A Transaction Data Study of the Forward Bias Puzzle*

Francis Breedon

Imperial College Business School†

Dagfinn Rime

Norges Bank and NTNU‡

Paolo Vitale

University d'Annunzio§

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†The Business School, Imperial College London, South Kensington Campus, 53 Prince's Gate, London SW7 2AZ (United Kingdom); telephone: ++44-(0)-20-7594-9146; webpage: `http:/www3.imperial.ac.uk`; e-mail: `f.breedon@imperial.ac.uk`

‡Norges Bank and Norwegian University of Science and Technology (NTNU). Bankplassen 2, PO box 1179 Sentrum N-0107, Oslo (Norway); telephone: ++47-2231-6757; webpage: `http://www.norges-bank.no/research/rime/`; e-mail: `dagfinn.rime@norges-bank.no`

§Faculty of Economics, Università d'Annunzio, Viale Pindaro 42, 65127 Pescara (Italy); telephone ++39-085-453-7647; webpage: `http:/www.ch.unich.it/~vitale`; e-mail: `p.vitale@unich.it`

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ABSTRACT

Using a unique data set we demonstrate that a large share of the FX forward discount bias can be accounted for by order flow. A simple microstructure-based decomposition suggests that order flow creates a time-varying risk premium that is correlated with the forward discount. The order flow related risk premium is particularly important in currency pairs traditionally associated with carry trade activity, as for these crosses it accounts for more than half of the forward bias. We also find evidence that order flow is partly driven by carry trade activity which is itself is driven by expectations of carry trade profits. However, carry trading increases currency-crash risk, in that the carry-induced order flow generates negative skewness in FX returns.

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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

1 Introduction

The uncovered interest rate parity (UIP) condition states that the gain from borrowing a low interest rate currency and investing in a higher interest rate one will, in equilibrium, be matched by a equally large expected cost in form of depreciation of the high interest rate currency. Combined with the hypothesis of rational expectations, this condition implies that the forward rate is an unbiased estimator of the corresponding future spot rate. The empirical literature, Bilson (1981), Fama (1984), Froot and Frankel (1989) and Burnside, Eichenbaum, and Rebelo (2007, 2009) among (many) others, suggests that the forward rate unbiasedness (FRU) is systematically violated.[1] This is termed the forward discount bias, and represents one of the longest standing puzzle in international finance. Despite the large range of alternative explanations put forward, there is no general consensus on the reasons why violations of the FRU persist. Much like the whereabouts of the mythological Phoenix in Metastasio's citation, the forward discount bias arguably remains an unresolved puzzle.

Recently, the forward discount bias has entered popular debate in the form of the carry trade strategy. This strategy, going long high interest rate currencies and short low interest rate ones, aims to exploit the forward bias to deliver excess returns. The discussion of carry trades has proved informative since it reveals how market participants view the processes underlying the forward bias. For example, the following quote from the Wall Street Journal from May 2007 is indicative of market commentary on carry trading: "The carry trade has lifted currencies linked to high interest rates to their most overvalued level in 25 years, increasing the risk of a potentially damaging selloff, industry experts warn"[2]. This quotation suggests that market participants (i) believe it is the very activity of carry trading that "lifts" high interest rate currencies; (ii) believe that carry trading raises high interest rate currencies to "overvalued"

[1]See Lewis (1995) and Engel (1996) for surveys of research on this topic.
[2]from "Carry Trade Prompts Warnings" WSJ 18 May 2007

levels relative to low interest rate ones; and (iii) also realize that there is significant risk of a dramatic reversal connected to carry trading. In this paper we explore all three of these themes in a framework that allows for order flow [3] related risk premia and expectational errors as well as presenting evidence on the connection between order flow and significant reversals.

A simple microstructural trading-framework, combined with data on FX order flow and information on market participants' expectations of future currency values, allows us to decompose the forward discount bias into two parts, one associated with time-varying risk premia as a function of order flow, the other with forecast errors. Overall, in line with previous studies, we find that forecast errors seem to play a role in the forward bias. More interestingly, we also find an equally important role for an order flow related risk premium. Such a role is particularly pronounced for currency pairs typically associated with carry trade. For these currencies we find that the forward discount generates order flow consistent with carry trading. In addition, we see that carry trading is sustained by expectations of carry trade profits, but that the trade imbalance it induces brings about skewness in FX returns. This means that carry traders expect profits from their activity but that this trading also increases crash risk.

Some of the strongest earlier results on the forward discount puzzle have come from the analysis of market expectations derived from survey data. Several studies (Froot and Frankel, 1989; Frankel and Chinn, 1993; Cavaglia, Verschoor, and Wolff, 1994; Chinn and Frankel, 2002; Bacchetta, Mertens, and van Wincoop, 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. Given the obvious problems in explaining systematic forecast errors over a long period it is reassuring that most of these studies also find that forecast errors cannot account for all of the forward bias, which suggests that a time-varying risk premium also plays a significant role in generating such bias. Measuring such a time-varying risk premium has, however, turned out to be very difficult.

The microstructure approach to foreign exchange, and order flow based models in particular, has recently made progress on exchange rate determination. Results such as those of Evans and Lyons (2007) and Rime, Sarno, and Sojli (2010), suggest that order flow may play an important role in the gradual transmission of information from heterogeneous agents to the exchange rate. This might help in the understanding of the underlying expectations that might

[3] Order flow is the net buying pressure for foreign currency and is signed positive or negative according to if initiating party in a transaction is buying or selling (Lyons, 2001).

generate forward bias. On the other hand, results such as those of Breedon and Vitale (2010) 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 the forward bias through that more traditional route.

Recently microstructure-based models have been applied to shed light on the forward bias. For example, Burnside, Eichenbaum, and Rebelo (2007) suggest a mechanism whereby the forward bias arises through adverse selection mechanisms. Burnside, Eichenbaum, and Rebelo (2009) 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 (2009) suggest that infrequent portfolio adjustment could generate forward bias.

Our empirical approach combines the Reuters survey of market participants' forecasts of future currency values and FX transactions data from Electronic Broking Services (EBS) over a period of 10 years between January 1997 and April 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 data sets previously used in the literature. For example, whereas Burnside, Eichenbaum, and Rebelo (2009) 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 for the major crosses. With respect to the work using survey data, e.g. Bacchetta, Mertens, and van Wincoop (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 the next Section, we provide a brief literature review. Section 3 describes the data set on trade imbalance and survey forecasts, provides some preliminary analysis of the properties of FX returns, the forward discount and order flow, and shows how the forward discount bias is large and significant and only partially due to forecast errors. Based on these preliminary results, Section 4 introduces a simple microstructure framework for the FX market which delivers a modified version of the UIP condition. This framework decomposes the forward bias into two components, one related to forecast errors, the other to trade imbalance, which are estimated using our data set of FX transactions and survey forecasts. In Section 5 we investigate the role of carry trade activity in generating order flow in FX markets and bringing about a bias in the forward rate. In the last Section we offer some final remarks and suggest further lines of research. An Appendix contains a summary statistics of our data set, alongside some robustness checks for our empirical analysis.

