DISCUSSION PAPER SERIES

No. 7791

A TRANSACTION DATA STUDY OF THE FORWARD BIAS PUZZLE

Francis Breedon, Dagfinn Rime and Paolo Vitale

INTERNATIONAL MACROECONOMICS

Centre for Economic Policy Research

www.cepr.org

Available online at: www.cepr.org/pubs/dps/DP7791.asp

ISSN 0265-8003

A TRANSACTION DATA STUDY OF THE FORWARD BIAS PUZZLE

Francis Breedon, Imperial College, London
Dagfinn Rime, Norges Bank
Paolo Vitale, G. D'Annunzio University and CEPR

Discussion Paper No. 7791
April 2010

Centre for Economic Policy Research
53–56 Gt Sutton St, London EC1V 0DG, UK
Tel: (44 20) 7183 8801, Fax: (44 20) 7183 8820
Email: cepr@cepr.org, Website: www.cepr.org

CEPR Discussion Paper No. 7791

April 2010

ABSTRACT

A Transaction Data Study of the Forward Bias Puzzle*

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. We find that both elements are significant contributors to the forward bias with risk premia being particularly important in currency pairs traditionally associated with carry trade activity. Part of order flow is driven by carry trade, and from our decomposition the carry trade driven risk premia account for about 50% of the forward bias.

JEL Classification: D82, G14 and G15
Keywords: carry trade, forward discount puzzle, FX microstructure and survey data

Francis Breedon
Imperial College
University of London
53 Prince's Gate
Exhibition Road
London
SW7 2PG
Email: f.breedon@imperial.ac.uk

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=158894

Dagfinn Rime
Norges Bank
Research Department
PO Box 1179
Sentrum
0107 Oslo
NORWAY
Email: Dagfinn.Rime@norges-bank.no

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=152235

Paolo Vitale
DEST, Faculty of Economics
G. D'Annunzio University
Viale Pindaro 42
065127 Pescara
ITALY
Email: p.vitale@unich.it

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=125175

* Vitale is grateful to the Imperial College Business School, where part of this research was undertaken, for its hospitality. Financial support from the Risk Lab at Imperial College Business School is gratefully acknowledged. We also wish to thank Michael Moore, Steinar Holden and participants at seminars at the University of Bologna, the University of Modena, the EIEF Research Center in Rome, Luiss University, Warwick Business School, Norges Bank, the Norwegian University of Science and Technology, and at the 2009 AEA Meeting in San Francisco for helpful comments. Hong Xu and Filip Zikes provided excellent research assistance. The authors alone are responsible for the views expressed in the paper and for any errors that may remain.

Submitted 09 April 2010

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, under rational expectations and risk neutrality, 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. The empirical literature, Bilson (1981), Fama (1984), Froot and Frankel (1989) and Burnside, Eichenbaum, and Rebelo (2007, 2009) among (many) others, systematically suggest the opposite.[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 UIP persist. Much like the whereabouts of the mythological Phoenix in Metastasio's citation, the forward discount bias arguably remains an unresolved puzzle.

In this study we empirically investigate the connection between the risk premium, forecast errors and the trading process in foreign exchange (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 as a function of order flow, the other with forecast errors.[2] Overall, in line with previous studies, we find that forecast errors seem to play a role in the forward bias, but we also find an equally important role for an order flow related risk premium. Furthermore, we find that the order flow that affects risk premia is partly explained by carry trading. Carry trading involves systematically going long high interest rate currencies and short low interest rate ones in order to profit from the forward bias.

[1]See Lewis (1995) and Engel (1996) for excellent surveys of research on this topic.
[2]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).

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. However, most of these studies also find that forecast errors cannot account for all of the forward bias, suggesting that a time-varying risk premium also plays a significant role in generating such bias. Additionally, these studies rarely attempt to explain why these forecast errors occur.

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, 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 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 (2009) 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.

Recently microstructure-based models have been applied in order 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 indeed 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. Based on this review Section 3 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. Section 4 describes the data set on trade imbalance and survey forecasts and provides some preliminary analysis of the properties of FX returns, the forward discount and order flow. The modified UIP relation is estimated in Section 5. In the last Section we offer some final remarks and suggest further lines of research.

2 A Brief Literature Review

UIP is a cornerstone condition for the FX market. This condition states that in a risk-neutral efficient market the gain from borrowing cheap in one currency for lending dearly in another currency (for same maturity and risk) equals an expected loss on the exchange rate in equilibrium (see Sarno and Taylor, 2002). Via the covered interest rate parity (CIP) this implies that the forward rate (f_t^k) at time t for delivery k periods ahead is the rational forecast for the spot rate in period $t + k$.[3] Following Fama (1984) UIP is usually tested by regressing FX return, $s_{t+k} - s_t$, on the forward discount, $fd_t^k = f_t^k - s_t$ (the so-called Fama regression),

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

and checking if $\alpha^k = 0$ and $\beta^k = 1$. As we see from the equation the Fama regression is, via the CIP-condition, also a test of the forward rate being an unbiased predictor for the future spot rate.

