Market expectation and dispersion in foreign exchange markets: A new approach

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Abstract

Actual transaction is closely related with each individual expectation: When individuals expect the future appreciation (depreciation) of their national currency, they buy (sell) their currency in foreign exchange markets immediately. This fact leads me to build a simple microstructure, which enables us to calculate market expectation and dispersion with transaction data. Since the market expectation and dispersion are derived from actual transaction data but not survey one, my method is superior to survey one when survey participants are unreliable. My method also allows us to calculate market expectation and dispersion with lower cost and more frequency than survey one.

JEL classification: F31; G15

Keywords: Exchange rate; Heterogeneity; Market expectation

*Email to: kitamu'AT'eco.u-toyama.ac.jp This is the revised version of 'The informational transparency of foreign spot exchange markets'.

1 Introduction

Keeping in mind a fact that heterogeneity in exchange rate is key in modern exchange rate models, I develop a simple model to calculate the mean and standard deviation of daily individual expectations. The former and latter correspond to market consensus and dispersion (heterogeneity) about future exchange rates, respectively.

Unlike Menkhoff, Rebitzky and Schröder (2009) who used the monthly financial market survey, my notable feature lies in no need of the survey data: I obtain bear and bull ratios of market participants with the data of number of sells and buys under the assumed market microstructure. By using Carlson and Parkin (1975), these obtained ratios enable me to calculate the mean and standard deviation of daily individual expectations. Without market survey which is very difficult for us to pursue every day, my method enables us to know daily and even more shorter intra-day market consensus and dispersion. Needless to say, it is important for not only market participants but also policy conductors to know market sentiment as soon as possible. Given an adequate market microstructure, I consider that my method gives useful market expectation and dispersion which reflect intraday market atmosphere. Moreover, since my market consensus and dispersion are derived from actual transaction data, my method is superior to the use of survey data when survey participants are less reliable.

As found by Meese and Rogoff (1983) and the subsequent literature, no model so far has evidently performed well over a random walk to predict foreign exchange (FX) rates in the short-run. [1] Therefore, as pointed out by Rime(2003), it is reasonable to consider that FX participants have different views on exchange rate at least in the short horizons. Westerhoff (2003) who considered chartists and fundamentalists as different agents in FX markets successfully displayed realistic exchange rate dynamics. The simulations by Westerhoff showed that disconnect of FX rate with its fundamentals is amplified by chartism in the short run and mean reversion of FX rate is achieved by not only fundamentalism but also chartism in the long run. Such dynamics was also confirmed by Bacchetta and van Wincoop (2006) who assumed that the low of iterated expectations does not hold and introduced heterogeneous information.

Given a fact that FX rate dynamics is closely related to heterogeneity, like Menkhoff, Rebitzky and Schröder (2009), I take a different approach from the above literatures. The main aim of mine is to show how to obtain daily market consensus and dispersion (heterogeneity) about future exchange rates from the sequence of trading in the electronic broking service (hereafter, EBS). Recent dominance of electronic broker in interbank FX markets over voice broker and direct trading[2] indicates the importance of information about the trading process emerging on monitors of electronic

[1] At the longer horizons (well over one year), Mark (1995) showed that the prediction of the monetary model of FX rates, in which the fundamental variable is defined with a linear combination of log relative money stocks and log relative real incomes in two countries, outperformed the driftless random walk.

[2] See, Table 4 in Rime (2003).

broker because the observation of market-wide trading process is crucial for market participants to set the 'correct' exchange rate (Rime, 2003). Since the EUR/USD and USD/JPY currency pairs are largely dominant by EBS, followed by Reuters, I focus on these pairs.

My model has a similar structure with Easley and O'Hara (1992) but not the same. [3] First, the model developed by them demonstrates how private information is detected by market makers from current trading. However, their model assumed no arrival of private information (this plays a crucial role in their model because it conveys the signal of no information arrival), and this is not adequate for the model of market sentiment [4] because market sentiment should *always* exist over trading periods. Meanwhile, my model does not care about whether private information[5] arrives or does not. This is proper to FX market analysis because there is no plausible analog to the inside information so common to equity markets (Ito, Lyons and Melvin, 1998). My model assumes that the opinions about future exchange rate formed by market participants are always classified into the three types (positive, negative and no movement). Secondly, in my model, individual opinions are key

[3]One drawback of my study is an omitted market maker, who quotes bid and ask rates in FX markets. It should be considered explicitly in future research. Easley and O'Hara (1992) considered the Bayesian, who quotes its price by observing current trade to capture the signal of arrival private information. Another drawbacks, which are common to Easley and O'Hara (1992) and mine, are mentioned in Chapter 4 of Lyons (2001).

[4]Market sentiment corresponds to market consensus and dispersion throughout this study.

[5]With Lyons (2001), private information satisfies the following two criteria; (1) it is not known by all people, and (2) it produces a better price forecast than public information alone.

notation and each market participant is both informed- and uninformed one because each knows its own opinion about future exchange rate and does not know others' ones. This does not allow us to separate market participants into informed- and uninformed ones obviously, meanwhile this separation was adopted by Easley and O'Hara (1992). This study develops an alternative model which does not need that separation and depicts how we can aggregate individual opinions and detect the market sentiment on future exchange rate. Third, I overcome the inflexibility of Easley and O'Hara (1992): the contemporaneous covariance between the number of buys and sells, which is calculated from Easley and O'Hara (1992), always takes negative sign and this is sometimes inconsistent with empirical evidences (Duarte and Young, 2009). Following Duarte and Young (2009), I allow the contemporaneous covariance calculated from my model to take both positive and negative signs by considering simultaneous positive shocks to both buy and sell order flows.

The outline of this paper is as follows. I explain the market structure and the model in Section 2. Section 3 empirically tests my hypothesis. Section 4 concludes this paper.

2 Modelling for dispersed opinions

In this section, I develop a simple model to estimate the market sentiment by searching the set of parameters that maximizes the likelihood function, which is the product of conditional probability with given parameters. The probability is that S sells and B buys[6] occur in one period.

