A Transaction Data Study of The Forward Bias Puzzle*

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ABSTRACT

Using a market microstructure analytical framework we decompose the FX forward discount bias into elements due to time-varying risk premia (related to EBS order flow) and forecast errors derived using the Reuters survey of FX market participants. In line with previous work we find that forecast errors make the most significant contribution. However, we also find some role for risk premia which, according to our analytical framework, are linked to order flow. Thus, while order flow does not have a clear role in explaining forecast errors, we do find that, by generating a risk premium, it influences returns and creates self-fulfilling carry trade profits.

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Come l'araba Fenice,
che vi sia ciascun lo dice,
ove sia nessun lo sa[a]
Metastasio, *Demetrio*

[a]Like the Arabian Phoenix,
everyone swears it exists,
but no one knows where

Introduction

The bias in the forward discount and the corresponding systematic deviation from the uncovered interest rate (UIP) parity represents one of the longest standing puzzle in international finance. It is documented among (many) others by Bilson (1981), Fama (1984), Froot and Frankel (1989) and Burnside *et al.* (2007, 2008).[1] Despite the large range of alternative explanations put forward, there is no general consensus on the reasons to why persistent violations of UIP are not exploited and eliminated. In other words, the forward discount bias remains an unresolved puzzle in search of a convincing and definitive explanation, which (like the whereabouts of the mythological Phoenix in Metastasio's citation) has so far remained elusive.

In this paper we combine two promising lines or enquiry that have previously been pursued separately, namely the analysis of forecast errors and the market microstructure approach to exchange rates. Some of the strongest results on the forward discount puzzle have come from the analysis of market expectations derived from survey data. Thus, several studies (Froot and Frankel (1989), Frankel and Chinn (1993), Cavaglia *et al.* (1994), Chinn and Frankel (2002) and Bacchetta *et al.* (2008)) despite analyzing different surveys and samples and even different markets, consistently find that measures of forecast errors derived from these surveys have a remarkably strong relationship with the predictable element of excess returns. In the case of FX markets, where the evidence is strongest, the results suggest that the forward discount puzzle is in fact due to predictable forecast errors. Unfortunately we have still to find an convincing explanation for those errors.

Recently the focus of the search for an explanation to the forward discount puzzle has moved toward microstructure-based models whereby the nature of the trading process itself creates or sustains the forward bias. For example, Burnside *et al.* (2007), suggest a mechanism whereby

[1]See Lewis (1995) and Engel (1996) for excellent surveys of research on this topic.

the forward bias arises through adverse selection mechanisms. Burnside *et al.* (2008) propose that transactions costs, whilst not necessarily explaining the puzzle, make it less obvious that the excess returns it implies can actually be achieved in practice. Ranaldo and Sarkar (2008) also find a role for illiquidity and volatility in explaining the puzzle. In a similar vein Bacchetta and van Wincoop (2007) suggest that infrequent portfolio adjustment could indeed generate forward bias.

More specifically the success of order flow based models of exchange rate determination suggests that order flow could help explaining the puzzle. Firstly, models and results such as those of Evans and Lyons (2007) and Rime *et al.* (2007), that suggest that order flow may play an important role in the gradual transmission of information from heterogenous agents to the exchange rate and so might help in the understanding of the underlying expectations that might generate forward bias. Secondly, results such as those of Breedon and Vitale (2004) and Breedon and Ranaldo (2008) suggest that order flow could be an important element of the FX risk premium through standard portfolio-balance effects and so could contribute to forward bias through that more traditional route.

In this study we investigate the connection between the FX risk premium, forecast errors and the trading process in FX markets and their contribution to the forward discount bias. By combining data on FX order flow with information on market participants' expectations of future currency values we characterize the FX risk premium and, via a simple microstructure framework, we decompose the forward discount bias into two parts, one associated with time-varying risk premia, the other function of forecast errors. Overall, in line with previous studies, we find that forecast errors seem to play a dominant role in the forward bias, but we also find some role for an order flow related risk premium. Thus, we find that order flow affects expected risk premia and that these condition FX returns and carry trade profitability.

Our empirical approach combines the Reuters survey data on individual market participants' forecasts of future currency values and FX transaction data from Electronic Broking Services (EBS) over a period of 10 years between January 1997 and June 2007. Although the main focus of this study is to combine these data-sets, it is worth noting that individually they are arguably superior to most used in the literature. For example, whereas Burnside *et al.* (2008) refer to indicative bid-ask quotes released by a large FX dealer, we have access to data on actual transactions completed on the main electronic trading platform which currently dominates spot FX markets. In addition, with respect to the work of Bacchetta *et al.* (2008), our survey of exchange rate forecasts, while shorter in length, focuses almost entirely on financial institutions and contains information on all individual forecasts rather than sample averages.

This paper is organized as follows. In Section 1 we describe our data and provide some preliminary analysis of the properties of FX returns, the forward discount and order flow. In Section 2 we extend this analysis, proposing some new results pertaining to the impact of order flow on forecast errors and expected risk premia. On the basis of this new evidence, in Section 3 we introduce a simple microstructure framework for the FX market which delivers a modified version of the uncovered interest rate parity (UIP) and hence a partition of the slope coefficient in Fama's regression into two components, one related to forecast errors, the other to trade imbalance. In Section 4 we analyze the forward discount bias using our survey of exchange rate forecasts and transaction data. In particular, using this data we estimate a modified version of Fama's regression consistent with our modified UIP and the two components of the Fama's slope coefficients. Section 5 conducts some robustness checks on the definition of our order flow variable. In the last Section we offer some final remarks and suggest further lines of research.

1 Data

This study employs two innovative data sets to explore the link between expectations, risk premia and order flow. The first is a detailed transactions data set for the period 1997 to 2007 from EBS. The second is a detailed survey of FX forecasts for EUR/USD, USD/JPY, and GBP/USD conducted by Reuters since the early 1990's (though we focus on the post 1997 sample in this study to match our transaction data).

FX TRANSACTIONS Our FX transactions data set comes from EBS who are the dominant Electronic broker for all but one of the FX crosses which we analyse in this paper (see Table 1). Over the whole sample 2/1/1997 to 1/5/2007 we have the number of customer initiated buy and sells and the price at which each trade was undertaken.[2]

[Table 1 about here.]

FX FORECASTS: Our forecast data set is based on the full set of forecasts that make up the Reuters survey of FX forecasts. At the beginning of each month, about 50 market participants

[2]For the period after 2/1/2000 we have an estimate of the size of each trade based on eight trade size indicators. In the robustness check section we compare results using this measure with those from the number of trades series.

provide their forecasts of future exchange rates. The forecast horizons are set to be one month, three months, six months, and twelve months respectively. Table 2 below contains summary statistics for the FX forecasts. Note that, in common with other forecast surveys, the median forecast does not outperform a naive, random walk, forecast (i.e. Theil statistics are greater than 1)

Besides offering a meticulous archive of individual forecasts (the longest uninterrupted sample available), the Reuters survey has a number of advantages over other FX forecast surveys such as those undertaken by Consensus Economics, WSJ, ZEW, Blue Chip and Forecasts Unlimited (formerly the FT currency forecasts and the Currency Forecast Digest). First, since it is conducted by the key FX news provider, it is very much focussed on FX market participants whereas other surveys often include many other forecasters such as professional forecast firms, corporations and academic institutions. We estimate that around 95% of contributors to the Reuters survey are active market participants compared to 85% for Consensus Economics and even less for the other major surveys. This is important since, as Ito (1990) finds, these other forecasters are not comparable with those actively trading in foreign exchange. Second, the pool of forecasters is relatively constant. Other surveys have both gaps in coverage (missing individuals months and in some cases years) and a relatively rapid turnover of contributors. Third, it is the only survey that collects 1, 3, 6 and 12 months ahead forecasts, thus offering the most complete short-term coverage.

[Table 2 about here.]

1.1 Preliminary Analysis

The data set is constructed so that all variables are matched to the compilation date of the survey expectation. Hence, all market prices are the ones quoted at this date, while the order flow variable is measured up to this date.

In this Section we look at some of the basic properties of FX returns, confirming the existence of the forward discount puzzle and the relationship between order flow and FX returns over our sample.