2 A Brief Literature Review

The FRU is a cornerstone condition for the study of the FX market. This condition states that in a risk-neutral efficient market, when agents are rational, the gain from borrowing cheap in one currency for lending dearly in another currency (for same maturity and risk) equals on average the loss on the exchange rate. Via covered interest rate parity (CIP) this implies that the forward rate f_t at time t for delivery in period $t+1$ is the rational forecast for the corresponding spot rate s_{t+1}. Following Fama (1984) the FRU is usually tested by regressing FX returns, $s_{t+1} - s_t$, on the forward discount, $fd_t = f_t - s_t$, (the so-called Fama regression)

$$s_{t+1} - s_t \;=\; \alpha \;+\; \beta\, fd_t \;+\; \epsilon_{t+1}\,, \tag{2.1}$$

and checking if $\alpha = 0$ and $\beta = 1$.[4]

However, in a multitude of studies (Lewis, 1995; Engel, 1996; Bacchetta, Mertens, and van Wincoop, 2008; Burnside, Eichenbaum, and Rebelo, 2009, among others) Fama's beta is found to be significantly smaller than 1 and usually negative. Thus, Froot and Thaler (1990) indicate that the average value of the coefficient β across 75 published estimates is -0.88. Hence researchers have to understand how breaches of the assumptions underlying the FRU contribute to the forward bias.

Froot and Frankel (1989) were amongst the first to investigate the role of forecast errors in explaining the failure of the FRU. They examined exchange rate forecasts for the USD against the the DEM, GBP, FRF, CHF, and JPY over several short horizons, recorded in the early and mid 1980s by *AMEX*, *The Economist* and the *MMS*. Pooling together forecasts for different exchange rates, they estimate the contribution of forecast errors on Fama's beta to lie between -6.07 and -0.52 depending on the survey data and the horizon of the forecasts.

Froot and Frankel's analysis has been extended by several authors, such as Frankel and Chinn (1993), Chinn and Frankel (2002), Cavaglia, Verschoor, and Wolff (1994), Bacchetta,

[4]The CIP states that $f_t - s_t = (i_t - i_t^*)\Delta t$ where i and i^* denote domestic and foreign interest rates, while Δt is the time interval, in years, between periods t and $t+1$. Akram, Rime, and Sarno (2008) show that CIP holds for the purposes of this paper.

Mertens, and van Wincoop (2008), who have considered alternative survey data, covering longer periods and more currency pairs. Bacchetta, Mertens, and van Wincoop (2008) employ monthly surveys of 3, 6 and 12 months forecasts for seven exchange rates over the period between August 1986 and July 2005. The estimated contribution from forecast errors to the coefficient β range from -3.62 to -0.76 across the seven exchange rates and the three horizons.

Although systematic forecast errors may seem irrational, these errors can also be due to either learning or a peso-problem, as shown by Lewis (1989a,b) and Evans and Lewis (1995). In addition, slow reaction to news, through either ambiguity aversion (Ilut, 2009) or infrequent portfolio adjustments, induced by rational inattention combined with random walk expectations (Bacchetta and van Wincoop, 2009), may also generate forecast errors and a negative Fama's beta. Unfortunately, there is no consensus among researchers on the correct explanation for the presence of systematic errors in exchange rate forecasts. Equally important, even after allowing for forecast errors the majority of these studies still find a statistically significant deviation from UIP, indicating a role for alternative explanations (Jongen, Verschoor, and Wolff, 2008).

If perfect capital substitutability does *not* hold a risk premium enters into the uncovered interest rate relationship. If this *time-varying* risk premium is *negatively* correlated with the forward discount, then Fama's beta can turn out to be smaller than 1. Detecting such risk premia has been a very active, but arguably unsuccessful, research area. Cumby (1988), Hodrick (1989), and Bekaert, Hodrick, and Marshall (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 whilst Bansal and Shaliastovich (2007), Verdelhan (2010) and Moore and Roche (2010) all find some success explaining the puzzle with non-standard preferences.

However, one should notice that no attempt has ever been made to directly measure this time-varying risk premium using transaction data. In this respect, the market microstructure approach to exchange rate determination has offered useful insights into exchange rate dynamics. Thus, Evans and Lyons (2002) and Berger, Chaboud, Chernenko, Howorka, and Wright (2008) find that trade imbalance in FX markets has *large* explanatory power for exchange rate returns. Payne (2003), Bjønnes and Rime (2005), Daníelsson and Love (2006), Killeen, Lyons, and Moore (2006) provide evidence that order flow has a *significant*, *large* and *persistent* impact on exchange rate returns. In addition, Evans and Lyons (2005), Froot and Ramadorai (2005) and Rime, Sarno, and Sojli (2010) show how order flow *anticipates* movements in exchange rate fundamentals. Finally, Breedon and Vitale (2010) and Breedon and Ranaldo (2008) suggest that order flow could be an important element of the FX risk premium through standard portfolio-balance effects.

The empirical evidence listed above has made some progress to understanding the disconnect puzzle in international finance. The empirical success of the microstructure approach gives hope that similar headway could be made on the forward bias puzzle. If market participants are risk averse one should expect that order flow gives rise to changes in the risk premia, irrespective of whether order flow is driven by informational differences or not. With our study we aim at plugging a gap in the existing literature and providing some new insights on the origin of the forward discount bias.

3 Data and Preliminary Analysis

3.1 The 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 from EBS for trading in EUR/USD, USD/JPY, and GBP/USD covering the period beginning of 1997 to April 2007. The second is a detailed monthly survey of FX forecasts, conducted by Reuters, covering the same exchange rates at the 1, 3, 6 and 12 month horizon (see the Appendix for a detailed presentation of our data of FX transactions and survey data of FX forecasts).

In addition to these data we also have data on interest rates and (at the money) implied volatilities for the same horizons as the forecasts. We construct monthly data (the frequency of the survey forecasts) by measuring all market prices (spot exchange rates, interest rates and implied volatilities) at the date of the survey compilation. Monthly order flow is then the aggregate order flow since the previous forecast date. This gives us 124 observations at the monthly frequency.

3.2 The Forward Discount Bias

The starting point for almost all studies of the forward discount bias is Fama's forward discount regression. In Panel A Table 1 we show GMM estimates of Fama style regressions on monthly observations of spot returns on forward discounts for four different horizons (1 month, 3 months, 6 months and one year) for EUR/USD, USD/JPY, and GBP/USD,

$$s_{t+1} - s_t \;=\; \alpha \;+\; \beta\, fd_t \;+\; \epsilon_{t+1}\,, \tag{3.1}$$

where $fd_t = f_t - s_t$ is the log of the forward rate observed at the beginning of period t for maturity in period $t+1$ and s_t is the log spot rate. In Panel B, we follow Froot and Frankel (1989) and report results from similar regressions using the expected return, $r_{e,t} = s_{t,e} - s_t$, constructed from the Reuters survey, as dependent variable.