I assume the two type traders in FX markets. The first one trades based on its own opinion about future exchange rate. Hereafter, I call him/her *speculator*. Speculators are assumed to be risk neutral and therefore, they will always trade when their opinions indicate future price movement. Chartists and fundamentalists, whose trading strategies are most common in FX markets (Tayler and Allen, 1992), are classified into speculators when their transactions are driven by their expectations. Without a loss of generality, it is assumed that the direction of their trade is always consistent with their own opinions.

The second one is *unspeculator* whose trading is independent of its own expectation. That is, they do not trade based on their opinions on future exchange rates. For example, unspeculators trade just for liquidity reason arising from such as their customers' order. Once unspeculators strategically adjust their inventory based on their opinions, my model classifies them into speculators. Following Duarte and Young (2009), the entry of unspeculators swells at both sell and buy sides with the probability θ. As shown later, this enables my model to consider not only the negative but also positive correlations between buys and sells. One possible cause of a symmetric order flow shocks on both buy and sell sides is that traders harmonize their own trading timing with others' one to reduce their transaction costs. Since the price impact of trading is relatively small when trading volume is high, un-

[6]Throughout this paper, buy (sell) refers to ask (bid) side trading.

speculators are willing to coordinate on trading on a certain timing (Admati and Pfleiderer, 1988).

For the process of entry of speculators and unspeculators into a FX market, I assume Poisson process, $Po(\mu)$ and $Po(\epsilon)$, respectively. Buyer and seller of unspeculators are assumed to entry into a FX market with intensity parameter ϵ_b and ϵ_s, respectively. With probability θ, unspeculators entry into a FX market with symmetric order shock on both buy and sell sides. For the process of entry of them, I assume Poisson process, $Po(\Delta\epsilon_b)$ (buy side) and $Po(\Delta\epsilon_s)$ (sell side).

Let denote α and β as probabilities of positive and negative future returns, respectively. $0 \leq \alpha, \beta, \theta \leq 1$ and $0 \leq \alpha + \beta \leq 1$ are assumed. $1 - \alpha - \beta$ is a probability of no future price movement (zero future return). In this study, α and β are key parameters in estimating market consensus and dispersion. To obtain plausible numerical values for them, the assumed market structure should be consistent with the real one. As shown in later, my market structure generates the plausible value for the correlation coefficient between buys and sells. Figure 1 summarizes the model structure.

*****Figure 1 around here*****

The model structure shown in Figure 1 enables me to calculate the market sentiment by observing current trading in EBS. Based on the structure in Figure 1, by maximizing the following probability, I obtain set of estimated parameters $\hat{\alpha}$, $\hat{\beta}$, $\hat{\theta}$, $\hat{\mu}$, $\hat{\epsilon_s}$, $\hat{\epsilon_b}$, $\hat{\Delta\epsilon_s}$ and $\hat{\Delta\epsilon_b}$.

$$
\begin{aligned}
&\Pr\left[y_T = (B_T, S_T)|\Gamma\right] \\
&= \alpha\theta \exp(-\mu - \epsilon_b - \epsilon_s - \Delta\epsilon_b - \Delta\epsilon_s)\frac{(\mu + \epsilon_b + \Delta\epsilon_s)^{B_T}(\epsilon_s + \Delta\epsilon_s)^{S_T}}{B_T!S_T!} \\
&\quad \alpha(1-\theta)\exp(-\mu - \epsilon_b - \epsilon_s)\frac{(\mu + \epsilon_b)^{B_T}\epsilon_s^{S_T}}{B_T!S_T!} \\
&\quad \beta\theta \exp(-\mu - \epsilon_b - \epsilon_s - \Delta\epsilon_b - \Delta\epsilon_s)\frac{(\epsilon_b + \Delta\epsilon_b)^{B_T}(\mu + \epsilon_s + \Delta\epsilon_s)^{S_T}}{B_T!S_T!} \\
&\quad \beta(1-\theta)\exp(-\mu - \epsilon_b - \epsilon_s)\frac{\epsilon_b^{B_T}(\mu + \epsilon_s)^{S_T}}{B_T!S_T!} \\
&\quad +(1-\alpha-\beta)\theta \exp(-\epsilon_b - \epsilon_s - \Delta\epsilon_b - \Delta\epsilon_s)\frac{(\epsilon_b + \Delta\epsilon_b)^{B_T}(\epsilon_s + \Delta\epsilon_s)^{S_T}}{B_T!S_T!} \\
&\quad +(1-\alpha-\beta)(1-\theta)\exp(-\epsilon_b - \epsilon_s)\frac{\epsilon_b^{B_T}\epsilon_s^{S_T}}{B_T!S_T!} \qquad (1)
\end{aligned}
$$

where, given the set of parameter, $\Pr\left[y_T = (B_T, S_T)|\Gamma\right]$ is a conditional probability of observing B_T number of buyers and S_T number of sellers in period T under the assumed market structure of Figure 1. $\Gamma = [\alpha\ \beta\ \theta\ \mu\ \epsilon_s\ \epsilon_b\ \Delta\epsilon_s\ \Delta\epsilon_b]$. Following Duarte and Young (2009), to avoid the numerical overflows caused by large value $'A'$ with intensity $'K_a'$, I compute $\exp(-K_a)K_a^A/A!$ as $\exp\left[-K_a + A\ln(K_a) - \sum_{i=1}^{A}\ln(i)\right]$ in eq.(1).

I construct the aggregate log likelihood function of the time series of buys and sells as a summation of the logarithm of the conditional probabilities:

$$
L(\{y_i\}_{i=1}^{T}) = \sum_{i=1}^{T}\ln\Pr\left[y_i = (B_i, S_i)|\Gamma\right]. \qquad (2)
$$

The structure in Figure 1 also enables me to calculate the contemporaneous covariance of buys and sells as follows:

$$\text{Cov}(B_T, S_T) = \theta(1-\theta)\Delta\epsilon_s\Delta\epsilon_b - \alpha\beta\mu^2. \tag{3}$$

The right side of eq.(3) can be positive or negative. Comparing the model of Easley, Kiefer, O'Hara and Paperman (1996), in which the covariance is always negative, the introduction of the symmetric shocks in unspeculators enables me to consider the more flexible covariance, which explains both positive and negative correlation between sells and buys.