1.1.1 The Forward Discount Bias

In Table 3 we show the results of GMM estimates of Fama's style regressions on monthly observations of spot returns and interest rate differentials for four different horizons (1 month, 3 months, 6 months and one year) for the EUR/USD, USD/JPY, and GBP/USD rates,

$$s_{t+k} - s_t \;=\; \alpha^k \,+\, \beta^k \, fd_t^k + \epsilon_{t+k}, \tag{1.1}$$

where $fd_t^k = f_t^k - s_t$, f_t^k is the log of the forward rate observed at the beginning of month t for maturity (in months) k and s_t is the log spot rate.

The results reported in Panel A in Table 3 are in line with previous studies: the estimated slope coefficient, β^k, is always negative and usually (particularly at the long horizons) significantly smaller than 1, the value consistent with the forward unbiasedness hypothesis. The Table suggests that, as found elsewhere, a profitable speculative strategy in these FX markets between 1997 and 2007 would have been that of betting against the forward discount, in that currencies with a positive forward discount would tend to appreciate (for $fd_t^k > 0$, $s_{t+k} - s_t$ is on average negative) and *viceversa*. In other words, with our data set we replicate the forward discount bias documented by many other researchers.

Panel B of Table 3 shows results from the same regression, but using as dependent variable the expected return obtained from survey data, $s_{t,e}^k - s_t$, in lieu of the realized return, $s_{t+k} - s_t$. The difference from Panel A is striking. Almost all coefficients are higher (except one), and most are positive. Most of the coefficients are not significantly different 1, the value predicted by the UIP. The positive coefficient on the forward discount confirms other studies' finding that the forward discount is linked to market expectations of future exchange rates. Nearly all coefficients are, however, lower than one, still leaving some room for an expected risk premium.

[Table 3 about here.]

1.1.2 Order Flow and Spot Returns

Empirical studies of the microstructure of FX markets, Lyons (1995), Evans and Lyons (2002), Payne (2003), Berger *et al.* (2005) and Bjønnes and Rime (2005) among others, conclude that the impact of trade imbalance on exchange rates is large, significant and persistent. Even if it is not the focus of our study, it is important to check whether our data set corroborates this evidence. Thus, in Table 4 we present contemporaneous correlations between order flow variables and spot returns.

[Table 4 about here.]

The Table presents contemporaneous correlations between order flow, o_t, and spot return, $(S_t - S_{t-1})/S_{t-1}$, at the daily and monthly frequency for the EUR/USD, USD/JPY and GBP/USD rates, using both the trade indicator and volume indicator variables as measure of order flow. We see that typically the correlations present, as expected, a positive sign. Moreover, the correlations are particularly large for the volume indicator, whereas no significant difference emerges when we move from daily to monthly observations. An exception, however, is represented by the correlation between the EUR/USD return and the corresponding order flow variables. The correlation values are small or, in one case, even negative. This is probably due to a particular phenomenon outlined by Killen *et al.* (2005), as in the run-up to the launch of the Euro in January 2001 investors started accumulating European currencies in their portfolios, breaking the link between trade imbalance and order flow.

Having confirmed that our data set offers results which are consistent with previous studies of the forward discount bias and the microstructure of FX markets, we are now ready to investigate the link between the risk premium, the trading process in FX markets and the forward discount bias.

2 Order Flow, Expected Risk Premia and Forecast Errors

The market microstructure approach to exchange rate determination offers useful insights on exchange rate dynamics. Thus, Lyons (1995), Evans and Lyons (2002), Berger *et al.* (2005) find that trade imbalance in FX markets has *large* explanatory power for exchange rate returns. In addition, Payne (2003), Biønnes and Rime (2005), Danielsson and Love (2006), Killen *et al.* (2006) provide evidence that order flow has a *significant*, *large* and *persistent* impact on exchange rate returns. Finally, Evans and Lyons (2005), Froot and Ramadorai (2005) show how order flow *anticipates* movements in exchange rate fundamentals.

This empirical evidence provides a rationale for the disconnect puzzle in international finance, indicating that similar headway could perhaps be made on the forward bias puzzle. Indeed, the results reported in Panel B of Table 3 for the expected return, although promising, still show that using forecasts do not solve the forward bias. The coefficients on the forward discount are in fact smaller than one. This may imply the existence of an expected risk premium.

FX microstructure suggests that order flow may give rise to an expected risk premium via a portfolio balance effect. In addition, given the evidence on the information aggregation role of order flow suggested by Evans and Lyons (2007) and Rime *et al.* (2007), amongst others we might expect order flow to have some role in explaining the forecast errors that seem to be the key driver of the forward discount puzzle.

Thus, in this Section we proceed by analyzing the relationship between order flow, the forecast error and the expected risk premium. In fact, our data set containing Reuters survey of FX forecasts allows us to directly measure the forecast error, $s_{t+k} - E_t[s_{t+k}]$, and the expected risk premium on the foreign currency, $E_t[s_{t+k}] - f_t^k$, as we can use the median value, $s_{t,e}^k$, of the log of the individual forecasts observed at the beginning of month t for the spot rate in month $t+k$ as a proxy for the market expectation $E_t[s_{t+k}]$. We can then employ EBS transaction data to study the dependence of the forecast error and the expected risk premium on the trading process in FX markets.

In order to have an order flow measure that matches the maturity of the forward contract, we aggregate order flow over a period of k months. So, for example, for the 3 month forecast horizon, order flow is calculated over the preceding 3 months. In addition, since a given size of a portfolio shift will demand a higher risk premium the more uncertain the investors are about the future, we also multiply the aggregated order flow by an estimate of the *average* conditional variance of the exchange rate s_t across FX investors at time $t-k$.[3] As a proxy of this conditional variance we employ the implied volatility observed at the beginning of month $t-k$ for the log spot rate in t.[4]

Since results reported in Table 3 suggests that the forecast error is clearly linked to the forward discount, we estimate a regression where the forecast error is regressed on both the order flow variable and the forward discount for the four maturities of 1, 3, 6 and 12 months.

[Table 5 about here.]

[3] In Section 3 we propose an analytical framework which formalizes such role for the conditional variance.

[4] As an alternative estimate we consider the conditional variance of the k months ahead exchange rate forecasts collected by Reuters at the beginning of month $t-k$.

Table 5 reports the results of the GMM estimations. It is evident that the strongest explanatory power is not from order flow, which is significant only for a few cases and small in coefficient value. On the contrary, as also found elsewhere (Froot and Frankel (1989), Frankel and Chinn (1993), Cavaglia *et al.* (1994), Chinn and Frankel (2002) and Bacchetta el al. (2006)), the forward discount helps explaining the errors market participants commit in forecasting future exchange rates. In other words, while it appears that order flow has an ambiguous role in explaining forecast errors, that is not the case for the forward discount. However, we should note that even the weak role we find for order flow as an predictor of forecast errors is intriguing and worthy of further study.

In Table 6 instead we investigate the impact of order flow on the expected risk premium,

$$s^k_{t,e} - f^k_t \; = \; \alpha^k_{ep} \, + \, \gamma^k_{ep} \, o_{t,k} \, + \, \eta_t,$$

with k =1, 3, 6 and 12. We see that the slope coefficient γ^k_{ep} in the regression of the expected risk premium on order flow is almost universally positive across rates and maturities. In addition, γ^k_{ep} is significantly larger than zero for the EUR/USD and USD/JPY rates across all maturities.

An interpretation of this result is that deviations from the UIP are possible, as a time-varying risk premium introduces a wedge between the forward discount and the expected return. When we measure the risk premium correctly, using the expected risk premium rather than the realized risk premium used by Fama and others, we see that part of this risk premium is driven by order flow. However, it should also be added that the size of this impact is fairly small. This may be taken as evidence of the depth of FX markets and their capacity to absorb large portfolio shifts with relative small changes in expected returns.

[Table 6 about here.]

3 A Decomposition of the Forward Discount Bias

The results outlined in Table 6 suggests that in FX markets uncovered interest rate parity does not hold and that expected risk premia are influenced by the trade imbalance. Thus, in this Section we formulate a simple market microstructure analytical framework which yields a modified uncovered interest rate parity (UIP). The modified UIP allows to obtain a simple decomposition of the beta coefficient in Fama's regression. Such decomposition offers a simple way to rationalize the forward discount bias which we can put to the test by employing our survey and transaction data.