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

[3] Akram, Rime, and Sarno (2008) show that the CIP holds for the purpose of this paper.

(1990) indicate that the average value of the coefficient β^k across 75 published estimates is -0.88. Hence researchers have to understand how breach of the assumptions for UIP, rational expectations and risk neutrality, 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 UIP. 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, 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^k 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 may 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 turns out to be smaller than 1. Detecting such risk premia has been a very active research area, but so far the empirical research has not been entirely successful. 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 on 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, which may indicate that order flow have some role in explaining the forecast errors that seem to be the key driver of the forward discount puzzle. Finally, Breedon and Vitale (2009) and Breedon and Ranaldo (2008) suggest that order flow could be an important element of the FX risk premium through standard portfolio-balance effects.

This empirical evidence provides a rationale for the disconnect puzzle in international finance. Even if there is still no consensus on what drives order flow, the empirical success of the microstructure approach gives hope that similar headway could be made on the forward bias puzzle. With our study we aim at plugging a gap in the existing literature and at providing some new insights on the origin of the forward discount bias.

In the next section we focus on the portfolio balance effect and present a new decomposition of the forward premium regression based on a simple order flow based model of the risk premium. This decomposition is derived from an analytical framework which is inspired by the market microstructure 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 (2009).

3 A New Decomposition of the Forward Discount Bias

In FX markets two different mechanisms of trading coexist. In the direct market, transactions are the result of private bilateral "meeting" between traders, as customers contact single FX dealers to execute individual orders. In the indirect market, inter-dealer trades are mediated via electronic trading platforms, such as *Electronic Broking Services* (EBS) and *Reuters Dealing System 2000-2* (Reuters D2)[4]. 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.[5] 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.

At the beginning of trading period t a FX dealer, d, possesses g_{t-1}^{d} units of domestic bonds. During period t, FX dealer 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

$$W_{t+1}^{d} \;=\; (1 \,+\, i_t\,\Delta_t)\; g_{t-1}^{d} \,+\, [(i_t^* \,-\, i_t)\;\Delta_t \,+\, (s_{t+1} \,-\, s_t)]\; o_t^{d},$$

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_t^d is the quantity of the foreign currency investor d will purchase (short-sell).

We assume that our FX dealers 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 $\tau_d = 1/\gamma_d$).

[4]Recently newer versions of the Reuters dealing system have been released such as Dealing 3000

[5]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.

Assuming that our investor is a price-taker, under normality the optimal quantity of foreign currency she will trade corresponds to a linear excess demand as a function of expected excess return,

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

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. $\pi_{s+,t}^d \equiv 1/\mathrm{Var}\,[s_{t+1} \mid \Omega_t^d\,]$.

Assuming that the FX dealers form a continuum of agents of mass 1, uniformly distributed in the interval $[0,1]$, we obtain the total period t demand by FX dealers as

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

where $\nu_t \;\equiv\; \int_0^1 \nu_t^{d'}\, dd'$ is the *aggregate* trading intensity of the population of FX dealers 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.

While the assumptions behind its derivation are specific to the current formulation, the demand function in equation (3.1) holds under alternative specifications. Thus, equation (3.1) can be derived from a mean-variance portfolio choice model, or from an OLG portfolio model, or even from an inter-temporal portfolio choice problem. In other words, we can claim that equation (3.1) is a fairly general representation of the demand of foreign currency on the part of the FX dealers.

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 in the market for the foreign currency.[6] Rearranging equation (3.1) we obtain a modified UIP equation,

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

[6]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.

Equation (3.2) 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, $\bar{\tau}$, 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.

Combining the modified UIP in equation (3.2) with the covered one, given by $(i_t - i_t^*)\,\Delta t = f_t - s_t$, where f_t is the log of the forward rate, 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. $\operatorname{plim} \hat{\beta}_{\text{OLS}} = \beta$), where

$$\beta = \frac{\operatorname{cov}\left(\Delta s_{t+1}, f d_t\right)}{\operatorname{var}(f d_t)}. \tag{3.4}$$

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 dealers. Using the modified UIP, one finds that

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

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

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

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

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, 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 beta.

Interestingly, our decomposition can also offer some insights on the impact of carry trades in FX markets. 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 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 apparent profitability of 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.

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[7]

$$o_t \;=\; c_t\,. \tag{3.7}$$

FX dealers' customers are mostly formed by the financial arms of industrial corporations and by other commercial and financial traders, whose trading in FX markets may be associated with current account transactions, such as trade in goods and services, transfers of capital income, public and private unilateral transfers of funds, or with capital movements, such as foreign direct and portfolio investment. In addition, their transactions can be motivated by carry trade activity.