The results reported in Panel A in Table 1 are in line with previous studies: the estimated slope coefficient, β, is always negative and usually (particularly at the long horizons) significantly smaller than 1 (indicated by †), the value consistent with the FRU. 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 have tended to appreciate (for $fd_t > 0$, $s_{t+1} - s_t$ is on average negative) and *vice versa*.

[Table 1 about here.]

In Panel B we present the related regression with the expected return (based on the Reuters survey) as the dependent variable rather than the realized return. As in previous studies, we find a substantial difference between Panel A and Panel B. Almost all coefficients are in fact larger in Panel B (except the one for USD/JPY 1 month), indicating that the forward discount is linked to market expectations of future exchange rates. However, all coefficients are still smaller than one, the value predicted by the UIP, and some, pertaining to the EUR/USD and USD/JPY exchange rates, are significantly so. This suggests that part of the forward discount bias is not explained by forecast errors, leaving some room for an expected risk premium.[5]

[5] Indeed, most other studies of survey data (Froot and Frankel, 1989; Frankel and Chinn, 1993; Cavaglia, Verschoor, and Wolff, 1994; Chinn and Frankel, 2002; Bacchetta, Mertens, and van Wincoop, 2008) find that in most instances the hypothesis of perfect substitutability (i.e. the restriction $\alpha = 0$ and $\beta = 1$ in the regression of $r_{e,t}$ on fd_t) is violated.

4 A New Decomposition of the Forward Discount Bias

4.1 A Market Microstructure Framework

The deviation of Fama's beta from unity can be due to violations of the key assumptions underlying the FRU, namely risk neutrality and rational expectations, leading to omitted variables in the Fama regression. If these omitted variables are negatively correlated with the forward discount then the estimates of beta from the Fama regression will be downward-biased.

In this section we present a simple analytical framework for the FX market, with the objective of decomposing the forward discount bias into elements due to forecast errors and risk-aversion. This illustrative framework, which is inspired by the model of exchange rate determination proposed by Bacchetta and van Wincoop (2006) and is based on the formulation of the FX market put forward by Breedon and Vitale (2010), is designed to capture the main features of the recent market microstructure approach to exchange rate determination popularized by Lyons (2001) and Evans and Lyons (2002).

In FX markets trading can either be direct between counterparties (bilateral), or indirectly mediated via electronic trading platforms such as *Electronic Broking Services* (EBS) and *Reuters Dealing System 2000-2* (Reuters D2). On these platforms transactions are completed via a centralized *limit order book*, where subscribers can at any time either add/delete *limit orders* or hit outstanding limit orders with *market orders* of opposite sign.

As our empirical study relies on FX transaction data from EBS our analytical framework attempts to represent the trading activity of FX dealers over a centralized trading platform. We assume that a single foreign currency is traded for the currency of a large domestic economy in the inter-dealer FX market. Trades are completed according to a sequence of Walrasian auctions which are intended to represent Reuters D2 and EBS electronic trading platforms.[6] Hence, we assume that in any period t FX dealers simultaneously enter either market or limit orders and then a clearing price (exchange rate) for the foreign currency is established.

We follow Breedon and Vitale (2010) in assuming that the FX dealers form a continuum of agents of mass 1, which select their portfolios of domestic and foreign bonds by maximizing the

[6] Customers have very limited access to these centralized electronic trading platforms. They purchase and sell foreign exchange either by trading in the indirect market via dealer-brokers, as these place orders in the inter-dealer market on behalf of their clients, or by trading bilaterally with FX dealers in the direct market.

expected utility of their end-of-period wealth.[7] Under normality, for a CARA utility function, the total period t demand by FX dealers is

$$o_t \equiv \nu_t \left(\bar{E}_t^1 \left[s_{t+1} \right] - s_t + (i_t^* - i_t) \Delta t \right), \tag{4.1}$$

where ν_t is the *aggregate* trading intensity of the population of FX dealers, given by the risk-tolerance weighted average of their conditional precision of next period spot rate, and $\bar{E}_t^1[s_{t+1}]$ is the weighted average of the expected value of next period spot rate across all FX dealers, where the individual FX dealers' weights are given by their trading intensities.[8]

While the assumptions behind its derivation are specific to the current formulation, the demand function in equation (4.1) holds under alternative specifications. Thus, equation (4.1) can be derived from a mean-variance portfolio choice model, or from an OLG portfolio model, as in Bacchetta and van Wincoop (2006), or even from an inter-temporal portfolio choice problem, as in Evans and Hnatkovska (2007).

As the (net) demand of foreign currency on the part of the FX dealers is entered on the centralized platform, o_t will correspond to order flow, ie. the difference between buyer and seller initiated transactions for the foreign currency.[9] Rearranging equation (4.1) we obtain a modified UIP equation,

$$\bar{E}_t^1 \left[s_{t+1} \right] - s_t = (i_t - i_t^*) \Delta t + \frac{1}{\nu_t} o_t. \tag{4.2}$$

Equation (4.2) implies that, thanks to the FX dealers' 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 dealers 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 dealers 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 dealers, the smaller the risk premium imposed on

[7] The assumption that FX dealers maximize the end-of-period expected utility is introduced for tractability, but it can also be justified on the ground that typically FX dealers are short-sighted while in our empirical analysis one period corresponds to one month.

[8] For more details of this derivation see Breedon and Vitale (2010).

[9] This order flow will be absorbed by broker-dealers which trade in the inter-dealer market on behalf of traders who do not have access to the centralized platform.

the foreign currency. Likewise, the smaller the perceived uncertainty of the currency return, measured by the inverse of the average precision, the less the perceived risk of the foreign currency and so the smaller the required risk premium.

Combining the modified UIP in equation (4.2) with the covered one, given by $(i_t - i_t^*)\,\Delta t = f_t - s_t$ one finds that the forward discount respects the following condition

$$f_t - s_t = \left(\bar{E}_t^1\left[\,s_{t+1}\,\right] - s_t\right) - \frac{1}{\nu_t}\,o_t, \tag{4.3}$$

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

Equation (4.3) may suggest a possible explanation for the forward discount bias documented in Table 1 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 conditions the OLS estimator $\hat{\beta}_{\text{OLS}}$ of the slope coefficient in Fama's regression converges in probability to

$$\beta = \frac{\operatorname{cov}\left(\Delta s_{t+1}, fd_t\right)}{\operatorname{var}(fd_t)}. \tag{4.4}$$

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 dealers. Using the modified UIP, one finds that

$$\Delta s_{t+1} = fd_t + \frac{1}{\nu_t}\,o_t + u_{t+1}. \tag{4.5}$$

Then, in equation (4.4) the coefficient β turns out to be equal to

$$\beta = 1 + \beta_o + \beta_u, \text{ where} \tag{4.6}$$

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

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, unlike 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 beta.

