_1 and R2 obtained by regressing the data of 100 trading days before each trading day, and form time series data. By analyzing the time series changes of β_1 and R2, we can obtain the impact of order flow on exchange rate fluctuations and the changes in explanatory power during the entire sample period, thereby verifying our hypothesis.

3.3 Interpretation of changes in base model R2

In theory, the explanatory power of order flow to exchange rate fluctuations will fluctuate to a certain extent in a long period of time. In particular, in the early stage of the economic crisis, market uncertainty increased. At this time, the panic of economic subjects will rise, and traders' understanding of the changes in order flow will become unstable, thereby reducing the R2 of the basic model. In times of economic crisis, order flow's explanation for exchange rate fluctuations will decline. In order to verify the effect of trader panic on the explanatory power of the model, we used the R2 obtained in the rolling regression as the explained variable, and the mean of the VIX index in the past 100 trading days was used as the explanatory variable to perform regression to verify the effect of panic on the explanatory power of the model.

4. Empirical Results

4.1 The impact of Order flow on exchange rate fluctuations

We first use the full sample data from 2004 to 2014, and use the empirical model (1) to estimate, the results are shown in Table 1. Obviously, we have exchange rates for GBP/USD, EUR/GBP, AUD/USD, EUR/USD, CAD/USD, NZD/USD, EUR/JPY, and

JPY/USD as The explained variable, with the corresponding order flow as the explanatory variable, to estimate the model. For all the above exchange rates, Order flow has a significant positive effect on exchange rate volatility at the 1% statistical level. In terms of explanatory power, most order flows explain exchange rate fluctuations more than 20%. Only the R2 of the three regressions of the EUR/GBP exchange rate, EUR/JPY, exchange rate, and JPY/USD exchange rate is less than 20%. The reason for this is that we use FX trading data from the European market, which is not a significant yen trading market and there is very little trading volume in yen-related currencies. The information reflected by order Flow is very limited in explaining the change of yen exchange rate. The above regression results show that our theoretical hypothesis 1 is established. That is, order flow has a positive impact on exchange rate fluctuations and has a high explanatory power.

4.2 The impact of Order flow on exchange rate fluctuations

We use rolling regression to estimate the coefficients and R2. For example, our data started from January 1, 2004, so the data of the previous 200 trading days were regression with Order Flow as the explanatory variable and return as the explained variable. In other words, the regression coefficient of Order Flow and R2 of the model could be obtained. After that, we started with the data on January 2, 2004, and continued to find the regression coefficient and R2 with the data of 100 consecutive trading days. By analogy, we can find the time series of regression coefficients and R2.

We take the order flow of buying GBP with USD as the explanatory variable (the net purchase of GBP with USD), and use the exchange rate change of GBP/USD as the explained variable (how much is one GBP to USD), and perform rolling regression, then the estimated results are shown in Figure 1. Each point in the graph corresponds to the regression result for the 100 trading days before the start of the day. Obviously, from 2008 to 2012, the international financial crisis and the European debt crisis broke out one after another. During this period, the impact of order flow on exchange rate changes has increased to a certain extent. This is consistent with the previous theoretical assumption, that is, in periods of higher market risk, non-public information has a greater impact on exchange rates.

In Figure 2-8, we take the exchange rate of EUR/GBP, AUD/USD, EUR/USD, CAD/USD, NZD/USD, EUR/JPY, and JPY/USD as the explained variables, take the corresponding order flow as the explanatory variable, to perform rolling regression on the model. Each point in the graph corresponds to the regression result for the 100 trading days before the start of the day. The correlation regressions are all consistent with our research hypothesis. From 2008 to 2012, during the international financial crisis and the European debt crisis, the impact of order flow on the exchange rate increased to a certain extent.

It should be noted that in most regressions, R2, which represents the strength of the model's explanation, has risen to a certain extent during the financial crisis and the European debt crisis. In the analysis of R2, it can be seen that when GBP/USD, EUR/GBP, EUR/USD, EUR/JPY and JPY/USD exchange rates were taken as the objects of analysis, R2 showed signs of temporary sharp rise in the practice range of 2008 international financial crisis and 2010 European debt crisis. In the analysis of AUD/USD, CAD/USD and NZD/USD, the fluctuation of R2 was much smaller.

My understanding is that from 2008 to 2010, the economic crisis had a great impact on major economies such as the United States, the European Union, Japan and the United Kingdom, which was reflected in the stronger interpretation of exchange rate fluctuations by non-public information. On the contrary, Canada, Australia and New Zealand have relatively small economic scale and a single economic structure. Most of them are exporters of raw materials and agricultural products, and their economies are less affected by external shocks. Currency markets have also been less affected.