Thus, let us assume that in the presence of a negative forward discount, $(i_t^k - i_t^{k,*})\Delta k = fd_t^k < 0$ $((i_t^k - i_t^{k,*})\Delta k = fd_t^k > 0)$, 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, $c_t > 0$ $(c_t < 0)$ and the opposite for a positive forward discount.

This simple carry trade activity can be represented by the following trading strategy on the part of the FX customers,

$$c_t \quad = \quad -\mu\, fd_t\,,$$

where μ is some positive constant, so that FX customers collectively sell the foreign currency, $c_t < 0$ $(c_t > 0)$ if this is a low interest rate currency (and vice versa if it is the high interest rate one).

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

In the presence of such carry trade activity, and using the dealer-customer condition (3.7), we derive a negative covariance between order flow and the forward discount, $\mathrm{cov}[o_t, fd_t] < 0$. 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

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

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.

4 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 beginning of 1997 to april 2007 from EBS. The second is a detailed monthly survey of FX forecasts for EUR/USD, USD/JPY, and GBP/USD conducted by Reuters since the early 1990's. Since we only use the the post 1997 sample in this study to match our transaction data this leaves us with 124 monthly observations.

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 (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.[8] 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.

[8]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.

[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 (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 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. 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.

[Table 2 about here.]

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

5 Results

The starting point for almost all studies of the forward discount bias is Fama's famous forward discount regression. In Panel A 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 EUR/USD, USD/JPY, and GBP/USD,

$$s_{t+k} - s_t \; = \; \alpha^k \, + \, \beta^k \, fd_t^k + \epsilon_{t+k}, \tag{5.1}$$

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. In Panel B, we follow Froot and Frankel (1989) and report results from similar regressions using expected return, $s_{t,e}^k - s_t$, constructed from the Reuters survey, as dependent variable.

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 (indicated by †), 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 *vice versa*.

[Table 3 about here.]

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 smaller than one, the value predicted by the UIP, and some, pertaining to the EUR/USD and USD/JPY, 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.[9]

In Table 4 we investigate if order flow is a determinant of such a expected risk premium, defined as $s_{t,e}^k - s_t - fd_t^k$. To be consistent with the framework outlined above, and in order to

[9]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 $\alpha^k = 0$ and $\beta^k = 1$ in the regression of $r_{e,t}^k$ on fd_t^k) is violated.

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 $t-k$. As a proxy of this conditional variance we employ the implied volatility of the appropriate maturity observed at the beginning of month $t-k$.[10]

[Table 4 about here.]

Results in Table 4 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 (3.3)). 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 4 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 buying dollar for lending the funds.

Indeed, the thesis that the impact of order flow on expected risk premia is related to carry trade is supported by the relatively large explanatory power of order flow for the USD/JPY, i.e. for a currency pair on which carry trade activity is usually intense. In fact, while not reported in Table 4, 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 49%.

We investigate the possibility of carry trades as a determinant of order flow more closely in Table 5 below. We regress order flow over the past k months, as above, on the interest rate differential k months ago. We find a strong and significant impact of interest rate differentials for the EUR/USD and USD/JPY. When US interest rates are higher than in Japan or the euro area market participants subsequently buy 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.

[10] 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 $t-k$, these results are discussed below.

The large values taken by the coefficient of multiple determination, $\bar{R}^2$, for the EUR/USD and USD/JPY are also telling: given the very restrictive formulation of the estimated regression, they confirm that in these markets carry trade motives generate a significant proportion of trade imbalance.

Results for GBP/USD in Table 5 offer different conclusions: across all horizons, the coefficient β_o^k is neither negative nor significant, while the coefficient of multiple determination, $\bar{R}^2$, 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 (both here and in later regressions). First, as shown in Table 1, 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, as noted above, 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.

[Table 5 about here.]

The evidence provided by Tables 4 and 5 suggests that carry trade activity relies on self-serving expectations. In fact, as carry trade motives generate a significant proportion of order flow in the EUR/USD and USD/JPY markets, the trade imbalance induced by movements in the forward discount alters the expected risk premium and creates expectations of carry trade profitability. Thus, when US interest rates are higher than in Japan, investors buy US dollars as they expect a larger risk premium on the American currency and profits from carry trade.