3.1 Basic Set Up

We briefly present an analytical framework inspired by the market microstructure model of exchange rate determination proposed by Bacchetta and van Wincoop (2006) and based on the formulation put forward by Breedon and Vitale (2004). In this formulation we assume that a single foreign currency is traded for the currency of a large domestic economy in the spot FX market. Trading takes place on a centralized market, according to a sequence of Walrasian auctions. This sequence of auctions is intended to represent the trading activity of FX investors over a centralized trading platform, such as EBS (an electronic platform which dominates the inter-dealer market for the major currency pairs). Thus, we assume that in any period t FX investors simultaneously enter either market or limit orders and then a clearing price (exchange rate) for the foreign currency is established.

At the beginning of trading period t a FX investor, d, possesses g^d_{t-1} units of domestic bonds. During period t, FX investor d can liquidate her endowment and invest in a new portfolio made of both domestic and foreign bonds. Since domestic and foreign bonds pay annualized interest rates i_t and i^*_t over the interval $(t, t+1]$, a log-linearization of the end-of-period wealth for investor d allows us to write it as follows

$$W^d_{t+1} \;=\; (1 \,+\, i_t\,\Delta_t)\, g^d_{t-1} \,+\, [\,(i^*_t \,-\, i_t)\,\Delta_t \,+\, (s_{t+1} \,-\, s_t)\,]\, o^d_t,$$

where s_t is the log of the spot rate, ie. the number of units of domestic currency required to purchase one unit of the foreign one. Δ_t is the time interval (measured in years) between period t and period $t+1$, and o^d_t is the quantity of the foreign currency investor d will purchase (short-sell).

We assume that our FX investors have a one period investment horizon. Thus investor d selects her optimal portfolio in order to maximize the expected utility of her end-of-period wealth, given by a CARA utility function with coefficient of absolute risk-aversion γ_d (and coefficient of risk-tolerance $\tau_d = 1/\gamma_d$).

Assuming that our investor is price-taker, the optimal quantity of foreign currency she will trade corresponds to a linear excess demand function, ie. a *limit order*, in the log of the spot rate,

$$o_t^d\,(s_t) \;=\; \nu_t^d \left(E_t^d\left[\, s_{t+1} \,\right] \,-\, s_t \,+\, (i_t^* \,-\, i_t)\,\Delta t \right),$$

where $E_t^d[s_{t+1}]$ denotes the conditional expectation of next period spot rate given the information investor d possesses in period t, and ν_t^d is investor d's *trading intensity*, given by $\nu_t^d = \tau_d\, \pi_{s+,t}^d$, where $\pi_{s+,t}^d$ is her conditional precision of s_{t+1} in period t, ie. $\pi_{s+,t}^d \equiv 1/\mathrm{Var}\,[s_{t+1} \mid \Omega_t^d\,]$.

Through aggregation we can obtain the total demand for the foreign currency on the part of the population of FX investors. In particular, we assume that the FX investors form a continuum of agents of mass 1, uniformly distributed in the interval $[0, 1]$. Thus, in period t

$$o_t \quad\equiv\quad \int_0^1 o_t^{d'}\, dd' \;= \nu_t \left(\bar{E}_t^1\left[\, s_{t+1} \,\right] \,-\, s_t \,+\, (i_t^* \,-\, i_t)\,\Delta t \right), \tag{3.1}$$

where $\nu_t \;\equiv\; \int_0^1 \nu_t^{d'}\, dd'$ is the *aggregate* trading intensity of the population of FX investors and $\bar{E}_t^1[s_{t+1}]$ is the weighted *average* of the expected value of next period spot rate across all FX investors, where the individual FX investors' weights are given by their trading intensities.

As the (net) demand of foreign currency on the part of the FX investors is entered on the centralized platform, o_t will correspond to order flow, ie. the difference between buyer and seller initiated transactions in the market for the foreign currency.

Considering equation (3.1) and the definition of order flow, one finds that

$$(i_t \,-\, i_t^*)\,\Delta t \;=\; \left(\bar{E}_t^1\left[\, s_{t+1} \,\right] \,-\, s_t \right) \,-\, \frac{1}{\nu_t}\, o_t. \tag{3.2}$$

Equation (3.2) implies that, thanks to the FX investors' risk-aversion, *uncovered interest rate parity* does not hold. Indeed, the interest rate differential, $i_t - i_t^*$, is *proportional* to the difference between the average expected devaluation of the domestic currency in period t and a risk-premium on the foreign currency the FX investors collectively require to hold foreign assets. This is a *time-varying* risk-premium, given by the product of the total demand of foreign assets the FX investors have to share and the inverse of their aggregate trading intensity, ν_t (which measures the investors' capacity to hold risky assets). In other words, the larger the average risk-tolerance of our population of FX investors, $\bar{\tau}$, the smaller the risk premium imposed on the foreign currency. Likewise, the smaller the perceived uncertainty of the currency return, measured by the inverse of the average precision $1/\bar{\pi}_{s+,t}$, the smaller the risk-ness of the foreign currency and the imposed risk premium.

3.2 The Origin of the Forward Discount Bias

Since there are no short-selling restrictions and transaction costs are negligible, *covered arbitrage* implies that the *covered interest rate parity* holds. With a log-linear approximation we we can write that $(i_t - i_t^*)\,\Delta t = f_t - s_t$, where f_t is the log of the forward rate in period t. Then, combining the modified UIP in equation (3.2) with the covered one, one finds that the forward discount respects the following condition

$$f_t - s_t = \left(\bar{E}_t^1 \left[s_{t+1} \right] - s_t \right) - \frac{1}{\nu_t}\, o_t, \tag{3.3}$$

so that it does *not* correspond to the expected devaluation of the domestic currency.

Equation (3.3) may suggest a possible explanation for the forward discount bias documented in Table 3 and elsewhere. Thus, let us re-consider Fama's regression,

$$\Delta s_{t+1} = \alpha + \beta f d_t + \epsilon_{t+1},$$

where $\Delta s_{t+1} \equiv s_{t+1} - s_t$ and $fd_t \equiv f_t - s_t$. Under standard asymptotic theory the OLS estimator of the coefficient β, $\hat{\beta}_{\text{OLS}}$, converges in probability to β (ie. $\text{plim}\,\hat{\beta}_{\text{OLS}} = \beta$), where

$$\beta = \frac{\text{cov}\,(\Delta s_{t+1}, fd_t)}{\text{var}(fd_t)}. \tag{3.4}$$

To calculate this ratio, consider that by definition $s_{t+1} = \bar{E}_t^1 \left[s_{t+1} \right] + u_{t+1}$, where u_{t+1} is the forecast error of the FX investors. We have that $\bar{E}_t^1 \left[u_{t+1} \right] = 0$. Using the modified UIP, one finds that

$$\Delta s_{t+1} = fd_t + \frac{1}{\nu_t}\, o_t + u_{t+1}. \tag{3.5}$$

Then, in equation (3.4) the coefficient β turns out to be equal to

$$\beta = 1 + \beta_o + \beta_u, \text{ where} \tag{3.6}$$

$$\beta_o = \frac{\text{cov}\left(\frac{1}{\nu_t} o_t, fd_t\right)}{\text{var}(fd_t)} \quad \text{and} \quad \beta_u = \frac{\text{cov}\left(u_{t+1}, fd_t\right)}{\text{var}(fd_t)}.$$

This decomposition is analogous to that provided by Froot and Frankel (1989). However, we give more substance to the interpretation of the time-varying risk premium, which is now a function of order flow, o_t, and the trading intensity ν_t. Thus, differently from traditional attempts to explain the forward discount bias via the portfolio-balance approach, using transaction data we are able to directly measure deviations from UIP and pin down their impact on Fama's coefficient beta.

Indeed, with our transaction data we can estimate the coefficient β_o by running a linear regression of order flow on the forward discount. Similarly, employing our survey data on market participants' forecasts of future spot rates, β_u can be estimated. In particular, if $s_{t,e}$ denotes the median value of the forecasts of professional traders and investors for next period spot rate, β_u can be estimated by running a linear regression of the forecast error, $s_{t+1} - s_{t,e}$, on the forward discount.