However, the fluctuation of R2 is significantly larger, indicating that there are other factors that affect exchange rate fluctuations from time to time.

4.3 The effect of trader panic on model explanatory power.

As analyzed above, we believe that market panic will affect exchange rate fluctuations, which is manifested in the fact that when market panic rises, the explanatory power of the order flow model, that is, R2, will decrease accordingly. According to the previous ideas, we used the R2 obtained by rolling regression with 8 groups of data as the explained variable, and performed regression analysis with the mean of the VIX index in the past 100 trading days as the explanatory variable. According to this idea, we can establish the regression model (2).

$$R2 = \alpha + \beta VIX + \varepsilon \qquad (2)$$

The results are shown in Table 2. Obviously, the regression coefficients of mean_vix100 are all significantly negative, which indicates that the market panic region will affect the explanation strength of the order flow model.

Then, will market panic strengthen the impact of Order Flow on exchange rate fluctuations? To verify this idea, the interaction terms of Order Flow and VIX index were added into the basic regression model (1) as explanatory variables, and regression analysis was conducted on the above eight exchange rates respectively. We add the interaction terms of VIX and ORDER into the model to form the regression model (3).

$$\Delta S_t = \beta_0 + \beta_1 orderflow_t + \beta_2 orderflow_t * VIX_t + \mu_t \qquad (3)$$

The results are shown in Table 3. We focus on the estimated value of β_2. When β_2 is greater than 0, it means that exchange rate is more sensitive to Order in market panic. Among all 8 regressions, there are 6 regressions. The regression coefficients of interaction terms are all positive and significant at least at the statistical level of 5%. Only the yen-related exchange rate, the interaction terms are either negative or not significant.

Consistent with the above analysis, we believe that since the trading volume of

Yen in the data adopted in this paper is small and the European market is not the main trading market of yen, the impact of Order Flow on the exchange rate of Yen is not obvious.

5. Conclusion

In this essay, The Portfolio Shifts Model is adopted to analyze the relationship between order flow and exchange rate fluctuations. The theoretical hypothesis is verified by using multi-country exchange rate and foreign exchange Order flow data. The empirical results show that there is a significant positive correlation between order flow and Exchange Rate fluctuation, and a higher Order flow means the possibility of currency appreciation in the short term.

In addition, we found that the relationship between Order Flow and Exchange Rate Fluctuation was not stable. We used rolling Regression to off-line the basic model and obtained the time series data of β and R2 in the basic model. The results show that during the period of international financial crisis and European debt crisis with high market risks, order Flow has a greater influence on Exchange Rate fluctuation, and the R2 of the model fluctuates more sharply during this period.

In addition, we further analyze the reason why model R2 fluctuates greatly in the period of rising financial risks. We believe that under panic, people become more sensitive to all kinds of information and more irrational, so panic will reduce the explanatory effect of the model. The results show that there is a significant negative relationship between R2 and the fear index VIX. When the market panic rises, the explanatory power of the model tends to decline.

Table 1

	(1) GBP-USD return	(2) EUR-GBP return	(3) AUD-USD return	(4) EUR-USD return	(5) CAD-USD return	(6) NZD-USD return	(7) EUR-JAP return	(8) JAP-USD return
GBP-USD flow	125.856^{***}							
	[30.30]							
EUR-GBP flow		97.431^{***}						
		[19.46]						
AUD-USD flow			135.810^{***}					
			[27.94]					
EUR-USD flow				318.687^{***}				
				[29.42]				
CAD-USD flow					136.675^{***}			
					[27.20]			
NZD-USD flow						346.067^{***}		
						[23.72]		
EUR-JAP flow							1432.212^{***}	
							[7.13]	
JAP-USD flow								458.224^{***}
								[11.38]
Constant	-6.945^{***}	-5.365^{***}	-7.809^{***}	-6.060^{***}	-12.804^{***}	-7.107^{***}	1.439	1.467
	[-5.99]	[-4.89]	[-4.30]	[-4.83]	[-9.67]	[-3.72]	[0.77]	[0.91]
N	1931	1931	1931	1931	1931	1931	1931	1931
r2_a	0.322	0.164	0.288	0.309	0.277	0.225	0.025	0.062
F	918.176	378.505	780.379	865.476	739.605	562.742	50.771	129.537