4.2 Decomposing Fama's Beta

With our transaction and forecast data we can now estimate the contribution from risk premia - the coefficient β_o - and forecast errors - the coefficient β_u - on Fama's beta (see equation(4.6)). The coefficient β_o can be estimated by running a linear regression of order flow, o_t, on the forward discount, fd_t, which allows us to identify the relationship between the risk premium related to order flow imbalance and the forward premium. Similarly, if we let $s_{t,e}$ denote the median value of the forecasts of professional FX traders for period $t+1$ exchange rate formulated at time t, β_u can be estimated by running a linear regression of the forecast error, $s_{t+1} - s_{t,e}$, on the forward discount. We estimate these jointly in the following system which gives us one overidentifying restriction,

$$s_{t+1} - s_t = \alpha + (1 + \beta_o + \beta_u) fd_t + \epsilon_{t+1}, \tag{4.7}$$

$$o_t = \alpha_o + \beta_o fd_{t-1} + \epsilon_t^o, \tag{4.8}$$

$$s_{t+1} - s_{t,e} = \alpha_u + \beta_u fd_t + \epsilon_{t+1}^u. \tag{4.9}$$

To be consistent with the framework outlined above, and to have an order flow measure that matches the maturity of the forward contract, we aggregate order flow over the preceding interval $(t-1, t)$. In addition, since a given order flow imbalance will create a greater risk premium the more uncertain 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 $t-1$. As a proxy of this conditional variance we employ the implied volatility of the appropriate maturity observed at the beginning of period $t-1$.[10]

[Table 2 about here.]

The results from GMM estimation of the system above are presented in Table 2. The first column reports the implied Fama beta-coefficient, $1 + \beta_o + \beta_u$. In square brackets below the coefficients we report p-values for the J-test of the over-identifying restriction in our system.

[10]As an alternative estimate we consider the conditional variance of the next period exchange rate forecasts collected by Reuters at the beginning of period $t-1$. These results are discussed in the Appendix.

The reported values show the restriction $\beta = 1 + \beta_o + \beta_u$ is never rejected, confirming the validity of our decomposition and suggesting that we capture all of the bias. In addition, the estimated values for the forecast error and the order flow coefficients, β_u and β_o, suggest the following: on the one hand, the forecast errors contribute significantly to a negative bias in the forward discount for the EUR/USD and GBP/USD, but not for the USD/JPY. On the other hand, order flow contributes significantly to a negative bias for the EUR/USD and USD/JPY but not for the GBP/USD.

Indeed, taking average values of the coefficients across the four horizons, we see that for EUR/USD risk-adjusted order flow explains roughly half of the deviation of beta from 1, ie. half of the forward discount bias, while the other half is explained by the forecast error (see Table 3). For USD/JPY an even stronger conclusion is reached, as nearly all the bias is explained by risk-adjusted order flow. By contrast, for GBP/USD the proportion explained by risk-adjusted order flow is less than 10%. The poor results for GBP/USD may well reflect the fact that EBS has a very small market share for that cross (see Table 8 in the appendix) so that our transaction data are not representative.

[Table 3 about here.]

5 Carry Trades and the Forward Discount Bias

5.1 Carry Trades and the Decomposition

Interestingly, our decomposition can offer some insights on the impact of carry trades in FX markets and on its role in generating the forward discount bias. Certainly, results from Table 2 indicate that the role of the time-varying risk premium in explaining the forward discount bias is more pronounced for USD/JPY, which is the archetypal carry trade cross.

Galati, Heath, and McGuire (2007), Burnside, Eichenbaum, and Rebelo (2009, 2007), and Jylhä and Suominen (2010), Lustig, Roussanov, and Verdelhan (2009) find *positive* returns for carry trade. Carry trade profitability is direct consequence of the failure of the FRU, as indeed, contrary to the prediction of the FRU high interest rate currencies tend to appreciate vis-a-vis low interest rate currencies.

Several explanations for the apparent profitability of the carry trade have been proposed. Thus, recent studies suggest that carry trade profits are mitigated by transaction costs (Burnside, Eichenbaum, and Rebelo, 2009), are associated with volatility and illiquidity (Ranaldo and Sarkar, 2008; Jylhä and Suominen, 2010), are counter-cyclical (Lustig, Roussanov, and Verdelhan, 2009) and subject to reversal risk (Breedon, 2001; Brunnermeier, Nagel, and Pedersen, 2009).

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 and by our results here.

Our simple analytical framework can accommodate carry trade activity and show how it contributes to the forward discount bias. Thus, consider that while our transaction data cover all inter-dealer trades completed on EBS, FX dealers can also trade with their customers in the direct section of the FX market. In particular, as FX dealers typically desire to close their risky portfolios by the end of their holding periods, we assume that, after the inter-dealer market closes, they will unwind their inventory of the foreign currency onto their customers.

Thus, let c_t denote order flow by FX customers to their FX dealers in period t. Such customers will entirely absorb the FX dealers' inventory of the foreign currency if the following equality between inter-dealer and customer order flow holds[11]

$$o_t \;=\; c_t. \tag{5.10}$$

Although the customers of FX dealers trade for a large variety of reasons, anecdotal evidence suggest that in several FX markets a significant component of the trading activity FX dealers' customer is motivated by carry trading. Thus, let us assume that in the presence of a negative forward discount, $(i_t - i_t^*)\Delta t = fd_t < 0$, these customers expect positive profits from a long carry trade strategy on the foreign currency. As they expect the foreign currency to appreciate, these customers will purchase the foreign currency. To capture our *carry trade hypothesis* we assume that customer order flow respects the the following formulation,

$$c_t \quad = \quad -\,\mu\, fd_t \;+\; n_t\,.$$

[11]We could, of course, add a constant slope to this relation, as in Evans and Lyons (2002), without altering any results.

Here μ is some positive constant, so that carry traders sell the foreign currency if this is a low interest rate currency (and vice versa if it is the high interest rate one), while n_t is a second component of customer order flow not related to the forward discount.

In the presence of such carry trade activity, and using the dealer-customer condition (5.10), we derive a negative covariance between order flow and the forward discount, $\text{cov}[o_t, fd_t] < 0$. This implies that β_o takes a negative value and hence that Fama's beta is smaller than 1. Specifically, for ν_t time-invariant, we find that

$$\beta_o \quad = \quad \frac{\text{cov}\left(\frac{1}{\nu_t} o_t, fd_t\right)}{\text{var}(fd_t)} \;=\; -\,\frac{\mu}{\nu}\,.$$

Assuming that the FX dealers are rational, so that $\beta_u = 0$, we conclude that

$$\beta \quad = \quad 1 \,-\, \frac{\mu}{\nu}\,.$$

In brief, according to our analytical framework, and in the presence of carry trade activity, Fama's beta is smaller than 1. Moreover, if such activity is particularly intensive, i.e. if μ is large, β can actually take a negative value as found in many empirical studies on the forward discount bias.

5.2 Order Flow, the Forward Discount and the Time-Varying Risk Premium

The negative correlation between order flow and forward discount is clearly documented for the USD/JPY and EUR/USD rates in Table 4. Here, we report the results of regressing order flow over the past period on the past interest rate differential. For these two exchange rates we find a strong and significant impact of interest rate differentials on order flow. As US interest rates rise relative to those in Japan or in the euro area market participants subsequently buy more US dollars. The negative coefficient for EUR/USD is due to a positive interest rate differential giving rise to negative order flow since euro is the base currency, while the negative coefficient for USD/JPY is due a negative interest rate differential giving rise to a positive order flow since dollar is the base currency in the USD/JPY. The large explanatory power for the EUR/USD and USD/JPY, given by the $\bar{R}^2$, confirms that in these markets carry trading generates a significant proportion of trade imbalance.