From Figure 1, I can also calculate the variances of buys and sells as follows[7]:

$$\text{Var}(B_T) = \alpha(1-\alpha)\mu + \theta(1-\theta)\Delta\epsilon_b \tag{4}$$

$$\text{Var}(S_T) = \beta(1-\beta)\mu + \theta(1-\theta)\Delta\epsilon_s. \tag{5}$$

In the following, with the data obtained from EBS, I search the parameter set which maximizes the left term of eq.(2).

[7] For the calculation, I used the similar technique to the appendix of Duarte and Young (2009).

3 Estimation and market expectation

3.1 data and estimation

For empirical analysis, I obtained the trading data from EBS Data Mine ver. 1.0. The sample period ran from August 25, 2005, to November 30, 2007 and the data of weekend was excluded. Finally, the maximum number of days, in which market sentiment could be estimated, is 589. As shown in the following Table 3, estimations achieved convergences in over 95 percent of days in all the cases. [8] I focus on the EUR/USD and USD/JPY currency pairs since these pairs are largely dominant by EBS, followed by Reuters. In my dataset, the U.S. dollar is quoted against the euro and the yen is quoted against the U.S. dollar, respectively. When I refer to buy of EUR/USD, it means the selling of the U.S dollar against the euro (ask side trade of EUR/USD). In the case of USD/JPY, the buy of USD/JPY means the selling of the yen against the U.S dollar.

I count the numbers of trade on bid and ask sides at 5, 10 and 15 minute intervals, respectively. This enables me to calculate daily market sentiment with different data intervals. The reason for it is to consider the independency of trade among different intraday period in one day; without this independency, the log likelihood of observing T buy orders $\{B_i\}$ and T sell orders $\{S_i\}$ does not take that form of eq.(2). Following Andersen and Bollerslev

[8] When I observed unusual light volume such as in July 4th, estimation did not achieve convergence.

(1998), who found that 5 minutes DM-$ returns are independent each other and the sum of squared these is accurate for its daily volatility, I set the minimal interval to 5 minute one.

*****Figure 2 around here*****

Figure 2 shows the sample averages of numbers of buy and sell which occur in every 15 minute interval. For 5 and 10 minute interval data, I also found the same intraday pattern as one of 15 minute interval. As we can see, there is a explicit intraday seasonality in the numbers of both sell and buy. In the following, I assume that market sentiment is stable throughout one day and estimate the market sentiment for each day. [9] In other words, for each minute interval data set, I search the parameter set that maximizes eq.(2) in each day. If I ignore the intraday seasonality of trade shown in Figure 2, my model might consider that the period of low trading volume has different market sentiment from that of high trading volume in one day. This possibly leads me to an incorrect conclusion. Therefore, before maximizing eq.(2), I should remove intraday seasonal patterns of numbers of sells and buys.

*****Table 1 around here*****

Ito and Hashimoto (2006) reported that intraday patterns of FX trading is time variant depending on the timing at which Europe and America adopt the daylight saving time (DST). This implies that I also have to consider

[9] Of course, this assumption is violated in some days. By considering shorter interval such as 1minute, my method allows me to calculate hourly market sentiment.

that timing when I remove the intraday seasonality. For this issue, I split my sample into the following four periods: (1) no DST, (2) only Europe adopting DST, (3) only America adopting DST and (4) Europe and America adopting DST. Table 1 shows the four periods. Then, for each four periods, I calculate the medians of buys and sells at each intraday period across days. The reason why I adopted median is due to small days of (2) only Europe adopting DST and (3) only America adopting DST. These median numbers are normalized by the median of these ones. I adopt this normalization to keep the numbers of sells and buys, which are divided by this normalized medians, over unity in most cases. Finally, I divided the numbers of buys and sells by the corresponding normalized medians and obtained the seasonally adjusted numbers of buys and sells. This is done for each four periods.

*****Table 2 around here*****

Table 2 reports the summary of statistics about the numbers of sells and buys for each interval data. These numbers of buys and sells are seasonally adjusted with the method mentioned above. As shown in the last row of Table 2, the mean of correlations between sells and buys across days suggest the strong positive correlation between sells and buys in both EUR/USD and USD/JPY markets. I consider this as an empirical evidence for introducing the symmetric shocks in the entry of unspeculators.

By searching the parameter set which maximizes the left term of eq.(2) with the seasonally adjusted sell and buy data, I obtain the set of estimated parameters in each day.

*****Table 3 around here*****

Table 3 reports the estimation result of eq.(2). Standard errors for the parameters $\hat{\alpha}$ $\hat{\beta}$ $\hat{\theta}$ $\hat{\mu}$ $\hat{\epsilon_s}$ $\hat{\epsilon_b}$ $\hat{\Delta\epsilon_s}$ and $\hat{\Delta\epsilon_b}$ are calculated with the outer-product-of-the gradient (Davidson and MacKinnon, 2004). 'Hat' over parameter refers to an estimated parameter. The standard errors for the others are obtained with the gradient method. One interesting finding in Table 3 is that the estimated correlations of buys and sells are strongly positive and show the similar values to those of Table 2. This is achieved with the introduction of symmetry shock in the entry of unspeculators into the model. I can consider that this introduction contributes to the correct estimation of key parameters α and β. Comparing to the results of Table 2, the estimated variances and covariances in Table 3 are seemed to be underestimated. This indicates that there still remain the other factors, which are not considered in my model. Once I consider the other factors, the model has more parameters to be estimated. To achieve calculation, I keep the other factors out of consideration.

Carlson and Parkin (1975) suggested that categorical survey data are converted into quantitative measure of expectation. By adopting same assumptions of Carlson and Parkin, I explain this method briefly.