t statistics in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

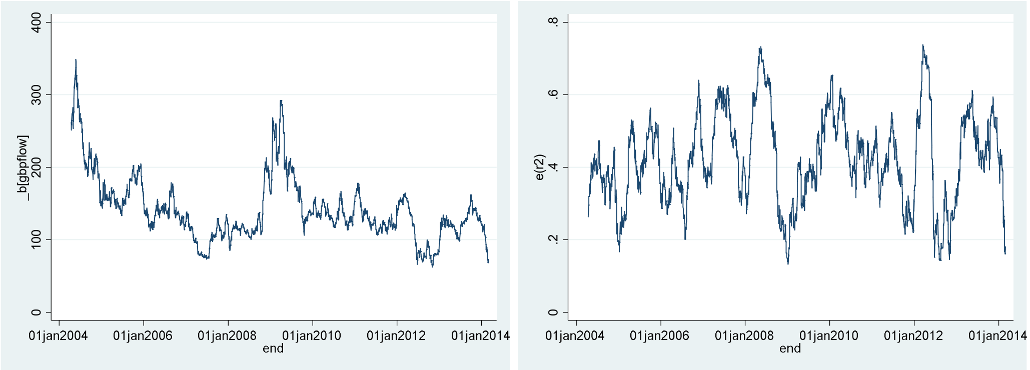

Figure 1 Explanation of order flow on GBP/USD exchange rate

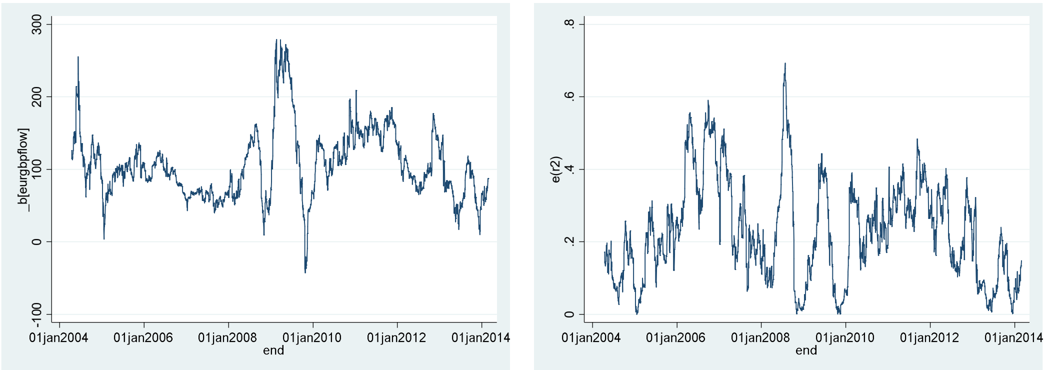

Figure 2 Explanation of order flow on EUR/GBP exchange rate

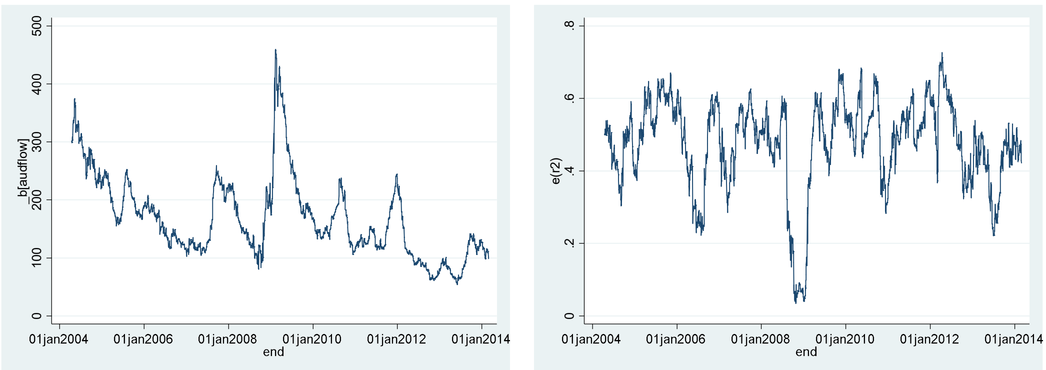

Figure 3 Explanation of order flow on the exchange rate of AUD/USD

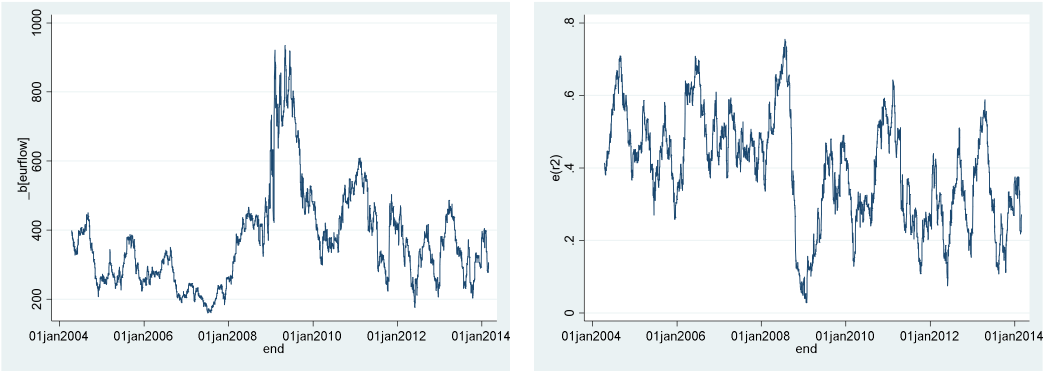

Figure 4 Explanation of order flow on EUR/USD exchange rate

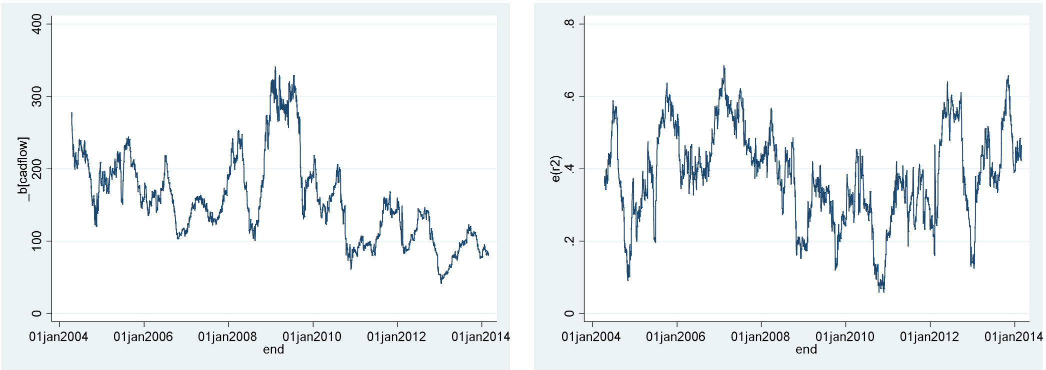

Figure 5 Explanation of order flow on CAD/USD exchange rate

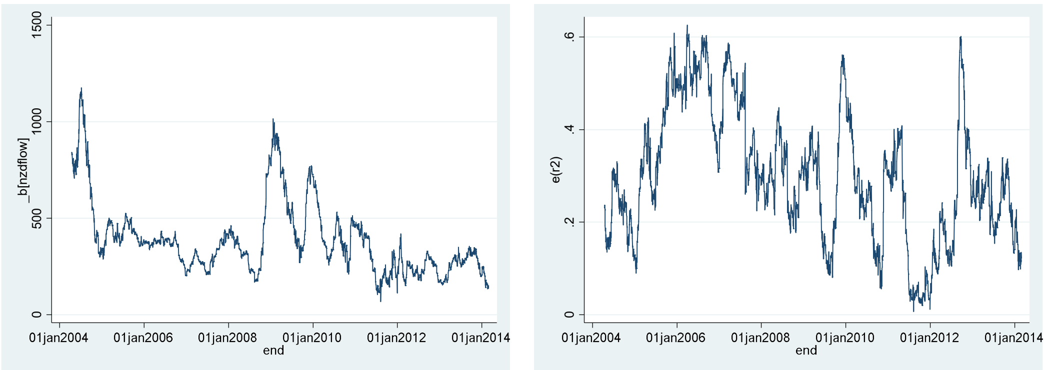

Figure 6 Explanation of order flow on NZD/USD exchange rate

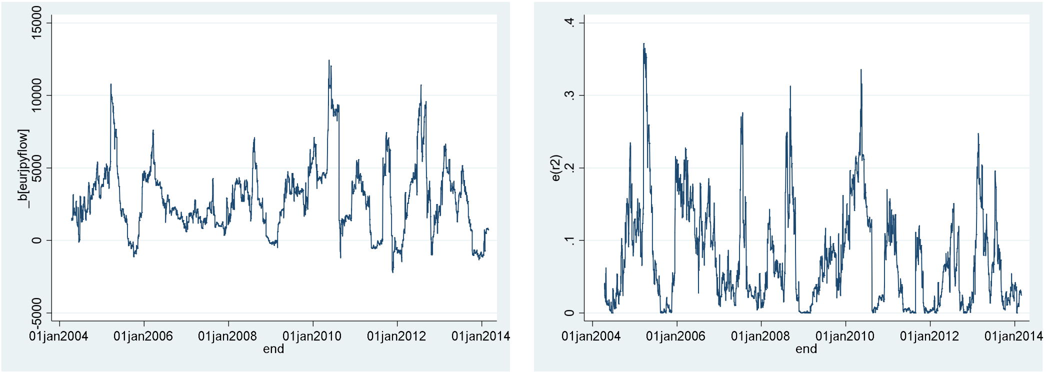

Figure 7 Explanation of order flow for EUR/JPY exchange rate

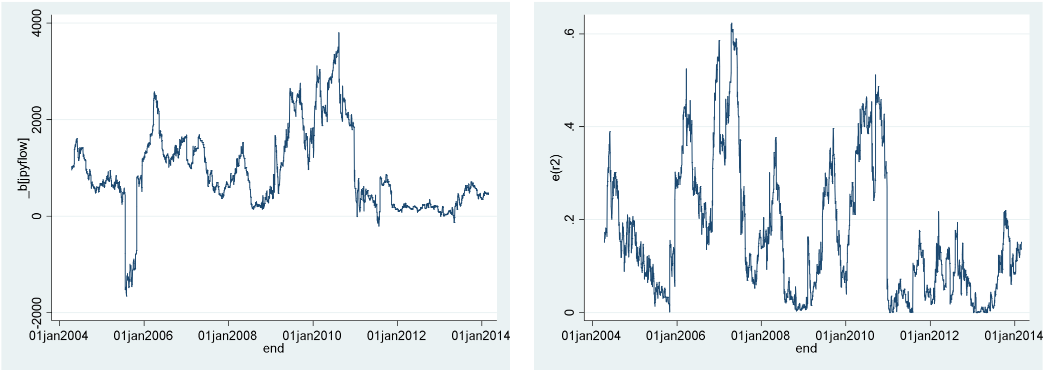

Figure 8 Explanation of order flow on JPY/USD exchange rate