3.3 Discussion of Related Literature

If FX investors are risk-neutral and perfect capital substitutability holds, no risk premium is imposed on the foreign currency and the coefficient β_o is null. In addition, under the assumption of rationality, the forecast error, u_{t+1}, and the forward discount, fd_t, are uncorrelated and hence the coefficient β_u is zero. Therefore, under these two conditions Fama's coefficient β is equal to 1, while the forward rate, f_t, is an unbiased estimator of next period spot rate, s_{t+1}.

However, in several studies (Lewis (1995), Engel (1996), Bacchetta *et al.* (2008), Burnside *et al.* (2008) among others) Fama's β is found to be significantly smaller than 1 and often even negative. Thus, Froot and Thaler (1990) indicate that the average value of the coefficient β across 75 published estimates is -0.88. According to our decomposition this could be the consequence of either negative correlation between the forward discount and the forecast error, leading to a negative β_u, or negative correlation between order flow and the forward discount, leading to a negative β_o.

Froot and Frankel (1989) examine exchange rate forecasts for the USD/DEM GBP/USD, USD/FRF, USD/CHF, and USD/JPY returns over several short horizons, recorded in the early and mid 1980s by *AMEX*, *The Economist* and *MMS*. Pooling together forecasts for different exchange rates, they are able to estimate the value of the coefficient β_u. Depending on the survey data and the horizon of the forecasts these estimates vary from -6.07 to -0.52.

Froot and Frankel's analysis has been extended by several authors, such as Frankel and Chinn (1993), Chinn and Frankel (2002), Cavaglia *et al.* (1994), Bacchetta *et al.* (2008), which have considered alternative survey data, covering longer periods and more currency pairs. Thus, Bacchetta *et al.* (2008) employ monthly surveys of 3, 6 and 12 months ahead forecasts for seven exchange rates over the period between August 1986 and July 2005. The estimated values of the coefficient β_u range from -3.62 to -0.76 across the seven exchange rates and the three horizons.

All in all these studies suggest that systematic errors in exchange rate forecasts violate the forward rate unbiasedness. However, these errors may be due to either learning or a peso-problem, as shown by Lewis (1989a, 1989b) and Evans and Lewis (1995)), rather than by irrationality. In addition, infrequent portfolio adjustments, induced by rational inattention, combined with random walk expectations may also generate forecast errors and a negative Fama's beta (Bacchetta and van Wincoop (2007)).

Our decomposition of Fama's slope coefficient β indicates an alternative route to rationalize the forward discount bias. Thus, if perfect capital substitutability does *not* hold a risk premium enters into the uncover interest rate parity. If this *time-varying* risk premium is *negatively* correlated with the forward discount, then Fama's beta turns out to be smaller than 1. So far the empirical research devoted to investigate this alternative explanation of the forward discount bias has not very successful. Cumby (1988), Hodrick (1989), Bekaert *et al.* (1997), find that *implausible* degrees of risk-aversion are required to obtain a negative beta in Fama's regression, though Lustig and Verdelhan (2007) find an important role for consumption risk. However, one should notice that no attempt has ever been made to directly measure this time-varying risk premium using transaction data. With our study we aim at plugging a gap in the existing literature and at providing some more insights on the origin of the forward discount bias.

In addition, our study can also offer some contribution to the investigation of carry trade in FX markets. Galati *et al.* (2007), Burnside *et al.* (2007, 2008), Jylhä *et al.* (2008), Lustig *et al.* (2008) find *positive* returns for carry trade. Carry trade profitability is direct consequence of the failure of UIP, as indeed, contrary to the prediction of UIP high interest rate currencies tend to appreciate vis-a-vis low interest rate currencies.

Several explanations for the profitability of carry trade have been proposed. Thus, recent studies suggest that carry trade profits are mitigated by transaction costs (Burnside *et al.* (2008)), are associated with volatility and illiquidity (Ranaldo and Sarkar (2008), Jylhä *et al.* (2008)), are counter-cyclical (Lustig *et al.* (2008)) and subject to reversal risk (Breedon (2001), Brunnermeier *et al.* (2008)).

Plantin and Shin (2008) show that in the presence of liquidity constraints expectations of carry trade profitability are self-fulfilling. In their model, when carry traders short a low interest rate currency to buy a high interest rate one they drive down the value of the former and up that of the latter, so that their expectations are fulfilled. This happens because in Plantin and Shin's model trade imbalance has a positive impact on exchange rate returns, as suggested by recent empirical evidence from the market microstructure approach to exchange rates.

Interestingly, our simple analytical framework accommodates Plantin and Shin's argument. If, in the presence of a negative forward discount ($fd_t < 0$), FX investors expect positive profits from carry trade, they will short the domestic currency for the foreign one, so that order flow in the FX market turns out to be positive ($o_t > 0$). According to our modified UIP, positive order flow increases the expected risk premium on the foreign currency and the expected profits from carry trade. In addition, the negative correlation between order flow and the forward discount brings about a negative value for Fama's beta.

4 Forward Discount Bias, Order Flow and Forecast Errors

Motivated by equation (3.5) we estimate a modified Fama regression, where the realized return is regressed on the forward discount and the order flow variable. In line with equation (3.5), and as previously done, the order flow variable, $o_{t,k}$, is the trade imbalance over the interval $(t-k, t)$ multiplied by the implied volatility observed at the beginning of month $t-k$ for the log spot rate in t. This value is an estimate of the *average* conditional variance of the exchange rate s_t across FX investors at time $t-k$.[5]

[Table 7 about here.]

[5]Indeed, as in equation (3.5) $1/\nu_t$ is equal to the product of the conditional variance of next period spot rate and the average coefficient of risk aversion among FX investors, $\bar{\gamma}$, the regression estimated in Table 7 corresponds to a direct estimation of equation (3.5) in sofar $\bar{\gamma} = 1$.

The results, presented in Table 7, show that adding the order flow variable to Fama's regression contributes to the explanation of the forward discount bias but does not resolve it. In fact, with respect to results obtained from Fama's original regression reported in Table 3 the slope coefficient on the forward discount is still negative and usually significantly smaller than 1. However, the coefficient on the order flow variable is typically significantly different from zero, while its value for the EUR/USD and USD/JPY rates is negative across all maturities. In sum, Table 7 confirms results reported in Tables 5 and 6 and corroborates our claim that to some extent microstructural mechanisms may originate the forward discount bias.

We can finally turn to a direct estimate of the coefficients β_u and β_o in the decomposition of Fama's beta in order to measure the relative contribution of forecast errors and risk premia to the forward discount bias. In other words, such exercise allows to quantify more precisely the contribution of microstructural mechanisms to the forward discount bias.

To implement the decomposition we need estimates of the relation between the forward discount and the forecast error and order flow, separately. In Table 8 we report individual estimates of the linear regression of the forecast error, $s_{t+k} - s_{t,e}^k$, on the forward discount, fd_t^k, for the four available maturities,

$$s_{t+k} - s_{t,e}^k \;=\; \alpha_u^k + \beta_u^k fd_t^k + \varepsilon_{t+k},$$

with k =1, 3, 6 and 12. The slope coefficient in this linear regression corresponds to β_u in our decomposition of Fama's beta (equation 3.6). The estimated values of β_u^k in Table 8 are *consistent* with those of β^k reported in Panel A of Table 3. Thus, β_u^k and β^k are *negative* for three currency pairs. In addition, for the EUR/USD and GBP/USD rates the coefficient β_u^k is generally either significantly smaller than 0 or close to the 5% significance level, while the corresponding adjusted R^2 is close to or even larger than 10% for the longer maturities. On the contrary, for the USD/JPY rate the coefficient β_u^k is not significantly smaller than 0.[6]

[Table 8 about here.]

In Table 9 we report the estimates of the linear regression of risk-adjusted, order flow, $o_{t,k}$, on the forward discount,

$$o_{t,k} \;=\; \alpha_o^k + \beta_o^k fd_{t-k}^k + \xi_{t+k}.$$

[6]Similar results, not reported, are obtained when the linear regressions are run as a SUR system under the restriction that β_u^k is constant across maturities.