[Table 4 about here.]

Results for GBP/USD in Table 4 gives a different picture. The coefficient β_o is neither negative nor significant, while the explanatory power is of an order of magnitude smaller, indicating that carry trade does not generate much order flow in this market. There are two main explanations for the weak results obtained for GBP/USD. First, as discussed above, EBS is not the dominate electronic trading platform for this cross and so our order flow measure is significantly less representative in this case. Second, GBP/USD is not often considered a carry trading cross and so the carry trade activity that we find to be important in the case of USD/JPY in particular is less relevant for GBP/USD. As a result, we drop GBP/USD from the rest of our analysis.

For carry trading to be a significant explanation of the forward discount puzzle three conditions must hold. Firstly, traders expect carry trade activity to generate positive profits. This is the case when, in the face of a negative (positive) forward discount, the expected excess return on a long (short) carry trade position is positive, i.e. if

$$\text{for } i_t \ < \ i_t^* \quad \Rightarrow \quad E_t[s_{t+1}] \ - \ s_t \ + \ (i_t^* \ - \ i_t)\,\Delta t \ > \ 0 \ \text{ and}$$
$$\text{for } i_t \ > \ i_t^* \quad \Rightarrow \quad E_t[s_{t+1}] \ - \ s_t \ + \ (i_t^* \ - \ i_t)\,\Delta t \ < \ 0\,.$$

This condition holds if in the regression of the expected return on the foreign currency, $r_{e,t} = s_{t,e} - s_t$, on the forward discount, fd_t,

$$r_{e,t} \ = \ \alpha_{er} \ + \ \beta_{er}\, fd_t \ + \ \epsilon_t^{er}\,,$$

β_{er} is smaller than one. Results reported in panel B of Table 1 indicate that such condition holds for the USD/JPY, as the slope coefficient is significantly smaller than one, the value consistent with the UIP, across all maturities. Results for the EUR/USD are less supportive as the slope coefficient, while always smaller than 1, is significantly so only for the 1- and 3-month horizons. This might be interpreted as indicating that carry traders mostly concentrate their speculative positions on the EUR/USD over shorter horizons.

Secondly, expectations of carry trade profitability generate trade imbalance. In particular, for $E_{t-1}[s_t] - s_{t-1}$ positive (negative), FX customers purchase the foreign (domestic) currency for the domestic (foreign) one, i.e. order flow in the interval $(t-1, t)$ is positive (negative). To test this condition we run a regression of the risk-adjusted order flow in the interval $(t-1, t)$, o_t, on the expected return at time $t-1$, $r_{e,t-1}$,

$$o_t \;=\; \alpha_o \;+\; \lambda_o \, r_{e,t-1} \;+\; \varepsilon_t^o \,,$$

to see whether expectations of an appreciation (depreciation) of the foreign currency, and hence expectations of profits from a long (short) carry trade position on the foreign currency, generate corresponding flows. This is the case if λ_o is positive. GMM estimates of this regression for the EUR/USD and USD/JPY rates, are in Table 5. The results are clearly supportive. In fact, the slope coefficient is positive for all maturities and rates. In addition, most values are significantly larger than zero, indicating that when FX customers expect profits from a long (short) position on the foreign currency, they purchase (sell) it.

[Table 5 about here.]

Thirdly, trade imbalance in the FX markets affects expected risk premia. In Table 6 we investigate if order flow is a determinant of the expected risk premia, defined as $s_{t,e} - s_t - fd_t$. Results in Table 6 are clear: for most horizons and exchange rates there is a positive and significant impact of order flow on expected risk premia, consistent with our analytical framework (see equation (4.3)). An example may clarify the effect: when the dollar is expected to appreciate against the yen, and the US interest rate is higher than the Japanese interest rate, the expected risk premium is positive. The results in Table 6 indicate that this occurs when there has been a period with net buying of dollars against yen (positive order flow). This would be the case e.g. if market participants are following carry trade strategies: borrowing in yen, and lending in dollars.

[Table 6 about here.]

Indeed, the thesis that the impact of order flow on expected risk premia is related to carry trades is supported by the relatively large explanatory power of order flow for the USD/JPY rate, i.e. for a currency pair on which carry trade activity is usually intense. In fact, while not reported in Table 6, for this rate the adjusted coefficient of multiple determination, $\bar{R}^2$, in the regressions of the expected risk premium on order flow ranges from 1% to 48%.

All in all, the evidence provided in Tables 1, 5 and 6 supports our carry trade hypothesis for the EUR/USD and USD/JPY rates, suggesting that for these rates the component of the forward discount bias associated with the time-varying risk-premium is generated by carry trade activity. In fact, we see that shifts in the forward discount induce expectations of carry trade profitability and generate trade imbalance accordingly. In turn, order flow affects expected risk-premia and brings about a Fama's beta smaller than 1.

5.3 Carry Trade Activity and Currency Crash Risk

The evidence from our analysis and earlier studies suggesting that carry trading is profitable is puzzling, in that one may wonder why risk-neutral arbitrageurs should not under-cut FX dealers' quotes and eliminate the excess returns such investors enjoy. However, as suggested by Brunnermeier, Nagel, and Pedersen (2009), such activity is subject to crash risk, in that movements in currency returns consistent with carry trade profitability may suddenly change direction and induce large losses for carry trading positions.

In our sample, EUR/USD daily returns display pronounced positive skewness, whereas the opposite holds for the USD/JPY. This corresponds with the fact that the US dollar generally is an investment currency in the carry trade strategy whereas the euro and the yen are funding currencies. For carry trading in the EUR/USD cross to be profitable the US dollar must appreciate vis-a-vis the euro (and hence the EUR/USD rate must decrease). However, *positive* skewness of EUR/USD returns indicates the risk of a currency crash, in that the appreciation of the US currency is subject to sudden and deep reversals, which cause carry traders to suffer speculative losses. A similar argument holds for the USD/JPY cross, as for carry trading to be profitable the USD/JPY rate must increase. In this case, currency crash risk translates into *negative* skewness of the return on the USD/JPY.

Brunnermeier, Nagel, and Pedersen (2009) claim that currency reversals are the result of the sudden unwinding of carry trades when these speculators hit liquidity constraints. An empirical implication of such a thesis is that the trade imbalance provoked by carry trading *per se* augments the risk of currency reversals (carry crashes). They provide some weak evidence of such an effect, but argue that their trade imbalance data (based on CFTC FX futures positions) is problematic.