Let τ and m_i denote the threshold of positive return and the mean of subjective probability distribution of ith individual's return forecast, respectively. When $m_i > \tau$, this agent forecasts positive return. Assuming symmetry, the agent forecast negative return when $m_i < -\tau$. τ is assumed to be common to all individuals. Let r^e denote the mean of each individual mean and I call it market consensus. By applying the Central-Limit Theorem, m_i follows a normal distribution which mean and variance are r^e and σ^2, respectively. Therefore, the normalized variable $(m_i - r^e)/\sigma$ follows a normal distribution with mean zero and unit variance. Since I assume that the threshold τ is common to all individuals, I obtain the following equations.

$$\hat{\alpha} = Pr\left(\frac{m_i - r^e}{\sigma} > a\right) = 1 - F(a) \tag{6}$$

$$\hat{\beta} = Pr\left(\frac{m_i - r^e}{\sigma} < b\right) = F(b), \tag{7}$$

where $\hat{\alpha}$ and $\hat{\beta}$ are estimated probabilities of positive and negative future returns, respectively. $Pr(.)$ refers to probability. $F(.)$ refers to cumulative distribution function (cdf) of the standard normal distribution. a and b are given as follows.

$$a = \frac{\tau - r^e}{\sigma} \tag{8}$$

$$b = \frac{-\tau - r^e}{\sigma}. \tag{9}$$

By computing the inverse of the cdf of the standard normal distribution, I obtain numerical values of a and b.

Equations (8) and (9) are solved for r^e (market consensus) and σ (dispersion):

$$r^e = -\tau \left(\frac{a+b}{a-b} \right) \tag{10}$$

$$\sigma = 2\tau \left(\frac{1}{a-b} \right). \tag{11}$$

I set $\tau = \sum |r| / \sum [|(a+b)/(a-b)|]$, where r is actual daily return. For the robustness, I also set $\tau = 0.03$ (see, Menkhoff, Rebitzky and Schröder, 2009).

In the next subsection, I check the economic implication of r^e and σ statistically.

3.2 Market consensus and dispersion

In this subsection, by using correlation analysis and regression one, I examine whether my calculating market consensus and dispersion are plausible or not.

*****Table 4 around here*****

Table 4 shows the summary of statistics for market consensus r^e and dispersion σ, which are calculated with each interval data of each currency pair. When $\tau = 0.03$, the maximum and minimum consensus tend to take unrealistic values in both the pairs. For example, the maximum consensus which is calculated with 5 minute interval data of EUR/USD is 0.294. This means that the market expects about 29 percent daily return and this number is enormous with comparison to 1.84 percent, which is the daily maximum realized return of EUR/USD in my sample. However, as shown in below, the consensus and dispersion which are calculated with $\tau = 0.03$ also have a statistical characteristic that is consistent with the definitions of consensus and dispersion.

Here, by using correlation analysis and regression one, I test the following hypothesis to check the usefulness of my calculating consensus and dispersion.

Hypothesis 1: *Market consensus r^e is a good predictor for realized daily return.*

*****Table 5 around here*****

*****Table 6 around here*****

To test this hypothesis, I calculate coefficient correlation between realized daily return and consensus (Table 5) and I regress the former onto constant term and the latter (Table 6). Here, I use the midquote q of EBS best bid and ask rates which are lastly observed in one day and obtain tth day return $r_t = (q_t - q_{t-1})/q_{t-1}$.

Table 5 shows the Pearson product-moment correlation coefficient. Since τ is a scaling parameter for r^e and, therefore, it does not affect the correlation coefficient between realized return and r^e, I report the result only with $\tau = 0.03$ in Table 5. In Table 6, the number of parenthesis is the Newey-West robust standard error, autocovariance of which is calculated with the lag of third root of sample size.

Unfortunately, the results of Tables 5 and 6 indicates that market consensus is a poor predictor for daily return. Does this indicates my failure? Or are there any other factors which have crucial effects on daily returns? Before my conclusion for this issue, to check the validity of my method in more ways, I test the following hypothesis:

Hypothesis 2: *Market consensus is a good predictor for daily returns when dispersion is relatively small.*

Hypothesis 3: *Returns are volatile when market dispersion is relatively large.*

Since the dispersion corresponds to the degree of market disagreement about a future FX return, I can consider that the prediction power of consensus for daily returns becomes large when dispersion is relatively small. In other words, I can observe a positive correlation between dispersion and absolute prediction errors, which are differences between realized daily returns and the consensus. To test the second hypothesis, I define $|r_t - r_t^e|$ as the absolute prediction error at day t.

*****Table 7 around here*****

Not depending on the threshold τ, Table 7 shows the strong positive correlation between dispersion and absolute prediction errors, and the results of Table 7 are strongly consistent with my hypothesis.

Additionally, I test the second hypothesis by regressing the absolute prediction error onto constant term and the dispersion.

*****Table 8 around here*****

In all cases, the estimated coefficients of dispersion are positive and also statistically significant at 1 percent level. In terms of adjusted R-square, the results with $\tau = 0.03$ are superior to the other in both the currency pairs. However, given a fact that the estimated coefficients of dispersion are positive and also statistically significant when $\tau = \sum |r| / \sum [|(a+b)/(a-b)|]$, it is safe to consider that the value of threshold τ is not crucial to the validity of the second hypothesis.

I consider the third hypothesis with the following reason: It is plausible to postulate that the larger the market disagreement is, the more volatile FX returns are. This is because trading volume and the number of price change are amplified by market participants who trade with persons with different beliefs. To check the third hypothesis, I calculate the correlation coefficient between the root of daily volatility and dispersion. To adjust the scale of the former to that of the later, I use the root of daily volatility. Following Andersen and Bollerslev (1998), I adopt the sum of squared five minute returns as a daily volatility of FX returns.

*****Table 9 around here*****

With the same reason as Table 5, I report the result only with $\tau = 0.03$ in Table 9. Although the absolute values in Table 9 relatively smaller by being compared to the result of Table 7, all of them are positive and statistically significant in all the cases.