The reported estimated values for the coefficient β_o^k represent an estimate of the coefficient β_o in our decomposition of Fama's beta insofar the average measure of risk-aversion, γ, is constant over time and equal to 1. This means that the results presented in Table 9 should be taken with a grain of salt. However, the values in the Table for the EUR/USD and USD/JPY markets are all negative and significantly so. On the contrary, while positive the values for the GBP/USD market are not statistically different from 0. Finally, notice that the adjusted R^2 for the EUR/USD market falls in the (0.22,0.30) range, suggesting that carry trades generate a large proportion of the trade imbalance in the EUR/USD market.

[Table 9 about here.]

In sum, for the EUR/USD rate there is strong evidence that the negative value of Fama's β is due both to a forecast error and a time-varying risk premium connected to order flow. More precisely, from Tables 8 and 9 it appears that for the EUR/USD rate both the forecast error and the risk premium are negatively correlated with the forward discount so that β_u and β_o are negative in our decomposition (equation 3.6) as expected. In addition, it seems that a mechanism similar to that envisaged by Plantin and Shin is at work. In fact, as order flow and the forward discount are negatively correlated, when interest rates in the euro area increase, carry traders buy the European currency and sell the US dollar. Since order flow has a positive impact on exchange rate returns (as widely documented by the FX market microstructure literature and in Table 4), the carry trade is sustained by self-fulfilling expectations.

5 Some Robustness Checks

Throughout the preceding Section we have adopted a standard definition of order flow that aims to be consistent with the model outlined in Section 3 whilst allowing us to use the longest sample of data possible (i.e. using our order flow based on number of trades that extends back to 1997 rather than our value of trades series that begins in 2000). In this Section we experiment with some alternative definitions to ensure that our key results are not driven by the precise definition we use.

Furthermore, while we so far have used implied volatility as our measure of uncertainty, we here also investigate the implications of using the dispersion of survey expectations as a measure of uncertainty. To ease comparison between the different alternatives we only use the shorter sample available for the volume-series.

Tables 10, 11, 12 13 present the robustness results for (i) the regression of the forecast errors, (ii) the relationship between the expected risk premium and order flow, (iii) the modified Fama-regression, and (iv) the relationship between order flow and the forward discount. The general picture is that our results are robust to these alternative definitions. Typically, the significance of the order flow variable is lower when using the survey dispersion as measure of uncertainty, especially for USD/JPY. In some cases the coefficients also switch sign, like in for the USD/JPY in the modified Fama regression, but then the coefficient is not significant.

[Table 10 about here.]

Thus, in Table 10 we find that over the sample period January 2000 to April 2007, both when using the trade indicator and the potentially more informative volume indicator and both when using the implied volatility and the dispersion of the survey forecasts, the forecast error across all maturities and currency pairs is heavily influenced by the forward discount. The coefficient on the forward discount is in fact always negative and mostly significant (particular for the longer maturities). In contrast the order flow variable does not have a systematic influence on the forecast error. Some evidence for the EUR/USD and USD/JPY rates found using the implied volatility is not confirmed when the dispersion of the survey forecasts is employed.

[Table 11 about here.]

Similarly, in Table 11 we still find, when using the two definitions of order flow and the two measures of conditional variance, that order flow has a positive impact on the expected risk premium, across the three currency pairs, as the coefficient on the order variable is nearly always positive. In addition this coefficient is mostly significantly larger than zero (particularly when the implied volatility is used) or close to the 5% significance level.

[Table 12 about here.]

Table 12 presents rather mixed results. Thus, with respect to the results reported in Table 7 it remains clear that the realized return has a large negative dependence on the forward discount, as the corresponding coefficient is typically smaller than zero and significantly smaller than 1. On the other hand, the dependence of the realized return on the order flow variable is no longer clear-cut. Thus, the coefficient on the order flow variable is negative for the EUR/USD and the USD/JPY rates, while its value is significantly smaller than zero only for the former.

[Table 13 about here.]

Finally, Table 13 confirms the results reported in Table 9. Thus the estimates of β_o for the EUR/USD and USD/JPY markets are still negative. Results are particularly convincing for the former, in terms of both t-statistics and econometric fit. Thus, particularly for the trade-indicator, the estimates of β_o for the EUR/USD market across the various maturities are significantly smaller than 0, while the corresponding adjusted R^2's confirm that the forward discount explains a sizeable portion of the trading activity in this market. All in all, this confirms that evidence of carry trade activity is particularly strong for this market.

6 Concluding Remarks

Recently a large body of research has been devoted to the forward discount bias and the profitability of carry trade. Our study contributes to this literature by analyzing the information contained in Reuters survey data of exchange rate forecasts and in EBS transaction data. We combine this information within a simple market microstructure analytical framework to decompose the forward discount bias into two parts, due to forecast errors and time-varying risk premia.

Our results suggest that forecast errors explain most of the forward discount bias, as when using expected returns in lieu of actual returns the coefficient on the forward discount does not appear to be significantly different from 1 for the EUR/USD, USD/JPY and GBP/USD rates. However, our study provides some evidence, particularly strong for the EUR/USD market, that order flow affects expected risk premia and that these condition realized returns, indicating that microstructural mechanisms contribute to the forward discount puzzle. In addition, our results suggest that carry trade activity may actually generate part of the forward discount bias. Thus, we detect a very strong negative dependence of order flow on the forward discount in the EUR/USD market. As we know that in FX markets order flow has a positive impact on exchange rate returns, this finding suggests that carry traders rely on self-fulfilling expectations following a mechanism similar to that suggested by Plantin and Shin (2008) .

Our study finds other interesting results. Thus, we observe that typically order flow has a positive impact on expected risk premia, but no one on forecast errors. This can be interpreted as follows. On the one hand, trade imbalance conditions market participants' opinions on future movements in exchange rates. In particular, amid an excess demand for (say) the euro vis-a-vis the US dollar, market participants expect the European currency to appreciate (and *viceversa*). On the other hand, as the information contained in trade imbalance is immediately impounded into exchange rates, order flow does not help in predicting future movements in exchange rates. However, since our analysis of the expectations formation process is somewhat cursory this result is open to question. In particular, a new line of research which, combining the two data sets we have employed with data on macroeconomic announcements, might offer greater insights into the link between news, expectations and the trading process in FX markets.

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Table 1
EBS Turnover Data Summary Statistics

This Table presents summary statistics for our sample of EBS turnover data. We show estimates of EBS share of electronic interdealer trading and overall FX turnover. We also show average trade size (2000-2007) and average bid ask spread (1997-2007) for all active trading hours (i.e. hours in which at least one trade took place). The share of electronic interdealer broking is derived from a comparable sample of EBS and Reuters Dealing-2002 (the other electronic interdealer broking platform) from August 2000 to January 2001 (see Breedon and Vitale (2004)). Overall market share is estimated from the 1998, 2001, 2004 and 2007 BIS surveys by assuming that all trading between reporting dealers is electronic. This is likely to be an over estimate at the start of the sample (as other trading methods were used) but an under estimate at the end of the sample (as EBS is now being used by some customers such as hedge funds).

	EUR/USD	USD/JPY	GBP/USD
EBS share of electronic	81%	95%	7%
Electronic share of total	54%	50%	54%
EBS share of total	44%	48%	4%
Average Trade Size	$4.49 mln.	$3.87 mln.	$3.57 mln.
Average Bid-Ask Spread	0.017%	0.018%	0.056%

Table 2
Foreign-exchange Forecasts Summary Statistics

This Table presents summary statistics for our sample of foreign-exchange forecasts. For each forecasting horizon, we show the maximum, average and minimum number of individual forecasts each month, the maximum, average and minimum standard deviation of those forecasts (expressed as a percentage of the average forecast) and the Theil statistic (RMSE of the average forecast divided by the RMSE of a random walk forecast).