5.1 Decomposing Fama's Beta

With our transaction and forecast data we can estimate the contribution from risk premia, the coefficient β_o^k in the decomposition, and forecast errors, the coefficient β_u^k, on Fama's beta directly (see equation(3.6)). The coefficient β_o^k can be estimated by running a linear regression of order flow on the forward discount which gives allows us to identify the relationship between the risk premium related to order flow imbalance and the forward premium. Similarly, if we let $s_{t,e}^k$ denote the median value of the surveyed exchange rate forecasts of professional FX traders for maturity k formulated at time t, β_u^k can be estimated by running a linear regression of the forecast error, $s_{t+k} - s^k_{t,e}$, on the forward discount, fd^k_t. We estimate these jointly in the following system where we use the restriction from the decomposition,

$$s_{t+k} - s_t = \alpha^k + \left(1 + \beta^k_o + \beta^k_u\right) fd^k_t + \epsilon_{t+k}, \tag{5.2}$$

$$o_{t,k} = \alpha^k_o + \beta^k_o fd^k_t + \varepsilon^o_{t+k}, \tag{5.3}$$

$$s_{t+k} - s^k_{t,e} = \alpha^k_u + \beta^k_u fd^k_t + \varepsilon^u_{t+1}, \tag{5.4}$$

where order flow $o_{t,k}$ is defined in a similar way as in the expected risk premium regression above.

[Table 6 about here.]

The results from GMM estimation of the system above are presented in Table 6. The first column reports the implied Fama beta-coefficient, $1 + \beta^k_o + \beta^k_u$. In square brackets below the coefficients we report p-values for a J-test of the over-identifying restriction in our system. The reported values show the restriction $\beta^k = 1 + \beta^k_o + \beta^k_u$ is never rejected, confirming the validity of our decomposition and that we capture a large share of the bias. In addition, the estimated values for the forecast error and the order flow coefficients, β^k_u and β^k_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. Once more, the negative coefficient β^k_o is consistent with a carry-trade driven order flow: when the US interest rate is higher than the euro (yen) interest rate this leads to selling of the euro (yen) and hence to negative order flow.

Indeed, as Table 7 shows, 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. For USD/JPY an even stronger conclusion is reached, as more than 80 percent of the bias is explained by risk-adjusted order flow. By contrast, for GBP/USD the proportion falls to a meagre 3 percent which is consistent with the problems we identify with order flow data for that cross.

[Table 7 about here.]

5.2 Does Order Flow Predict Forecast Errors?

So far our focus has been on the role of order flow as a determinant of the risk premium, however the microstructure literature has also highlighted the role of order flow in the formation of expectations and the transmission of fundamental information into exchange rates. For example, both Evans and Lyons (2007) and Rime, Sarno, and Sojli (2010) find evidence that order flow can predict future exchange rates and ascribe that predictive power to the role of order flow in transmitting new about fundamentals through heterogenous expectations (though, in contrast, Daníelsson, Luo, and Payne (2002) and Sager and Taylor (2008) find no evidence that order flow models can outperform a random walk). Our data can offer an alternative test of this proposition not only because of the quality of the order flow data that we use, but also because, using our survey data we can disentangle the impact of risk premia from that of expectations.

[Table 8 about here.]

Table 8 presents evidence on the ability of order flow and the forward discount to predict forecast errors. As we found in Table 3 the forecast error is clearly linked to the forward discount, whilst the role of order flow is less clear. We find strong results for order flow in the case of USD/JPY at all maturities but not for the other crosses. Notwithstanding these mixed results, it is worth noting that our test is limited by the fact that we are not testing an explicit model of how order flow influences expectations formation - since our focus is on risk premia. This suggests that identifying the role of order flow in expectations formation may be a promising route to explore in future research.

5.3 Carry Trade and the Forward Discount Bias

In presenting our decomposition of Fama's beta we have suggested that the component of the forward discount bias which can be attributed to a time-varying risk premium can actually be generated by the carry trade activity of FX customers. Thus, according to this *carry trade hypothesis* when the forward discount, $fd_t^k = (i_t^k - i_t^{k,*})\Delta k$, is negative (positive), so that the domestic currency is a low (high) interest rate currency vis-a-vis the foreign one, carry trade activity causes order flow to be positive (negative). Such activity then results in a negative correlation between order flow and the forward discount, as documented in our decomposition of Fama's beta, contributing to the forward discount bias.

The carry trade hypothesis will hold if two conditions are met:

1. Carry traders expect carry trade activity to generate positive profits. This will be 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

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

   and

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

2. Expectations of carry trade profitability generate trade imbalance. In particular, for $E_{t-k}[s_t]-s_{t-k}$ positive (negative), FX customers purchase the foreign (domestic) currency for the domestic (foreign) one, i.e. order flow in the interval $(t-k, t)$ is positive (negative).

Condition 1. holds if in the regression of the expected return on the foreign currency, $r_{e,t}^k = s_{t,e}^k - s_t$, on the forward discount, fd_t^k,

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

with $k =, 1, 3, 6, 12$, β_{er}^k is smaller than one. Results reported in panel B of Table 3 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 of condition 1. 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. Finally, evidence for the GBP/USD is definitely less compelling, as none of the estimates for β_{er}^k is significantly smaller than 1. This is not surprising, given our discussion above concerning the properties of the GBP/USD.