A way to test their empirical implication using our data of FX transactions consists of regressing the skewness of FX returns on order flow. In particular, as speculators accumulate US dollars vis-a-vis the euro a negative order flow in the EUR/USD market should translate into larger positive skewness for the corresponding FX return, if carry trading increases currency crash risk. Similarly, as the same investors purchase US dollars vis-a-vis the yen a positive order flow in the USD/JPY market should now translate into larger negative skewness of the FX return. In both cases regressing the skewness of the FX returns on order flow should yield a negative slope coefficient. In order to compare our results with those of Brunnermeier, Nagel, and Pedersen (2009) we also include the forward discount and implied volatility as controls.

[Table 7 about here.]

Results of the regression of the realized skewness of daily FX returns in the period $(t-1, t)$, ζ_t, on lagged order flow, forward discount and implied volatility (all of the appropriate maturity) are reported in Table 7. The coefficient on order flow is correctly signed (negative) and significant on all horizons except the 12-month for EUR/USD and the 1-month for USD/JPY. The forward discount is correctly signed for both exchange rates (in the sense that positive carry is a predictor of currency crashes), but significant only for USD/JPY. Interestingly, we find a significant relationship between implied volatility and skewness at the 3 month horizon for EUR/USD and 3 month horizon and above for USD/JPY. This result is interesting since for both crosses it implies that low volatility is a predictor of carry crashes which is seemingly at odds with Brunnermeier, Nagel, and Pedersen (2009) who suggest that carry crashes and volatility are positively related. The main explanation for this difference is that Brunnermeier, Nagel, and Pedersen (2009) look at the *contemporaneous* relationship between volatility and skew whilst we undertake a predictive regression. As, admittedly tenuous, out-of-sample evidence it is intriguing to note that for both EUR/USD and USD/JPY the implied volatility reached multi-year lows in mid-2007 just before the financial crisis and a significant carry crash for both currency pairs.

In brief, we conclude that while carry traders can expect profits from their speculative activity in the EUR/USD and JPY/USD markets, they also face significant crash risk which is at its highest when carry trading has resulted in significant order flow imbalance and when the interest rate differential is high and/or volatility is low.

6 Concluding Remarks

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 order flow related risk premia.

Our results suggest that forecast errors only partially explain the forward discount bias, as when using expected returns in lieu of actual returns the coefficient on the forward discount is still smaller than 1, the value consistent with uncovered interest rate parity. Indeed, our study provides some evidence, particularly strong for EUR/USD and USD/JPY crosses, that order flow affects expected risk premia and that these condition realized returns, indicating that microstructural mechanisms contribute to the forward discount puzzle. Thus, according to our decomposition of Fama's beta, the portfolio-balance effect of trade imbalance explains roughly 50 percent of the forward discount bias for the EUR/USD and more than 90 percent of the bias for the USD/JPY rate. We do not find any similar importance of order flow for the GBP/USD forward bias, and we argue that this is partly because the EBS trading platform is not the main trading platform for this cross.

In addition, our results suggest that carry trade activity may actually generate part of the forward discount bias. Thus, we find that: i) movements in interest rate differentials generate order flow imbalance in FX markets in line with carry trading; ii) such activity is sustained by expectations of carry trade profits; and iii) it affects expected risk premia resulting in the appreciation of high interest rate currencies. Finally, we see that carry trading activity does not represent *free lunch*, in that the positive profits it is expected to gain are offset, to some extent, by the currency crash risk it provokes.

As we find that the time-varying risk premium contributes the most to the forward discount bias for USD/JPY, i.e. for the currency pair for which carry trade activity is the strongest, it would be interesting to investigate whether similar results hold for other rates typically associated with carry trade, such the USD/NZD and the CHF/USD.

A The Data

FX TRANSACTIONS: Our FX transactions data set comes from EBS who are the dominant electronic broker for the EUR and JPY rates, but not for the GBP-rate. Table 8) contains summary statistics on the FX transaction data). 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.Chinn and Moore (2008) and Berger, Chaboud, Chernenko, Howorka, and Wright (2008), among others, have previously found that EBS order flow have a strong positive impact on exchange rates. This relation is, however, not the focus of the current paper.

[Table 8 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 (generally the first Tuesday of the month), Reuters call about 50 market participants to 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 9 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).

[Table 9 about here.]

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. Fourth, Reuters publish a ranking of forecasters each month that is widely followed and quoted by market participants thus the contributors have a strong incentive to take the survey seriously.

B Some Robustness Checks: Sensitivity to volatility

According to our analytical framework, the variable o_t is obtained by multiplying the cumulative order flow between $t-1$ and t by an estimate of the average conditional variance of the exchange rate s_t across FX investors at time $t-1$. As a measure of this conditional variance we have employed the implied volatility observed at the beginning of period $t-1$. However, as an alternative estimate we can use the cross section variance of the individual FX forecasts in period $t-1$ of the exchange rate at time t contained in Reuters survey. This definition captures the concept of differences in beliefs that is found to be important in FX markets by Beber, Breedon, and Buraschi (2010). In Table 10 we report the results of the regressions using the cross-section variance of Reuters individual forecasts in lieu of the implied volatility.

[Table 10 about here.]

Since our order flow measure in the regressions is multiplied with volatility one may wonder whether the contribution from this variable comes from variation in the transaction data or from the volatility-measure. We address this by extending our system for estimating the decomposition, given by equations (4.7)-(4.9), with an equation for volatility, making it a four-equation system, and at the same time dropping order flow's dependence on volatility. This way we measure the separate role of each variable on the bias. Results are reported in Table 11, where only the implied beta from the system and the contribution of order flow is reported in order to save space. The implied beta-coefficient is again of a similar magnitude as the unconstrained estimate in Table 1, while the contribution from order flow is equally strong and significant.

[Table 11 about here.]

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Table 1
Fama's Regression: Monthly Data

Panel A presents results from GMM estimates of β^k from the regression

$$r_t^k \ = \ \alpha^k \ + \ \beta^k \, fd_t^k + \epsilon_{t+k} \, ,$$

where $r_t^k = s_{t+k} - s_t$ is the return over the next k months, $fd_t^k = f_t^k - s_t$ is the corresponding forward discount, while f_t^k and s_t are the log of the forward rate (for maturity k) and the spot rate observed at the beginning of month t. Panel B presents results from GMM estimates of β_{er}^k from the regression

$$r_{e,t}^k \ = \ \alpha_{er}^k \ + \ \beta_{er}^k \, fd_t^k + \epsilon_{t,k}^{er} \, ,$$

where $r_{e,t}^k = s_{t,e}^k - s_t$ is the expected return over the next k months the interval $(t, t+k)$ and $s_{t,e}^k$ denotes the median value in month t of the k months ahead exchange rate forecasts contained in Reuters survey. The maturity k is equal to 1, 3, 6 and 12, while t-statistics are reported in brackets. Coefficient values indicated by † are significantly smaller than 1 at the 5%-level. Sample: Jan 1997 - Apr 2007.