*****Table 10 around here*****

Table 10 reports the result of regression of the root of daily volatility onto constant term and dispersion. Although low levels of adjusted R-square and statistical insignificance of dispersion in Table 8 are less supportive for my hypothesis, the positive sign condition are fulfilled in all the cases.

In summary, the results of Tables 7 and 8 indicate that my calculating consensus and dispersion show a consistent characteristic with their own definitions. I also conclude that the results of Table 9 and 10 support the usefulness of my dispersion calmly. Finally, I conclude that the negative results of Tables 5 and 6 are due to other factors which have significant impact on daily returns. Again, I consider that these results of Tables 7-10 support the validity of my method to obtain daily market consensus and dispersion.

I also examined whether dispersion is closely related to the deviation from PPP and speed of exchange rate change. Menkhoff, Rebitzky and Schöder (2009) assumed that the former and latter affect the behaviors of fundamentalists and chartists, respectively. Their results indicate larger deviation from PPP diminishes dispersion and, in turn, the fast speed of exchange rate change enlarges that. Although my result is not reported, my results are mixing; some cases are consistent with Menkhoff, Rebitzky and Schöder (2009) but others are not. For this issue, one possible reason is that my dispersion is derived from inter-dealer transactions and, therefore, it is heavily affected by very short-term expectation of inter-dealers. It is plausible that the very short-term expectation often differs from longer-term one, which is derived from monthly census data used by Menkhoff, Rebitzky and Schöder (2009).

4 Conclusion

My market consensus and dispersion about future exchange rate are calculated with actual transaction data but not survey one. This brings the following two merits.

First, since it is plausible that the sign of actual transaction by speculation[10] is consistent with individual expectation, my method gives more reliable measures for market consensus and dispersion than survey data when survey responsers are not honest. My model also covers the case when the sign of unspeclator's transaction depends on its customer order but not its expectation. By doing so, I can consider the possibility that the sign of unspeculator's trade is not consistent with its expectation. I think that this enables my measures to be more adequate as actual market consensus and dispersion.

Secondly, no need of survey data enables me to calculate market consensus and dispersion frequently whenever we want. This is desirable for policy

[10]See my definition for speculator at section 2.

conductors who have to know market sentiment as soon as possible.

One possible usage of my method is to evaluate FX market intervention at ex-post: After the intervention, if market expectation is consistent with the sign of the intervention and maker dispersion becomes smaller, we possibly consider that market interpretation for that policy is supportive for the monetary authority. Moreover, if policy conductors estimate the market sentiment correctly, it would help them to conduct effective market operations (FX interventions) at best timings.

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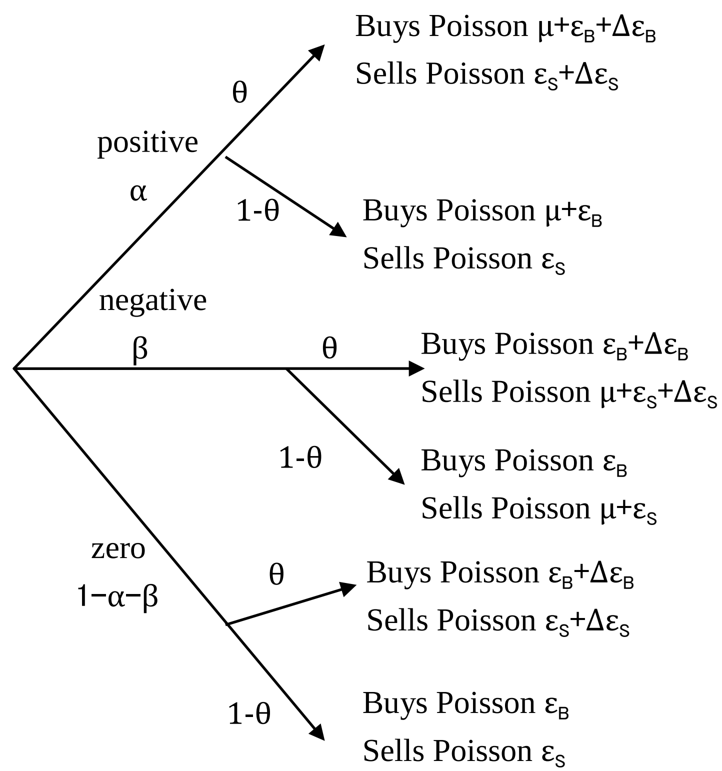
Figure 1. The model structure

The rerun at *t* will be

Realized return at *t-1*



The arrival rate of speculators follows Poisson process with the intensity parameter μ. The arrival rate of selling and buying unspeculators follows Poisson process with the intensity parameters ε_B and $\varepsilon_{B,}$ respectively. The arrival rate of swelling selling and buying unspeculators follows Poisson process with the intensity parameters $\Delta\varepsilon_B$ and $\Delta\ \varepsilon_{B,}$ respectively.

Figure 2.

The averages of number of buy and sell.