[Table 9 about here.]

To test condition 2. we can just run a regression of the risk-adjusted order flow in the interval $(t-k, t]$, $o_{t,k}$ on the expected return at time $t-k$, $r_{e,t-k}^k$,

$$o_{t,k} \;=\; \alpha_o^k \,+\, \lambda_o^k\, r_{e,t-k}^k \,+\, \varepsilon_t^o, \qquad \text{with } \; k \;=\; 1,\, 3,\, 6,\, 12\,,$$

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^k is positive. GMM estimates of this regression are in Table 9.

Its results are clearly supportive of condition 2. 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. To some extent, however, the results of Table 6 might suggest that these carry trade profits would not be sufficient to motivate trading once risk premia are allowed for. In fact, there are many ways to reconcile the two results, for example our survey of expectations includes no hedge funds or algorithmic traders both of whom might be more likely to expect significant risk-adjusted profits from carry trading.

All in all the evidence provided in Tables 3 and 9 suggests that the component of the forward discount bias associated with the time-varying risk-premium could be generated, at least partially, by carry trade activity.

5.4 Some Robustness Checks

In this Section we experiment with some alternative definitions of our order flow variable to ensure that our key results are not driven by the precise definition we use. Tables 10 and 11 present the robustness results for the decomposition of Fama's beta, and the regression of the forecast errors.

In Section 3 we have seen that to construct the variable $o_{t,k}$ we need to cumulate order flow between month $t-k$ and t. Given the specifics of our dataset, the cumulative order flow variable used above is derived from the balance between the *number* of buyer- and seller-initiated trades completed within a given interval of time on EBS. However, from January 2000 to April 2007 we also have an estimate of the size of each trade, based on eight trade size indicators. Results using trade volume are reported in panel A of Tables 10 and 11.

According to our analytical framework, the variable $o_{t,k}$ is obtained by multiplying the cumulative order flow between month $t-k$ and t by an estimate of the average conditional variance of the exchange rate s_t across FX investors at time $t-k$. As a measure of this conditional variance we have employed the implied volatility for maturity k observed at the beginning of month $t-k$. However, as an alternative estimate we can use the cross section variance of the individual FX forecasts in month $t-k$ for maturity k contained in Reuters survey. This definition captures the concept of differences in beliefs that has found to be important in FX markets by Beber, Breedon, and Buraschi (2010). Thus, in panel B of Tables 10 and 11 we report the results of the regressions using the cross-section variance of Reuters individual forecasts in lieu of the implied volatility.

The general picture we derive from Tables 10 and 11 is that our results are robust to alternative definitions of the order flow variable, $o_{t,k}$.

[Table 10 about here.]

Results reported in Table 10 confirm the earlier conclusion that both forecast errors and order flow contribute significantly to a negative bias in the forward discount for the EUR/USD and USD/JPY. Though, the evidence on the role of a time-varying risk premium in explaining the forward discount bias is less compelling when using the volume indicator. For both the EUR/USD and USD/JPY we see now that the magnitude of the coefficient β_o^k is smaller and its value is for some horizons not significant. On the other hand, results obtained when using the dispersion of survey forecasts are similar to those obtained employing the implied volatilities.

[Table 11 about here.]

In Table 11 we see that when using either the volume indicator or the dispersion of survey forecasts to build our order flow variable, $o_{t,k}$, there is no systematic dependence of the expectation error on order flow, not even for the USD/JPY rate for which some evidence is documented in Table 8. In brief, we do not find systematic evidence that order flow may help explaining the forecast errors committed by professional forecasters in FX markets though our results do not rule out such a mechanism completely.

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 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, 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 80 percent of the bias for the USD/JPY. 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 movements in interest rate differentials generate trading activity and order flow imbalance in FX markets. 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 a self-fulfilling mechanism similar to that suggested by Plantin and Shin (2008).

As we find that the time-varying risk premium contributes the most to the forward discount bias for the EUR/USD and USD/JPY, i.e. for those currency pairs 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. Furthermore, as carry trades are subject to reversal risk, it would also be interesting to see whether the contribution of the time-varying risk premium to the forward discount bias is significantly smaller when carry trade strategies are reversed as in the recent aftermath of the collapse of Lehman Brothers. Clearly, such analysis is beyond the scope of the current study, given that we do not have access to the required data set.

References

Akram, Q. F., D. Rime, and L. Sarno, 2008, Arbitrage in the Foreign Exchange Market: Turning on the Microscope, Journal of International Economics, 76, 237–253.

Bacchetta, P., E. Mertens, and E. van Wincoop, 2008, Predictability in Financial Markets: What Do Survey Expectations Tell Us?, Journal of International Money and Finance, 28(3), 406–426.