		EUR/USD	USD/JPY	GBP/USD
Panel A: One-month horizon				
No. of forecasts	Max no.	66	66	65
	Ave. no.	52.1	51.2	51.0
	Min. no	30	30	30
Forecast dispersion	Max stdev.	2.9	13.4	2.1
	Ave. stdev.	1.7	3.1	1.3
	Min stdev.	0.9	1.1	0.8
Forecast accuracy	Theil stat.	1.00	1.04	1.03
Panel B: Three-month horizon				
No. of forecasts	Max no.	67	67	66
	Ave. no.	52.5	51.9	51.5
	Min. no	29	29	29
Forecast dispersion	Max stdev.	4.5	6.9	4.0
	Ave. stdev.	2.9	2.9	2.2
	Min stdev.	1.5	1.4	1.5
Forecast accuracy	Theil stat.	1.07	1.15	1.01
Panel C: Six-month horizon				
No. of forecasts	Max no.	66	66	65
	Ave. no.	52.3	51.7	51.2
	Min. no	29	29	29
Forecast dispersion	Max stdev.	6.0	14.6	4.9
	Ave. stdev.	4.1	3.1	3.1
	Min stdev.	2.3	1.7	2.1
Forecast accuracy	Theil stat.	1.13	1.15	1.02
Panel D: One-year horizon				
No. of forecasts	Max no.	66	66	65
	Ave. no.	51.8	51.4	50.7
	Min. no	29	29	29
Forecast dispersion	Max stdev.	9.0	7.8	5.9
	Ave. stdev.	5.6	3.7	4.2
	Min stdev.	3.3	1.4	3.0
Forecast accuracy	Theil stat.	1.13	1.21	0.98

Table 3
Fama's Regression: Monthly Data

The columns denoted by "1 Month" to "1 Year" present the results from GMM estimates of β^k from the regression $r_t^k = \alpha^k + \beta^k fd_t^k + \epsilon_{t+k}$, where r_t^k is the return over the next k months, $fd_t^k = f_t^k - s_t$ and f_t^k and s_t is the log of the forward rate (for maturity k) and the spot rate observed at the beginning of month t. The column "System" present estimates of the same coefficient when estimating it within a SUR system of equations, $r_t^k = \alpha^k + \beta fd_t^k + \epsilon_{t+k}$ ($k = 1, 3, 6, 12$ months). In the system-approach the coefficient on the forward discount is restricted be be constant across horizons. Panel A presents results for the realized return, $r_t^k = s_{t+k} - s_t$, while Panel B presents results for the expected return, $r_{e,t}^k = s_{t,e}^k - s_t$, where $s_{t,e}^k$ denotes the median value in month t of the k months ahead exchange rate forecasts contained in Reuters survey. Below coefficients in parenthesis are standard errors of the slope coefficient β. Sample: Jan 1997 - Apr 2007.

Currency	1 Month	3 Month	6 Month	1 year	System
		Panel A: Realized return			
EUR/USD	-3.4787	-5.1205	-4.4030	-4.3412	-3.73
	(1.76)	(1.48)	(1.10)	(0.83)	(0.99)
USD/JPY	-0.7830	-1.1758	-1.9420	-1.7078	-1.34
	(1.75)	(1.54)	(1.16)	(0.81)	(0.92)
GBP/USD	-1.1317	-2.6545	-1.8768	-2.0326	-1.27
	(1.82)	(1.74)	(1.40)	(1.16)	(1.29)
		Panel B: Expected return			
EUR/USD	0.4569	0.3845	0.7652	0.7996	0.88
	(0.90)	(0.62)	(0.41)	(0.32)	(0.51)
USD/JPY	-0.8530	-0.7768	-0.0947	0.1872	0.04
	(0.76)	(0.74)	(0.60)	(0.43)	(0.59)
GBP/USD	1.0972	0.4061	0.6031	0.6394	0.80
	(0.74)	(0.50)	(0.36)	(0.30)	(0.39)

Table 4
Correlations: Spot Returns - Order Flow

This table presents the contemporaneous correlation between order flow, o_t, and the exchange rate return, $(S_t - S_{t-1})/S_{t-1}$ at the daily and monthly frequency. Order flow, o_t, is measured over the interval between $t-1$ and t and is normalized by dividing flow imbalance by total turnover. The volume indicator variable runs from 2/1/2000 to 1/6/2007, the trade indicator. Sample: Feb 1997 - Apr 2007.

	Daily Observations		Monthly Observations	
	Trade Indicator	Volume Indicator	Trade Indicator	Volume Indicator
EUR/USD	-0.0929	0.2746	0.0045	0.0144
USD/JPY	0.2140	0.6016	0.1123	0.6002
GBP/USD	0.2182	0.2099	0.3694	0.4002

Table 5
Regression Estimates of Forecast Error Equation

The Table reports results of GMM estimates of the forecast error regressed on the forward discount and the order flow variable, $s_{t+k} - s^k_{t,e} = \alpha^k_{ee} + \beta^k_{ee} fd^k_t + \gamma^k_{ee} o_{t,k} + \varepsilon_{t+k}$ ($k = 1, 3, 6, 12$ months). The order flow variable $o_{t,k}$ is cumulate between month $t-k$ and t, and is also pre-multiplied by the k months ahead exchange rate variance, measured by squared implied volatility, at the end of month $t-k$, while $s^k_{t,e}$ denotes the median value in month t of the k months ahead exchange rate forecasts contained in Reuters survey. Column headings "FD" and "OF" denotes Forward Discount and Order Flow, respectively. t-statistics in parentheses. Sample: Feb 1997 - Apr 2007.

	EUR/USD		USD/JPY		GBP/USD	
	FD	OF	FD	OF	FD	OF
1 Month	-4.7401	-0.2097	-1.6075	-0.3065	-2.2253	0.1388
	(-1.86)	(-0.80)	(-0.96)	(-2.18)	(-1.13)	(0.55)
3 Month	-6.9781	-0.3396	-3.4193	-0.4445	-3.0012	0.3084
	(-3.36)	(-1.55)	(-2.35)	(-3.94)	(-1.68)	(1.01)
6 Month	-7.1875	-0.4611	-4.6357	-0.4591	-2.5244	0.2124
	(-4.60)	(-2.16)	(-4.50)	(-5.53)	(-1.70)	(1.05)
12 Month	-5.6841	0.0522	-3.6114	-0.2751	-2.0164	0.4529
	(-4.07)	(0.31)	(-3.79)	(-2.31)	(-1.74)	(1.57)

Table 6
The Impact of Order Flow on Expected Risk Premia

The table reports GMM estimates of the coefficient γ_{ep}^k in the regression of the expected risk-premium on order flow, $s_{t,e}^k - f_t^k = \alpha_{ep}^k + \gamma_{ep}^k o_{t,k} + \eta_t$ ($k = 1, 3, 6, 12$ months). The order flow variable $o_{t,k}$ is cumulate between month $t-k$ and t, and is also pre-multiplied by the k months ahead exchange rate variance, measured by implied volatility squared, at the end of month $t-k$. t-statistics in parentheses. Sample: Feb 1997 - Apr 2007.

Currency	1 Month	3 Month	6 Month	12 Month
EUR/USD	0.1021	0.1454	0.1141	0.0810
	(1.50)	(3.37)	(3.01)	(3.27)
USD/JPY	0.1785	0.2073	0.1819	0.1647
	(3.68)	(4.36)	(5.48)	(5.29)
GBP/USD	-0.0213	0.0926	0.1348	0.1382
	(-0.54)	(1.82)	(2.80)	(2.58)

Table 7
Realized Return, the Forward Discount and Order Flow

This Table reports GMM estimates of a linear regression of realized k-period return on the forward discount, fd_t^k, and on order flow, $o_{t,k}$, $s_{t+k} - s_t = \alpha^k + \beta^k fd_{t-k}^k + \gamma^k o_{t,k} + \xi_{t+k}$ with $k = 1, 3, 6, 12$ months. The order flow variable $o_{t,k}$ is cumulate between month $t - k$ and t, and is also pre-multiplied by the k months ahead exchange rate variance, measured by implied volatility squared, at the end of month $t - k$. Column headings "FD" and "OF" denotes Forward Discount and Order Flow, respectively. t-statistics in parentheses. Sample: Feb 1997 - Apr 2007.