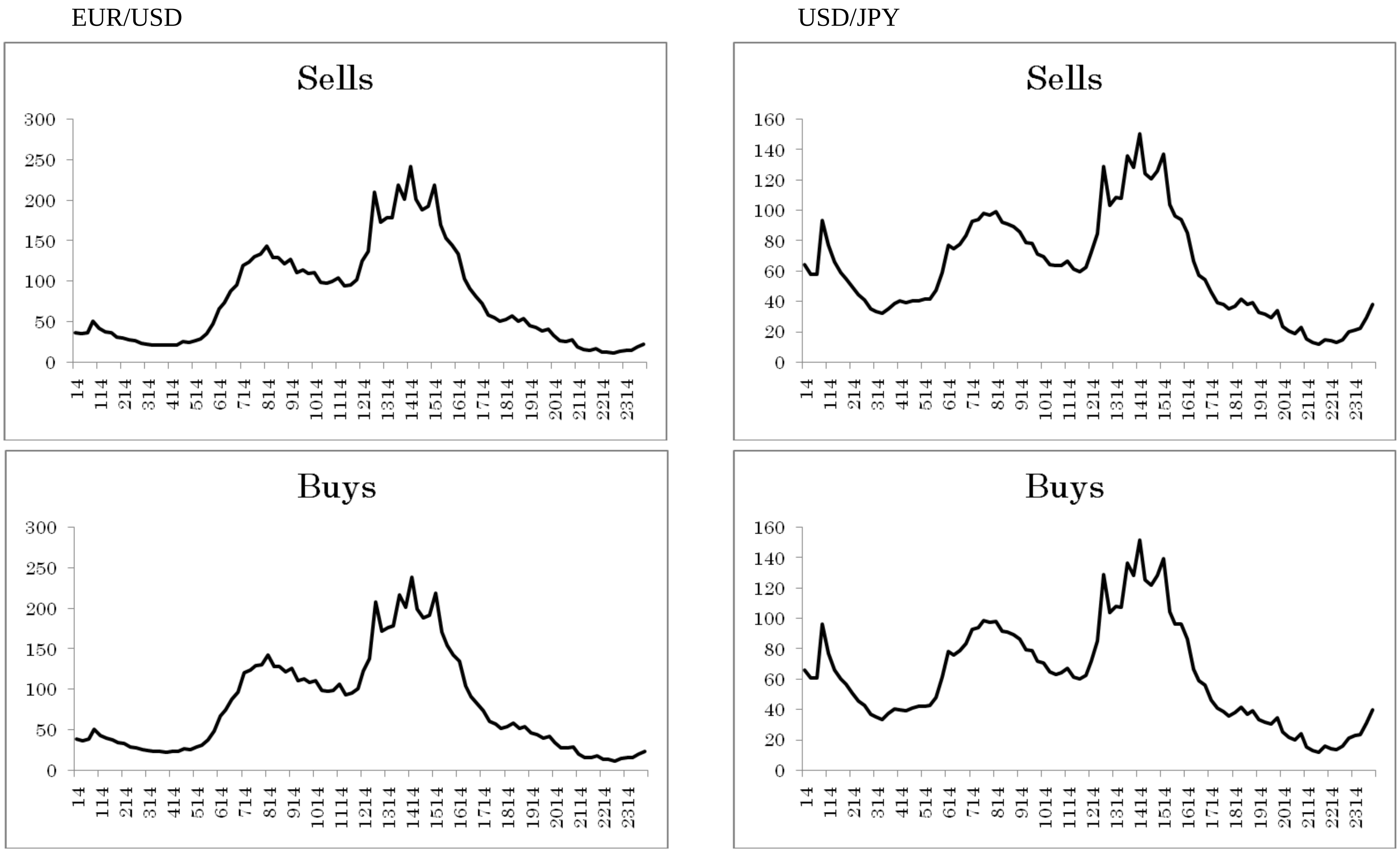


Figure 2 is made with 15 minute interval data. Horizontal axis is GMT time line.

Table 1

The timing of the daylight saving time (DST).

DST adoption	period
Both Eur. and Ame.	2005/8/25-2005/10/30, 2006/4/2-2006/10/29, 2007/3/25-2007/10/28
Only Eur.	2006/3/27-2006/4/1
Only Ame.	2007/3/11-2007/3/24, 2007/10/30-2007/11/4
No DST	2005/10/31-2006/3/26, 2006/10/30-2007/3/24, 2007/11/5-2007/11/30

Eur. and Ame. are Europe and America, respectively.

Table 2

Summary of statistics of seasonally adjusted buys and sells

	EUR/USD			USD/JPY		
Data interval	5 min.	10 min.	15 min.	5 min.	10 min.	15 min.
Sample mean of buys	20.17	40.97	60.90	21.31	43.16	64.23
Standard error of buys	4.52	9.21	13.67	7.34	14.87	20.17
Sample mean of sells	19.85	39.87	59.50	20.82	41.86	62.26
Standard error of sells	4.50	9.09	13.57	7.56	15.19	20.36
Mean covariance between sells and buys across days	170.09	613.33	1254.58	217.76	782.13	1483.75
Mean variance of buys across days	212.58	692.89	1375.37	265.35	877.71	1613.02
Mean variance of sells across days	215.07	726.90	1426.93	266.08	902.96	1682.70
Mean correlation between sells and buys across days	0.76	0.84	0.88	0.78	0.85	0.88

The first row shows currency pair and the second is the interval of data.

Table 3

		EUR/USD						
		5 min.	10 min.	15 min.		5 min.	10 min.	15 min.
	NOB	576	573	563				
ε_b					β			
	Mean	12.133	24.181	37.500		0.111	0.149	0.183
	(Mean S.E.)	(0.279)	(0.572)	(1.689)		(0.028)	(0.042)	(0.066)
	Median	12.158	23.925	37.926		0.070	0.075	0.111
	S.D.	3.223	7.397	11.612		0.119	0.164	0.185
ε_s					θ			
	Mean	11.932	23.595	36.565		0.225	0.224	0.237
	(Mean S.E.)	(0.271)	(0.842)	(0.942)		(0.030)	(0.042)	(0.067)
	Median	11.568	23.385	36.662		0.221	0.213	0.226
	S.D.	3.244	6.848	11.366		0.105	0.116	0.128
μ					Cov(B,S)			
	Mean	18.485	25.519	33.411		81.739	287.306	593.668
	(Mean S.E.)	(2.072)	(1.516)	(3.045)		(14.517)	(70.592)	(297.628)
	Median	16.404	21.140	29.041		56.473	204.140	450.199
	S.D.	10.736	15.090	19.713		91.631	322.867	566.600
$\Delta\varepsilon_b$					Var(B)			
	Mean	24.966	46.644	64.532		108.689	379.619	755.174
	(Mean S.E.)	(0.971)	(2.058)	(4.737)		(18.382)	(84.357)	(416.423)
	Median	18.471	36.785	52.390		78.447	271.209	545.279
	S.D.	21.999	33.811	41.520		109.300	401.942	737.621
$\Delta\varepsilon_s$					Var(S)			
	Mean	24.657	44.583	64.020		106.483	341.490	727.877
	(Mean S.E.)	(0.962)	(2.244)	(4.538)		(18.386)	(77.678)	(320.267)
	Median	18.596	34.875	52.417		78.144	248.467	545.222
	S.D.	20.733	31.556	39.329		102.904	361.428	634.356
α					Corr(B,S)			
	Mean	0.117	0.177	0.178		0.732	0.781	0.794
	(Mean S.E.)	(0.028)	(0.045)	(0.070)		(0.071)	(0.070)	(0.110)
	Median	0.070	0.104	0.118		0.752	0.802	0.819
	S.D.	0.133	0.179	0.181		0.116	0.109	0.117