Bacchetta, P., and E. van Wincoop, 2006, Can Information Heterogeneity Explain the Exchange Rate Determination Puzzle?, American Economic Review, 96(3), 552–576.

——— , 2009, Infrequent Portfolio Decisions: A Solution to the Forward Discount Puzzle, American Economic Review, forthcoming.

Bansal, R., and I. Shaliastovich, 2007, Risk and return in bond, currency and equity markets, mimeo, Duke University.

Beber, A., F. Breedon, and A. Buraschi, 2010, Difference in Beliefs and Currency Option Markets, Journal of Financial Economics, forthcoming.

Bekaert, G., R. J. Hodrick, and D. Marshall, 1997, The Implications of First-Order Risk Aversion for Asset Market Risk Premiums, Journal of Monetary Economics, 40(1), 3–39.

Berger, D. W., A. P. Chaboud, S. V. Chernenko, E. Howorka, and J. H. Wright, 2008, Order Flow and Exchange Rate Dynamics in Electronic Brokerage System Data, Journal of International Economics, 75(1), 93–109.

Bilson, J. F. O., 1981, The "Speculative Efficiency" Hypothesis, Journal of Business, 54(3), 435–451.

Bjønnes, G. H., and D. Rime, 2005, Dealer Behavior and Trading Systems in Foreign Exchange Markets, Journal of Financial Economics, 75(3), 571–605.

Breedon, F., 2001, Market Liquidity under Stress: Observations from the FX Market, Bank of International Settlements: Conference Proceedings.

Breedon, F., and A. Ranaldo, 2008, Time-of-day Patterns in FX Returns and Order Flow, mimeo, Imperical College Business School.

Breedon, F., and P. Vitale, 2009, An Empirical Study of Liquidity and Information Effects of Order Flow on Exchange Rates, Journal of International Money and Finance, forthcoming.

Brunnermeier, M. K., S. Nagel, and L. H. Pedersen, 2009, Carry Trades and Currency Crashes, in D. Acemoglu, K. Rogoff, and M. Woodford , eds., NBER Macroeconomics Annual 2008. MIT Press, Cambridge, MA, vol. 23, pp. 313–347.

Burnside, C., M. Eichenbaum, and S. Rebelo, 2007, The Returns to Currency Speculation in Emerging Markets, American Economic Review Papers and Proceedings, 97(2), 333–338.

Burnside, C., M. S. Eichenbaum, and S. Rebelo, 2009, Understanding the Forward Premium Puzzle: A Microstructure Approach, American Economic Journal: Macroeconomics, forthcoming.

Cavaglia, S. M. F. G., W. F. C. Verschoor, and C. C. P. Wolff, 1994, On the Biasedness of Forward Foreign Exchange Rates: Irrationality or Risk Premia?, Journal of Business, 67(3), 321–343.

Chinn, M., and J. A. Frankel, 2002, Survey Data on Exchange Rate Expectations: More Currencies, More Horizons, More Tests, in W. Allen, and D. Dickinson , eds., Monetary Policy, Capital Flows and Financial Market Developments in the Era of Financial Globalization: Essays in Honor of Max Fry. Routledge, London.

Chinn, M. D., and M. J. Moore, 2008, Private Information and a Macro Model of Exchange Rates: Evidence from a Novel Data Set, Working Paper 14175, National Bureau of Economic Research.

Cumby, R. E., 1988, Is it Risk? Explaining Deviations from Uncovered Interest Rate Parity, Journal of Monetary Economics, 22(2), 279–300.

Daníelsson, J., and R. Love, 2006, Feedback Trading, International Journal of Finance and Economics, 11(1), 35–53.

Daníelsson, J., J. Luo, and R. Payne, 2002, Exchange Rate Determination and Inter-Market Order Flow Effects, typescript, London School of Economics.

Engel, C., 1996, The Forward Discount Anomaly and the Risk Premium: A Survey of Recent Evidence, Journal of Empirical Finance, 3(2), 123–191.

Evans, M. D. D., and K. K. Lewis, 1995, Do Long-Term Swings in the Dollar Affect Estimates of the Risk Premia?, Review of Financial Studies, 8(3), 709–742.

Evans, M. D. D., and R. K. Lyons, 2002, Order Flow and Exchange Rate Dynamics, Journal of Political Economy, 110(1), 170–180.

——— , 2005, Meese-Rogoff Redux: Micro-Based Exchange-Rate Forecasting, American Economic Review Papers and Proceedings, 95(2), 405–414.

———, 2007, Exchange Rate Fundamentals and Order Flow, Working Paper 13151, National Bureau of Economic Research.

Fama, E. F., 1984, Forward and Spot Exchange Rates, Journal of Monetary Economics, 14, 319–338.