	1 Month	3 Month	6 Month	12 Month
	Panel A: Realized return			
EUR/USD	−4.810†	−4.920†	−5.076†	−5.254†
	(−2.59)	(−3.13)	(−4.29)	(−6.02)
USD/JPY	−1.874	−1.608	−1.761†	−1.854†
	(−1.19)	(−1.09)	(−1.48)	(−2.34)
GBP/USD	−2.514	−2.040	−1.950†	−2.186†
	(−1.30)	(−1.23)	(−1.36)	(−1.90)
	Panel B: Expected return			
EUR/USD	−3.603†	−0.766†	0.316	0.642
	(−1.87)	(−1.10)	(0.74)	(1.86)
USD/JPY	−2.870†	−1.404†	−0.432†	−0.036†
	(−1.80)	(−1.75)	(−0.72)	(−0.09)
GBP/USD	−1.351	0.007	0.333	0.474
	(−0.64)	(0.01)	(0.76)	(1.47)

Table 2
Decomposition of Fama's Beta

The Table presents the coefficient value of β_o^k and β_u^k (with t-statistics below) from GMM estimation of the system

$$\begin{aligned} s_{t+k} - s_t &= \alpha^k + \left(1 + \beta_o^k + \beta_u^k\right) fd_t^k + \epsilon_{t+k} , \\ o_{t,k} &= \alpha_o^k + \beta_o^k \, fd_{t-k}^k + \epsilon_{t,k}^o , \\ s_{t+k} - s_{t,e}^k &= \alpha_u^k + \beta_u^k \, fd_t^k + \epsilon_{t+k}^u . \end{aligned}$$

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 $t-k$, $fd_t^k = f_t^k - s_t$ is the forward discount; f_t^k and s_t are the log of the forward rate (for maturity k) and the spot rate observed at the beginning of month t; $s_{t,e}^k$ denotes the median value in month t of the k months ahead exchange rate forecasts contained in Reuters survey. The column "Implied" reports the implied Fama's beta $(1 + \beta_o^k + \beta_u^k)$ and in squared brackets is the p-value from the J-test of the over-identifying restriction (that the implied Beta is equal to Fama's beta). A † indicates that $\beta_o^k + \beta_u^k$ is not significantly different from zero at the 5% level (i.e. UIP cannot be rejected). Sample: Jan 1997 - Apr 2007.

	EUR/USD			USD/JPY			GBP/USD		
	Implied	OF	ExpE	Implied	OF	ExpE	Implied	OF	ExpE
1 Month	-4.31	-4.25	-1.06	-2.04	-3.97	0.92	-0.57†	-0.10	-1.47
	[0.71]	(-3.44)	(-1.28)	[0.82]	(-3.21)	(1.04)	[0.16]	(-0.08)	(-2.09)
3 Month	-4.73	-2.63	-3.11	-2.31	-2.70	-0.61	-1.82†	-0.54	-2.27
	[0.13]	(-2.55)	(-2.18)	[0.31]	(-2.26)	(-0.39)	[0.23]	(-0.72)	(-1.52)
6 Month	-5.43	-2.81	-3.62	-2.99	-3.23	-0.76	-2.09†	-0.35	-2.74
	[0.13]	(-3.14)	(-2.37)	[0.17]	(-2.70)	(-0.48)	[0.37]	(-0.58)	(-1.61)
12 Month	-6.01	-2.80	-4.21	-3.37	-4.23	-0.14	-2.82	0.29	-4.11
	[0.15]	(-3.43)	(-2.81)	[0.14]	(-4.44)	(-0.12)	[0.22]	(0.64)	(-2.72)

Table 3
Share of Forward Bias Explained by Order Flow

The Table presents estimates of the overall forward bias ($\beta_u^k + \beta_o^k$) and the share explained by order flow $\beta_o^k/(\beta_u^k + \beta_o^k)$ derived from our GMM estimates presented in Table 2.

	EUR/USD		USD/JPY		GBP/USD	
	Forward bias	OF share	Forward bias	OF share	Forward bias	OF share
1 Month	-5.31	0.80	-3.04	1.30	-1.57	0.06
3 Month	-5.73	0.46	-3.31	0.81	-2.82	0.19
6 Month	-6.43	0.44	-3.99	0.81	-3.09	0.11
12 Month	-7.01	0.40	-4.37	0.97	-3.82	-0.08
Mean	-6.12	0.52	-3.68	0.97	-2.82	0.07

Table 4
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,

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

with $k = 1, 3, 6, 12$ months. The order flow variable $o_{t,k}$ is cumulated 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 $t-k$; the forward discount is $fd_t^k = f_t^k - s_t$, where f_t^k and s_t are the log of the forward rate (for maturity k) and the spot rate observed at the beginning of month t. Sample: Jan 1997 - Apr 2007.

Currency	Horizon	β_o^k	t-stat	adj.R^2
EUR/USD	1	-0.037	-3.58	0.17
	3	-0.039	-3.90	0.21
	6	-0.039	-3.94	0.22
	12	-0.039	-3.59	0.23
USD/JPY	1	-0.047	-2.23	0.06
	3	-0.055	-2.68	0.11
	6	-0.058	-3.09	0.14
	12	-0.064	-3.99	0.21
GBP/USD	1	0.005	0.39	-0.01
	3	0.006	0.50	0.00
	6	0.005	0.48	0.00
	12	0.010	1.40	0.07

Table 5
The Impact of the Expected Return on Risk-Adjusted Order Flow

The Table reports results of GMM estimates of the regression of risk-adjusted order flow on the expected return on the foreign currency,

$$o_{t,k} \;=\; \alpha_o^k \,+\, \lambda_o^k \, r_{e,t-k}^k \,+\, \epsilon_{t,k}^o \,,$$

where $k = 1, 3, 6, 12$ 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 $t-k$. The expected return on the foreign currency is $r_{e,t}^k = s_{t,e}^k - s_t$, where $s_{t,e}^k$ denotes the median value in month t of the k months ahead exchange rate forecasts contained in Reuters survey; the forward discount is $fd_t^k = f_t^k - s_t$, where f_t^k and s_t are the log of the forward rate (for maturity k) and the spot rate observed at the beginning of month t. The Table contains the estimates of the slope coefficient λ_o^k (in brackets the corresponding t-statistics). Sample: Jan 1997 – Apr 2007.

	1 Month	3 Month	6 Month	12 Month
EUR/USD	0.00	0.26	0.56	0.80
	(0.02)	(2.78)	(2.85)	(2.46)
USD/JPY	0.11	0.90	1.42	1.64
	(0.97)	(3.10)	(2.51)	(1.66)

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,

$$s_{t,e}^{k} - f_{t}^{k} \;=\; \alpha_{ep}^{k} + \gamma_{ep}^{k}\, o_{t,k} + \epsilon_{t,k}^{ep}\,,$$

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 at the end of month $t-k$. t-statistics in brackets. Sample: Jan 1997 - Apr 2007.