Table 2 Whether market panic can reduce R2 of the model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	r2_gbpflow	r2_eurgbpflow	r2_audflow	r2_eurflow	r2_cadflow	r2_nzdflow	r2_eurjpyflow	r2_jpyflow
mean_vix100	-0.004***	-0.002***	-0.003***	-0.008***	-0.006***	-0.004***	-0.002***	-0.003***
	[-16.41]	[-7.88]	[-14.08]	[-33.68]	[-28.90]	[-17.97]	[-15.72]	[-12.56]
_cons	0.495***	0.270***	0.540***	0.559***	0.508***	0.392***	0.115***	0.235***
	[101.74]	[48.22]	[108.46]	[105.90]	[107.57]	[70.69]	[41.89]	[41.34]
N	3608	3608	3608	3608	3608	3608	3608	3608
r2_a	0.069	0.017	0.052	0.239	0.188	0.082	0.064	0.042
F	269.191	62.090	198.116	1134.139	834.991	322.791	247.120	157.752

t statistics in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3 Does VIX affect the sensitivity of exchange rate to Order Flow

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	gbpreturn	eurgbpreturn	audreturn	eurreturn	cadreturn	nzdreturn	eurjpyreturn	jpyreturn
gbpflow	107.871^{***}							
	[11.86]							
gbpflow_vix	0.846^{**}							
	[2.22]							
eurgbpflow		73.177^{***}						
		[6.82]						
eurgbpflow_vix		1.145^{**}						
		[2.56]						
audflow			96.581^{***}					
			[8.81]					
audflow_vix			1.805^{***}					
			[3.99]					
eurflow				189.216^{***}				
				[6.63]				
eurflow_vix				7.224^{***}				
				[4.90]				
cadflow					62.002^{***}			
					[5.62]			
cadflow_vix					3.569^{***}			
					[7.58]			

nzdflow						149.983***		
						[4.90]		
nzdflow_vix						9.318***		
						[7.25]		
eurjpyflow							2607.239***	
							[7.19]	
eurjpyflow_vix							-32.162***	
							[-3.89]	
jpyflow								369.037***
								[3.59]
jpyflow_vix								4.501
								[0.94]
_cons	-6.791***	-5.140***	-7.606***	-5.547***	-12.922***	-7.114***	1.223	1.432
	[-5.85]	[-4.68]	[-4.20]	[-4.43]	[-9.90]	[-3.77]	[0.66]	[0.89]
N	1931	1931	1931	1931	1931	1931	1931	1931
r2_a	0.324	0.166	0.293	0.317	0.297	0.246	0.032	0.062
F	462.497	193.063	401.176	449.911	409.305	315.190	33.130	65.210

t statistics in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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