Frankel, J. A., and M. D. Chinn, 1993, Exchange Rate Expectations and the Risk Premium: Tests for a Cross Section of 17 Countries, Review of International Economics, 1(2), 136–144.

Froot, K. A., and J. A. Frankel, 1989, Forward Discount Bias: Is it an Exchange Risk Premium?, Quarterly Journal of Economics, 104(1), 139–161.

Froot, K. A., and T. Ramadorai, 2005, Currency Returns, Intrinsic Value, and Institutional-Investor Flows, Journal of Finance, 60(3), 1535–1566.

Froot, K. A., and R. T. Thaler, 1990, Anomalies: Foreign Exchange, Journal of Economic Perspectives, 4, 179–192.

Galati, G., A. Heath, and P. McGuire, 2007, Evidence on carry trade activity, BIS Quarterly Review, pp. 27–41.

Hodrick, R. J., 1989, Risk, Uncertainty and Exchange Rates, Journal of Monetary Economics, 23, 433–459.

Ilut, C. L., 2009, Ambiguity aversion: implications for the uncovered interest rate parity puzzle, mimeo, Duke University.

Jongen, R., W. F. Verschoor, and C. C. Wolff, 2008, Foreign Exchange Rate Expectations: Survey And Synthesis, Journal of Economic Surveys, 22(1), 140–165.

Jylhä, P., and M. Suominen, 2010, Speculative Capital and Currency Carry Trade, Journal of Financial Economics, forthcoming.

Killeen, W. P., R. K. Lyons, and M. J. Moore, 2006, Fixed versus Flexible: Lessons from EMS Order Flow, Journal of International Money and Finance, 25(4), 551–579.

Lewis, K. K., 1989a, Can Learning Affect Exchange Rate Behavior? The Case of the Dollar in the Early 1980s, Journal of Monetary Economics, 23(1), 79–100.

———, 1989b, Changing Beliefs and Systematic Rational Forecast Errors with Evidence from Foreign Exchange, American Economic Review, 79, 621–636.

——— , 1995, Puzzles in International Financial Markets, in G. M. Grossman, and K. Rogoff , eds., Handbook of International Economics. North Holland, Amsterdam, vol. 3, chap. 37, pp. 1913–71.

Lustig, H., and A. Verdelhan, 2007, The Cross Section of Foreign Currency Risk Premia and Consumption Growth Risk, American Economic Review, 97(1), 89–117.

Lustig, H. N., N. L. Roussanov, and A. Verdelhan, 2009, Common Risk Factors in Currency Markets, typescript, UCLA.

Lyons, R. K., 2001, The Microstructure Approach to Exchange Rates. Mit Press, Cambridge, MA.

Moore, M. J., and M. J. Roche, 2010, Solving Exchange Rate Puzzles with neither Sticky Prices nor Trade Costs, Journal of International Money and Finance, forthcoming.

Payne, R., 2003, Informed Trade in Spot Foreign Exchange Markets: An Empirical Investigation, Journal of International Economics, 61(2), 307–329.

Plantin, G., and H. H. Shin, 2008, Carry Trades and Speculative Dynamics, mimeo, Princeton University.

Ranaldo, A., and A. Sarkar, 2008, Exchange rate risk, transactions costs and the forward bias puzzle, typescript, Swiss National Bank.

Rime, D., L. Sarno, and E. Sojli, 2010, Exchange Rate Forecasting, Order Flow and Macroeconomic Information, Journal of International Economics, 80(1), 72–88.

Sager, M. J., and M. P. Taylor, 2008, Commercially Available Order Flow Data and Exchange Rate Movements: *Caveat Emptor*, Journal of Money, Credit and Banking, 40(4), 583–625.

Sarno, L., and M. P. Taylor, 2002, Economics of Exchange Rates. Cambridge University Press, Cambridge.

Verdelhan, A., 2010, A Habit-Based Explanation of the Exchange Rate Risk Premium, The Journal of Finance, 65, 123–146.

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 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, 2009). 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) Notice that one forecasters consistently only provided one-month forecast.

		EUR/USD	USD/JPY	GBP/USD
	Panel A: One-month horizon			
	Max no.	66	66	65
No. of forecasts	Ave. no.	52.1	51.2	51.0
	Min. no	30	30	30
	Max stdev.	2.9	13.4	2.1
Forecast dispersion	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			
	Max no.	67	67	66
No. of forecasts	Ave. no.	52.5	51.9	51.5
	Min. no	29	29	29
	Max stdev.	4.5	6.9	4.0
Forecast dispersion	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			
	Max no.	66	66	65
No. of forecasts	Ave. no.	52.3	51.7	51.2
	Min. no	29	29	29
	Max stdev.	6.0	14.6	4.9
Forecast dispersion	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			
	Max no.	66	66	65
No. of forecasts	Ave. no.	51.8	51.4	50.7
	Min. no	29	29	29
	Max stdev.	9.0	7.8	5.9
Forecast dispersion	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. 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. t-statistics in brackets. Coefficient values indicated by † are significantly smaller than 1. Sample: Jan 1997 - Apr 2007.