(continued)

		USD/JPY						
		5 min.	10 min.	15 min.		5 min.	10 min.	15 min.
	NOB	575	571	566				
ε_b					β			
	Mean	13.390	26.849	40.218		0.142	0.199	0.190
	(Mean S.E.)	(0.279)	(0.519)	(1.506)		(0.030)	(0.048)	(0.062)
	Median	12.345	25.148	38.955		0.104	0.146	0.134
	S.D.	5.188	10.220	16.352		0.122	0.175	0.177
ε_s					θ			
	Mean	12.817	25.442	40.051		0.227	0.245	0.251
	(Mean S.E.)	(0.270)	(0.525)	(0.849)		(0.030)	(0.045)	(0.063)
	Median	11.831	23.747	37.608		0.221	0.236	0.237
	S.D.	4.676	10.780	16.156		0.096	0.110	0.128
μ					Cov(B,S)			
	Mean	17.404	26.949	37.442		130.034	429.106	873.637
	(Mean S.E.)	(0.866)	(1.468)	(1.846)		(19.095)	(83.547)	(233.215)
	Median	14.659	23.266	31.890		80.314	265.779	556.133
	S.D.	9.735	13.097	22.871		201.528	524.344	898.005
$\Delta\varepsilon_b$					Var(B)			
	Mean	28.611	49.910	72.918		167.170	516.516	1103.375
	(Mean S.E.)	(0.977)	(1.630)	(3.781)		(21.899)	(89.953)	(283.907)
	Median	22.963	40.324	60.862		110.500	337.972	722.589
	S.D.	20.308	32.057	41.550		208.183	589.650	1176.257
$\Delta\varepsilon_s$					Var(S)			
	Mean	28.700	50.293	72.106		163.994	540.614	1071.988
	(Mean S.E.)	(0.931)	(1.653)	(3.509)		(21.371)	(91.165)	(241.495)
	Median	22.680	41.099	60.556		107.787	355.157	718.052
	S.D.	24.011	31.865	40.757		239.093	593.500	1059.672
α					Corr(B,S)			
	Mean	0.158	0.159	0.194		0.741	0.787	0.792
	(Mean S.E.)	(0.032)	(0.043)	(0.067)		(0.054)	(0.061)	(0.094)
	Median	0.125	0.111	0.141		0.761	0.799	0.815
	S.D.	0.124	0.154	0.180		0.129	0.086	0.121

Table 3 reports summary of statistics of estimated parameters in eq.(1). The first row shows currency pair and the second is the interval of data. NOB is the number of days in which estimations achieve convergences (the full sample is 589 days). Mean is the mean of estimator across days. Mean S.E is the mean of standard errors of estimator across days. S.D. is standard deviation of mean estimators. Cov (covariance) and Var (variance) are defined in eqs.(3)-(5). B and S refer to numbers of buys and sells, respectively. Corr (correlation) is $\mathrm{Cov(B,S)}/\sqrt{\mathrm{Var(B)Var(S)}}$.

Table 4

Summary of statistics of market consensus and dispersion

Data interval		$\tau = \Sigma$ |actual return| / Σ |(a+b)/(a-b)|				τ=0.03			
		EUR/USD		USD/JPY		EUR/USD		USD/JPY	
		Consensus	Dispersion	Consensus	Dispersion	Consensus	Dispersion	Consensus	Dispersion
5 min.	Mean	3.09E-04	0.0078	3.47E-04	0.0097	9.07E-04	0.0230	9.44E-04	0.0264
	S.D.	0.0062	0.0026	0.0050	0.0019	0.0182	0.0078	0.0135	0.0053
	Min.	-0.0199	0.0033	-0.0254	0.0046	-0.0585	0.0096	-0.0689	0.0124
	Max.	0.1001	0.0466	0.0141	0.0185	0.2940	0.1369	0.0385	0.0503
10 min.	Mean	4.55E-04	0.0054	-6.83E-04	0.0068	2.25E-03	0.0265	-2.87E-03	0.0288
	S.D.	0.0047	0.0016	0.0051	0.0018	0.0232	0.0080	0.0216	0.0077
	Min.	-0.0220	0.0026	-0.0288	0.0029	-0.1087	0.0126	-0.1213	0.0123
	Max.	0.0330	0.0178	0.0263	0.0170	0.1629	0.0880	0.1109	0.0715
15 min.	Mean	-3.39E-05	0.0050	1.35E-04	0.0064	-1.96E-04	0.0289	6.40E-04	0.0305
	S.D.	0.0045	0.0019	0.0056	0.0024	0.0260	0.0109	0.0267	0.0116
	Min.	-0.0194	0.0021	-0.0409	0.0025	-0.1121	0.0121	-0.1942	0.0118
	Max.	0.0273	0.0202	0.0414	0.0387	0.1578	0.1164	0.1965	0.1834

Market consensus and dispersion are defined with equations (10) and (11), respectively.

Table 5.

Correlation coefficient between market consensus and realized daily return.

	EUR/USD		USD/JPY	
5 min.	0.0053	***	0.0388	***
10 min.	0.0481	***	-0.0163	***
15 min.	-0.0122	***	-0.0624	***

Asterisks *** indicate statistical significance at 1 percent or better. P-value for correlation coefficient is obtained with $|\rho|\sqrt{n^2-2}/\sqrt{1-\rho^2}$, where ρ and n are coefficient correlation and sample size, respectively.