	EUR/USD		USD/JPY		GBP/USD	
	FD	OF	FD	OF	FD	OF
1 Month	-4.67	-0.195	-2.02	-0.386	-2.22	0.126
	(-1.75)	(-0.67)	(-1.19)	(-2.63)	(-1.13)	(0.56)
3 Month	-7.78	-0.557	-2.76	-0.396	-3.15	0.564
	(-4.09)	(-2.65)	(-1.61)	(-2.32)	(-1.92)	(1.83)
6 Month	-7.63	-0.630	-4.05	-0.386	-2.90	0.674
	(-6.03)	(-3.81)	(-3.31)	(-4.11)	(-1.95)	(2.12)
12 Month	-7.34	-0.554	-3.99	-0.350	-3.41	0.661
	(-8.83)	(-7.77)	(-4.57)	(-8.22)	(-2.89)	(3.01)

Table 8
The Impact of the Forward Discount on the Forecast Error

This Table reports estimates of a linear regression of the forecast error on the forward discount, $s_{t+k} - s^k_{t,e} = \alpha^k_u + \beta^k_u fd^k_t + \varepsilon_{t+k}$, with $k = 1, 3, 6, 12$ months. Sample: Feb 1997 - Apr 2007.

Currency	Horizon	β^k_u	t-stat	adjR^2
EUR/USD	1	-4.0893	-1.85	0.02
	3	-5.5108	-2.94	0.11
	6	-5.2617	-3.97	0.27
	12	-5.278	-5.65	0.49
USD/JPY	1	0.0798	0.04	-0.01
	3	-0.373	-0.20	-0.01
	6	-1.773	-1.18	0.02
	12	-1.7467	-1.70	0.06
GBP/USD	1	-2.1775	-1.08	0.00
	3	-3.0654	-1.59	0.06
	6	-2.5876	-1.72	0.09
	12	-2.8873	-2.45	0.23

Table 9
The Impact of the Forward Discount on Order Flow

This Table reports estimates of a linear regression of order flow, $o_{t,k}$, on the forward discount, fd_t^k, $o_{t,k} = \alpha_o^k + \beta_o^k fd_{t-k}^k + \xi_{t,k}$ with $k = 1, 3, 6, 12$ months. The order flow variable $o_{t,k}$ is cumulate between month $t-k$ and t, and is also pre-multiplied by the k months ahead exchange rate variance, measured by implied volatility squared, at the end of month $t-k$. Sample: Feb 1997 - Apr 2007.

Currency	Horizon	β_o^k	t-stat	adjR^2
EUR/USD	1	-0.0387	-3.43	0.22
	3	-0.0415	-3.47	0.24
	6	-0.0387	-3.58	0.28
	12	-0.0368	-3.45	0.30
USD/JPY	1	-0.0481	-2.29	0.06
	3	-0.0591	-2.90	0.11
	6	-0.0578	-3.06	0.14
	12	-0.0645	-3.96	0.22
GBP/USD	1	0.0045	0.35	-0.01
	3	0.0034	0.31	-0.01
	6	0.0044	0.44	0.00
	12	0.0090	1.21	0.05

Table 10
Regression Estimates of Forecast Error Equation

The Table reports results of GMM estimates of the forecast error regressed on the forward discount and the order flow variable, $s_{t+k} - s^k_{t,e} = \alpha^k_{ee} + \beta^k_{ee}\, fd^k_t + \gamma^k_{ee}\, o_{t,k} + \varepsilon_{t+k}$ ($k = 1, 3, 6, 12$ months). The order flow variable $o_{t,k}$ is cumulate between month $t-k$ and t, and is also pre-multiplied by the k months ahead exchange rate variance, , measured by squared implied volatility in Panel A and by the variance of the survey forecasts in Panel B, at the end of month $t-k$. Column headings "FD" and "OF" denotes Forward Discount and Order Flow, respectively. t-statistics in parentheses. Sample: Jan 2000 - Apr 2007.

	Trade Indicator						Volume					
	EUR/USD		USD/JPY		GBP/USD		EUR/USD		USD/JPY		GBP/USD	
Maturity	FD	OF	FD	OF	FD	OF	FD	OF	FD	OF	FD	OF
Panel A: Implied Volatility												
1 Month	-3.7263	-0.1511	-1.8592	-0.1835	-2.4478	0.1791	-3.3057	-0.0588	-2.0038	-0.1150	-2.3942	0.1003
	(-1.40)	(-0.57)	(-1.07)	(-1.12)	(-1.14)	(0.60)	(-1.27)	(-0.27)	(-1.15)	(-0.48)	(-1.10)	(0.34)
3 Month	-7.4353	-0.4793	-3.7822	-0.4533	-3.0840	0.3825	-6.5829	-0.5306	-4.1038	-0.5429	-2.6649	0.4689
	(-3.14)	(-2.02)	(-2.77)	(-4.10)	(-1.60)	(1.11)	(-2.91)	(-2.64)	(-2.93)	(-3.17)	(-1.45)	(1.30)
6 Month	-8.4719	-0.7284	-4.6519	-0.2753	-2.3109	0.2341	-6.7154	-0.6485	-5.2071	-0.3068	-1.3680	0.1725
	(-5.44)	(-3.55)	(-4.61)	(-2.43)	(-1.54)	(1.00)	(-4.79)	(-4.43)	(-5.01)	(-1.56)	(-0.99)	(0.68)
12 Month	-5.6265	-0.1821	-4.7747	-0.1011	-1.3110	0.5583	-5.2622	-0.3925	-5.5746	-0.5421	0.9055	0.6597
	(-4.18)	(-0.54)	(-7.43)	(-2.69)	(-1.06)	(1.85)	(-3.22)	(-1.51)	(-5.67)	(-6.11)	(0.75)	(2.48)
Panel B: Survey Dispersion												
1 Month	-3.3672	-0.0565	-2.0184	0.0501	-2.3855	0.1463	-3.1315	0.0222	-1.9597	0.0600	-2.3556	0.0298
	(-1.29)	(-0.31)	(-1.20)	(1.91)	(-1.11)	(0.50)	(-1.19)	(0.11)	(-1.16)	(1.59)	(-1.08)	(0.10)
3 Month	-6.8194	-0.4451	-3.0339	-0.0139	-3.1573	0.4001	-6.4233	-0.6183	-3.5456	0.0137	-2.7343	0.4727
	(-3.02)	(-1.72)	(-1.82)	(-0.21)	(-1.65)	(1.43)	(-2.89)	(-2.16)	(-2.11)	(0.13)	(-1.48)	(1.59)
6 Month	-7.0802	-0.5520	-4.0081	0.0206	-2.4300	0.2996	-6.3200	-0.7789	-4.9688	0.0329	-1.4722	0.2659
	(-4.66)	(-2.21)	(-3.29)	(1.17)	(-1.65)	(1.54)	(-5.40)	(-4.04)	(-4.29)	(1.23)	(-1.09)	(1.29)
12 Month	-4.9622	-0.1153	-3.7855	-0.0075	-1.8590	0.3023	-3.7315	-0.5059	-4.2732	0.0629	0.6031	0.5224
	(-3.95)	(-0.71)	(-5.93)	(-0.42)	(-1.47)	(0.78)	(-3.82)	(-4.44)	(-4.87)	(1.53)	(0.51)	(1.70)

Table 11
The Impact of Order Flow on Expected Risk Premia

The table reports GMM estimates of the coefficient γ^k_{ep} in the regression of the expected risk-premium on order flow, $s^k_{t,e} - f^k_t = \alpha^k_{ep} + \gamma^k_{ep} o_{t,k} + \eta_t$ ($k = 1, 3, 6, 12$ months). The order flow variable $o_{t,k}$ is cumulate between month $t-k$ and t, and is also pre-multiplied by the k months ahead exchange rate variance, measured by squared implied volatility in Panel A and by the variance of the survey forecasts in Panel B, at the end of month $t-k$. t-statistics in parentheses. Sample: Jan 2000 - Apr 2007.