	1 Month	3 Month	6 Month	12 Month
EUR/USD	0.198	0.212	0.100	0.027
	(1.04)	(2.82)	(2.24)	(0.92)
USD/JPY	0.054	0.154	0.150	0.153
	(0.35)	(3.54)	(3.32)	(5.89)

Table 7
The Impact of Order Flow on the Skewness of FX Returns

The Table reports GMM estimates of the coefficients from the regression of the average skewness of daily FX returns in the period $(t-k,t)$, ζ_t^k,

$$\zeta_t^k \;=\; \alpha_{sk}^k \;+\; \gamma_{sk}^k\, o_{t,k} \;+\; \beta_{sk}^k\, fd_{t-k}^k \;+\; \delta_{sk}^k\, ImpVol_{t-k}^k \;+\; \epsilon_{t,k}^{sk}\,,$$

with k = 1,3,6, 12 months. The order flow variable $o_{t,k}$ is cumulate between month $t-k$ and t; the forward discount is $fd_t^k = f_t^k - s_t$, where f_t^k and s_t are the log of the forward rate (for maturity k) and the spot rate observed at the beginning of month t; $ImpVol_t^k$ denotes the k months ahead exchange rate variance measured by squared implied volatility at the end of month t. t-statistics in parenthesis. Sample: Jan 1997 - Apr 2007.

	EUR/USD			USD/JPY		
	OF	FD	IV	OF	FD	IV
1 Month	-13.78	37.88	-1.14	-3.07	48.10	-0.19
	(-1.85)	(0.78)	(-0.40)	(-0.58)	(2.08)	(-0.10)
3 Month	-5.97	9.40	-8.55	-4.25	34.92	4.54
	(-1.88)	(0.50)	(-2.58)	(-2.21)	(4.50)	(2.69)
6 Month	-3.94	4.72	-7.03	-2.90	22.78	6.86
	(-2.01)	(0.45)	(-1.82)	(-4.08)	(5.83)	(4.28)
12 Month	-1.27	5.85	-6.10	-1.29	7.97	4.41
	(-1.16)	(0.99)	(-1.41)	(-4.03)	(5.40)	(2.99)

Table 8
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 inter-dealer 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 inter-dealer 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 (Breedon and Vitale, 2010). 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 9
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) Notice that one forecasters consistently only provided one-month 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 10
Decomposition of Fama's Beta: Dispersion of Forecasts as Measure of Uncertainty

The Table presents the coefficient value of β_o^k and β_u^k (with t-statistics below) from GMM estimation of the system. The column "Implied" reports the implied Fama's beta $(1+\beta_o^k+\beta_u^k)$ and in squared brackets is the p-value from the J-test of the over-identifying restriction (that the implied beta is equal to Fama's beta). A † indicates that $\beta_o^k+\beta_u^k$ is not significantly different from zero at the 5% level (i.e. UIP cannot be rejected). Sample: Jan 2000 – Apr 2007.

	EUR/USD			USD/JPY			GBP/USD		
	Implied	OF	ExpE	Implied	OF	ExpE	Implied	OF	ExpE
1 Month	-5.07	-4.00	-2.07	-1.42†	-3.12	0.70	-1.83	-0.51	-2.32
	[0.90]	(-2.77)	(-2.46)	[0.69]	(-2.20)	(0.84)	[0.82]	(-0.45)	(-3.00)
3 Month	-4.71	-1.97	-3.74	-1.12†	-1.89	-0.23	-2.00†	-0.46	-2.55
	[0.11]	(-1.55)	(-2.45)	[0.42]	(-2.01)	(-0.15)	[0.40]	(-0.61)	(-1.63)
6 Month	-5.36	-2.23	-4.13	-1.83	-1.48	-1.36	-2.33	-0.27	-3.06
	[0.27]	(-1.55)	(-2.49)	[0.75]	(-1.93)	(-0.83)	[0.36]	(-0.44)	(-1.90)
1 Year	-6.17	-2.60	-4.57	-2.77	-1.77	-2.00	-3.31	0.18	-4.49
	[0.14]	(-1.96)	(-2.69)	[0.18]	(-1.75)	(-1.45)	[0.20]	(0.30)	(-3.64)

Table 11
Decomposition of Fama's Beta: Sensitivity to Volatility

The Table presents GMM estimates of the following 4-equation system,

$$\begin{aligned} s_{t+k} - s_t &= \alpha^k + \left(1 + \beta_o^k + \beta_u^k + \beta_v^k\right) fd_t^k + \epsilon_{t+k}\,, \\ o_{t,k} &= \alpha_o^k + \beta_o^k\, fd_{t-k}^k + \epsilon_{t,k}^o\,, \\ s_{t+k} - s_{t,e}^k &= \alpha_u^k + \beta_u^k\, fd_t^k + \epsilon_{t+k}^u\,, \\ ImpVol_{t-k}^k &= \alpha_v + \beta_v\, fd_{t-k}^k + \epsilon_{t-k,k}^v\,. \end{aligned}$$

In this system order flow and volatility have separate equations and effects. The order flow variable $o_{t,k}$ is cumulate between month $t-k$ and t; the forward discount is $fd_t^k = f_t^k - s_t$, where f_t^k and s_t are the log of the forward rate (for maturity k) and the spot rate observed at the beginning of month t; $ImpVol_t^k$ denotes the k months ahead exchange rate variance at the end of month t. Sample: Jan 2000 – Apr 2007. The column "OF" reports the coefficient β_o^k (with t-statistics below); the column "Implied" reports the implied Fama's beta $(1+\beta_o^k+\beta_u^k+\beta_v^k)$ and in squared brackets is the p-value from the J-test of the over-identifying restriction (that the implied beta is equal to Fama's beta). A † indicates that $\beta_o^k+\beta_u^k+\beta_v^k$ is not significantly different from zero at the 5% level (i.e. UIP cannot be rejected).

	EUR/USD		USD/JPY		GBP/USD	
	Implied	OF	Implied	OF	Implied	OF
Panel A: Implied Volatility						
1 Month	-4.46	-4.30	-0.79	-1.18	-1.26†	-0.64
	[0.78]	(-3.55)	[0.37]	(-1.45)	[0.37]	(-0.57)
3 Month	-4.73	-3.19	-1.30	-1.59	-1.87†	-0.74
	[0.14]	(-3.45)	[0.56]	(-1.89)	[0.54]	(-1.03)
6 Month	-5.33	-3.29	-1.76	-1.16	-2.09†	-0.41
	[0.18]	(-4.66)	[1.00]	(-3.75)	[0.55]	(-0.70)
12 Month	-5.79	-3.16	-1.98	-1.25	-2.96	0.21
	[0.16]	(-3.90)	[0.36]	(-6.60)	[0.28]	(0.52)
Panel B: Forecast Dispersion						
1 Month	-4.23	-4.26	-0.86†	-0.97	-1.13†	-0.60
	[0.65]	(-3.18)	[0.30]	(-1.18)	[0.35]	(-0.53)
3 Month	-4.72	-3.34	-1.12	-1.89	-1.95†	-0.68
	[0.14]	(-3.37)	[0.34]	(-2.05)	[0.57]	(-0.89)
6 Month	-5.29	-3.35	-1.66	-1.36	-2.12†	-0.42
	[0.18]	(-4.60)	[0.78]	(-3.54)	[0.53]	(-0.69)
12 Month	-5.78	-3.18	-1.96	-1.26	-3.00	0.22
	[0.16]	(-3.86)	[0.38]	(-6.80)	[0.29]	(0.54)