Table 6.

The result of regressing realized daily return onto constant term and market consensus.

		τ=Σ |actual return| / Σ |(a+b)/(a-b)|		τ=0.03	
		EUR/USD	USD/JPY	EUR/USD	USD/JPY
5 min.	const.	0.0003 *	0.0000	0.0003 *	0.0000
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
	consensus	0.0038	0.0430	0.0013	0.0158
		(0.0302)	(0.0542)	(0.0103)	(0.0199)
	Adj. R^2	-0.002	0.000	-0.002	0.000
	NOB	575	574	575	574
10 min.	const.	0.0003 *	0.0000	0.0003 *	0.0000
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
	consensus	0.0458	-0.0173	0.0093	-0.0041
		(0.0352)	(0.0389)	(0.0071)	(0.0093)
	Adj. R^2	5.7E-04	-1.5E-03	5.7E-04	-1.5E-03
	NOB	572	570	572	570
15 min.	const.	0.0003 *	0.0000	0.0003 *	0.0000
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
	consensus	-0.0119	-0.0605	-0.0021	-0.0128
		(0.0347)	(0.0582)	(0.0060)	(0.0123)
	Adj. R^2	-0.002	0.002	-0.002	0.002
	NOB	562	565	562	565

The number in parenthesis the Neway-West robust standard error, autocovariance of which is calculated with the lag of third root of sample size. An asterisk * indicates statistical significance at 10 percent. Adj. R^2 is adjusted R-square.

Table 7.

Correlation coefficient between market dispersion and absolute prediction error of consensus.

	$\tau=\Sigma$ |actual return| / Σ |(a+b)/(a-b)|		τ=0.03	
	EUR/USD	USD/JPY	EUR/USD	USD/JPY
5 min.	0.6516 ***	0.1509 ***	0.7705 ***	0.3364 ***
10 min.	0.5008 ***	0.4029 ***	0.7493 ***	0.6592 ***
15 min.	0.5613 ***	0.5880 ***	0.7695 ***	0.7725 ***

Asterisks *** indicate statistical significance at 1 percent or better. The prediction error is a difference between market consensus and realized daily return.

Table 8.

The result of regressing absolute prediction error onto constant term and market dispersion.

	τ=Σ |actual return| / Σ |(a+b)/(a-b)|		τ=0.03	
	EUR/USD	USD/JPY	EUR/USD	USD/JPY
const.	-0.0067 **	0.0018 *	-0.0264 ***	-0.0049 **
	(0.0029)	(0.0010)	(0.0077)	(0.0021)
dispersion	1.4647 ***	0.3755 ***	1.5783 ***	0.5993 ***
	(0.3749)	(0.1085)	(0.3444)	(0.0843)
Adj. R^2	0.424	0.021	0.593	0.112
NOB	575	574	575	574
const.	-0.0025 ***	-0.0018 *	-0.0275 ***	-0.0226 ***
	(0.0008)	(0.0010)	(0.0030)	(0.0031)
dispersion	1.3231 ***	1.0994 ***	1.6270 ***	1.3480 ***
	(0.1530)	(0.1420)	(0.1194)	(0.1130)
Adj. R^2	0.250	0.161	0.561	0.434
NOB	572	570	572	570
const.	-0.0016 ***	-0.0034 ***	-0.0219 ***	-0.0238 ***
	(0.0005)	(0.0009)	(0.0023)	(0.0029)
dispersion	1.2632 ***	1.4010 ***	1.3762 ***	1.3766 ***
	(0.0998)	(0.1467)	(0.0868)	(0.1007)
Adj. R^2	0.314	0.345	0.591	0.596
NOB	562	565	562	565

The number in parenthesis the Neway-West robust standard error, autocovariance of which is calculated with the lag of third root of sample size. Asterisks *, ** and *** indicate statistical significance at 10, 5 and 1 percent, respectively. Adj. R^2 is adjusted R-square.

Table 9.

Correlation coefficient between market dispersion and the root of realized daily volatility.

	EUR/USD		USD/JPY	
5 min.	0.0810	***	0.1900	***
10 min.	0.0363	***	0.0174	***
15 min.	0.1143	***	0.0710	***

Asterisks *** indicate statistical significance at 1 percent or better. The realized volatility is a sum of squared 5 minute returns in one day.

Table 10.

The result of regressing the root of realized daily volatility onto constant term and market consensus.

		τ=Σ |actual return| / Σ |(a+b)/(a-b)|		τ=0.03	
		EUR/USD	USD/JPY	EUR/USD	USD/JPY
5 min.	const.	0.0042 ***	0.0037 ***	0.0042 ***	0.0037 ***
		(0.0002)	(0.0006)	(0.0002)	(0.0006)
	dispersion	0.0384	0.1833 ***	0.0131	0.0674 ***
		(0.0325)	(0.0656)	(0.0111)	(0.0241)
	Adj. R^2	0.005	0.034	0.005	0.034
	NOB	576	575	576	575
10 min.	const.	0.0044 ***	0.0053 ***	0.0044 ***	0.0053 ***
		(0.0002)	(0.0003)	(0.0002)	(0.0003)
	dispersion	0.0277	0.0170	0.0056	0.0040
		(0.0308)	(0.0341)	(0.0062)	(0.0081)
	Adj. R^2	-4.3E-04	-1.5E-03	-4.3E-04	-1.5E-03
	NOB	573	571	573	571
15 min.	const.	0.0041 ***	0.0051 ***	0.0041 ***	0.0051 ***
		(0.0002)	(0.0003)	(0.0002)	(0.0003)
	dispersion	0.0757 **	0.0513	0.0131 **	0.0108
		(0.0302)	(0.0446)	(0.0052)	(0.0094)
	Adj. R^2	0.011	0.003	0.011	0.003
	NOB	563	566	563	566

The number in parenthesis the Neway-West robust standard error, autocovariance of which is calculated with the lag of third root of sample size. Asterisks ** and *** indicate statistical significance at 5 and 1 percent, respectively. Adj. R^2 is adjusted R-square.