	Trade Indicator				Volume Indicator			
Currency	1 Month	3 Month	6 Month	12 Month	1 Month	3 Month	6 Month	12 Month
Panel A: Implied Volatility								
EUR/USD	-0.0342	0.1091	0.1432	0.1194	-0.0158	0.1463	0.2031	0.1707
	(-0.48)	(2.24)	(3.08)	(2.55)	(-0.24)	(3.77)	(4.66)	(6.33)
USD/JPY	0.1571	0.2305	0.2369	0.0719	0.1760	0.3088	0.3681	0.2785
	(1.82)	(3.66)	(6.25)	(3.47)	(2.21)	(3.27)	(5.38)	(8.25)
GBP/USD	-0.0268	0.0945	0.1342	0.1247	-0.0318	0.0887	0.1336	0.1552
	(-0.54)	(1.93)	(2.55)	(2.32)	(-0.64)	(1.58)	(2.32)	(2.76)
Panel B: Survey Dispersion								
EUR/USD	-0.0088	0.0485	0.0187	0.0062	0.0105	0.1354	0.1251	0.1171
	(-0.15)	(0.73)	(0.23)	(0.07)	(0.16)	(2.04)	(1.74)	(1.86)
USD/JPY	0.0265	0.0425	-0.0008	0.0208	0.0429	0.0402	-0.0047	-0.0349
	(2.88)	(0.99)	(-0.05)	(1.85)	(3.25)	(0.60)	(-0.19)	(-1.76)
GBP/USD	0.0148	0.0629	0.1173	0.0702	0.0095	0.0553	0.1081	0.0560
	(0.28)	(1.32)	(2.37)	(1.01)	(0.18)	(1.02)	(2.01)	(0.70)

Table 12
Realized Return, the Forward Discount and Order Flow

This Table reports GMM estimates of a linear regression of realized k-period return on the forward discount, fd_t^k, and on order flow, $o_{t,k}$, $s_{t+k} - s_t = \alpha^k + \beta^k fd_{t-k}^k + \gamma^k o_{t,k} + \xi_{t+k}$ with $k = 1, 3, 6, 12$ months. The order flow variable $o_{t,k}$ is cumulate between month $t-k$ and t, and is also pre-multiplied by the k months ahead exchange rate variance, measured by squared implied volatility in Panel A and by the variance of the survey forecasts in Panel B, at the end of month $t-k$. Column headings "FD" and "OF" denotes Forward Discount and Order Flow, respectively. t-statistics in parentheses. Sample: Jan 2000 - Apr 2007.

	Trade Indicator						Volume					
	EUR/USD		USD/JPY		GBP/USD		EUR/USD		USD/JPY		GBP/USD	
Maturity	FD	OF	FD	OF	FD	OF	FD	OF	FD	OF	FD	OF
Panel A: Implied Volatility												
1 Month	-3.16	-0.1981	-1.90	-0.0137	-1.60	0.1533	-2.61	-0.0791	-1.94	0.0673	-1.54	0.0693
	(-1.39)	(-0.82)	(-1.11)	(-0.08)	(-0.80)	(0.54)	(-1.20)	(-0.41)	(-1.15)	(0.29)	(-0.76)	(0.25)
3 Month	-6.02	-0.3567	-3.01	-0.2229	-2.63	0.4639	-5.57	-0.3877	-3.37	-0.2365	-2.33	0.5425
	(-3.06)	(-1.78)	(-2.21)	(-1.84)	(-1.56)	(1.50)	(-2.79)	(-2.13)	(-2.45)	(-1.43)	(-1.43)	(1.68)
6 Month	-6.05	-0.4897	-3.46	-0.0123	-1.62	0.3118	-4.59	-0.3846	-3.96	0.1133	-0.79	0.2479
	(-4.11)	(-2.75)	(-3.71)	(-0.10)	(-1.19)	(1.41)	(-2.93)	(-2.38)	(-4.36)	(0.59)	(-0.65)	(1.01)
12 Month	-3.53	-0.0218	-3.60	-0.0264	-0.10	0.7090	-4.32	-0.2550	-3.68	-0.1725	1.74	0.7932
	(-2.88)	(-0.07)	(-6.79)	(-1.17)	(-0.09)	(2.26)	(-2.60)	(-0.99)	(-4.04)	(-1.85)	(1.45)	(2.61)
Panel B: Survey Dispersion												
1 Month	-2.68	-0.0731	-1.85	0.0761	-1.55	0.1616	-2.38	0.0283	-1.75	0.1008	-1.52	0.0393
	(-1.20)	(-0.44)	(-1.20)	(2.62)	(-0.79)	(0.58)	(-1.07)	(0.15)	(-1.13)	(2.35)	(-0.76)	(0.14)
3 Month	-5.81	-0.4059	-2.78	0.0333	-2.72	0.4517	-5.59	-0.4949	-3.25	0.0596	-2.41	0.5140
	(-3.12)	(-1.84)	(-1.97)	(0.68)	(-1.60)	(1.76)	(-2.85)	(-2.08)	(-2.33)	(0.84)	(-1.47)	(1.88)
6 Month	-5.89	-0.5712	-3.52	0.0217	-1.77	0.3705	-5.10	-0.6754	-4.16	0.0282	-0.92	0.3272
	(-4.73)	(-2.90)	(-3.73)	(0.93)	(-1.33)	(2.08)	(-4.37)	(-4.17)	(-4.39)	(0.81)	(-0.78)	(1.66)
12 Month	-3.86	-0.2788	-3.24	0.0051	-0.69	0.4531	-3.58	-0.5374	-3.25	0.0309	1.39	0.6362
	(-3.79)	(-1.95)	(-6.89)	(0.38)	(-0.59)	(1.13)	(-3.53)	(-4.45)	(-4.64)	(0.93)	(1.17)	(1.78)

Table 13
The Impact of the Forward Discount on Order Flow

This Table reports estimates of a linear regression of order flow, $o_{t,k}$, on the forward discount, fd_t^k, $o_{t,k} = \alpha_o^k + \beta_o^k fd_{t-k}^k + \xi_{t,k}$ with $k = 1, 3, 6, 12$ months. The order flow variable $o_{t,k}$ is cumulate between month $t-k$ and t, and is also pre-multiplied by the k months ahead exchange rate variance, measured by squared implied volatility in Panel A and by the variance of the survey forecasts in Panel B, at the end of month $t-k$. Sample: Jan 2000 - Apr 2007.

		Trade indicator			Volume		
Currency	Horizon	β_o^k	t-stat	adjR^2	β_o^k	t-stat	adjR^2
		Panel A: Implied volatility					
EUR/USD	1	-0.0342	-1.94	0.09	-0.0207	-0.95	0.02
	3	-0.0389	-2.36	0.16	-0.0275	-1.29	0.06
	6	-0.0340	-2.78	0.21	-0.0268	-1.51	0.10
	12	-0.0308	-3.07	0.20	-0.0237	-1.32	0.08
USD/JPY	1	0.0140	0.97	0.01	0.0054	0.46	-0.01
	3	-0.0152	-1.04	0.02	-0.0097	-0.91	0.01
	6	-0.0309	-2.02	0.10	-0.0151	-1.52	0.06
	12	-0.0805	-3.32	0.15	-0.0331	-3.41	0.29
GBP/USD	1	0.0050	0.41	-0.01	0.0034	0.30	-0.01
	3	0.0040	0.39	-0.01	0.0031	0.32	-0.01
	6	0.0043	0.50	0.00	0.0051	0.63	0.00
	12	0.0075	1.22	0.04	0.0109	2.14	0.12
		Panel B: Survey dispersion					
EUR/USD	1	-0.0325	-1.76	0.07	-0.0215	-1.11	0.03
	3	-0.0398	-3.04	0.20	-0.0314	-1.97	0.12
	6	-0.0414	-4.26	0.38	-0.0332	-2.52	0.22
	12	-0.0405	-5.10	0.41	-0.0349	-3.15	0.28
USD/JPY	1	-0.0249	-0.39	-0.01	-0.0292	-0.61	0.00
	3	0.0281	1.44	0.01	0.0214	1.41	0.01
	6	0.0283	1.03	0.00	0.0195	0.90	0.00
	12	-0.0584	-1.41	0.04	-0.0010	-0.07	-0.01
GBP/USD	1	0.0002	0.01	-0.01	-0.0022	-0.21	-0.01
	3	0.0047	0.43	-0.01	0.0034	0.33	-0.01
	6	0.0065	0.74	0.01	0.0066	0.76	0.01
	12	0.0096	1.69	0.08	0.0126	2.55	0.15