	1 Month	3 Month	6 Month	1 Year
	Panel A: Realized return			
EUR/USD	-4.969†	-4.950†	-5.101†	-5.286†
	(-2.77)	(-3.29)	(-4.46)	(-6.22)
USD/JPY	-1.585	-1.537	-1.748†	-1.794†
	(-0.98)	(-1.04)	(-1.50)	(-2.25)
GBP/USD	-2.561	-2.186	-2.072†	-2.251†
	(-1.36)	(-1.36)	(-1.52)	(-1.96)
	Panel B: Expected return			
EUR/USD	-2.960†	-0.519†	0.423	0.692
	(-1.60)	(-0.77)	(1.00)	(2.00)
USD/JPY	-2.318†	-1.266†	-0.352†	0.004†
	(-1.50)	(-1.57)	(-0.59)	(0.01)
GBP/USD	-0.271	0.309	0.469	0.553
	(-0.13)	(0.44)	(1.11)	(1.73)

Table 4
The Impact of Order Flow on Expected Risk Premia

The Table reports GMM estimates of the coefficient λ_{ep}^{k} in the regression of the expected risk-premium on order flow, $s_{t,e}^{k} - f_{t}^{k} = \alpha_{ep}^{k} + \lambda_{ep}^{k} o_{t,k} + \eta_t$ ($k = 1, 3, 6, 12$ 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 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	1 Year
EUR/USD	0.185	0.221	0.095	0.021
	(0.99)	(2.95)	(2.07)	(0.75)
USD/JPY	0.107	0.176	0.149	0.154
	(1.14)	(4.72)	(3.57)	(5.52)
GBP/USD	0.104	0.237	0.245	0.198
	(0.75)	(2.62)	(5.53)	(3.99)

Table 5
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 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. Sample: Jan 1997 - Apr 2007.

Currency	Horizon	β_o^k	t-stat	adj.R^2
EUR/USD	1	-0.037	-3.68	0.17
	3	-0.039	-4.01	0.21
	6	-0.038	-3.99	0.22
	12	-0.039	-3.63	0.23
USD/JPY	1	-0.047	-2.21	0.05
	3	-0.055	-2.70	0.11
	6	-0.058	-3.07	0.13
	12	-0.064	-4.03	0.21
GBP/USD	1	0.004	0.32	-0.01
	3	0.005	0.43	0.00
	6	0.004	0.41	0.00
	12	0.010	1.34	0.06

Table 6
Decomposition of Fama's Beta

The Table presents the coefficient value of β_o^k (labeled OF) and β_u^k (labeled ExpE) 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 1997 - Apr 2007.

	EUR/USD			USD/JPY			GBP/USD		
	Implied	OF	ExpE	Implied	OF	ExpE	Implied	OF	ExpE
1 Month	-4.96	-3.95	-2.00	-1.93	-3.54	0.61	-1.40†	0.00	-2.40
	[0.99]	(-3.14)	(-2.23)	[0.68]	(-2.68)	(0.57)	[0.41]	(0.00)	(-3.13)
3 Month	-4.85	-2.65	-3.20	-2.30	-2.63	-0.67	-2.03†	-0.41	-2.62
	[0.12]	(-2.55)	(-2.30)	[0.29]	(-2.05)	(-0.40)	[0.34]	(-0.57)	(-1.73)
6 Month	-5.51	-2.82	-3.70	-3.06	-2.62	-1.44	-2.22†	-0.31	-2.91
	[0.13]	(-3.25)	(-2.50)	[0.39]	(-1.98)	(-0.82)	[0.44]	(-0.53)	(-1.74)
1 Year	-6.06	-2.80	-4.26	-3.45	-3.95	-0.50	-2.81	0.37	-4.18
	[0.15]	(-3.45)	(-2.90)	[0.12]	(-3.57)	(-0.35)	[0.24]	(0.93)	(-2.75)

Table 7
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 6.

	EUR/USD		USD/JPY		GBP/USD	
	Forward Bias	OF share	Forward Bias	OF share	Forward Bias	OF share
1 Month	-5.96	0.66	-2.93	1.21	-2.40	0.00
3 Month	-5.85	0.45	-3.30	0.80	-3.03	0.14
6 Month	-6.51	0.43	-4.06	0.65	-3.22	0.10
1 Year	-7.06	0.40	-4.45	0.89	-3.81	-0.10
Mean	-6.34	0.49	-3.68	0.88	-3.12	0.03

Table 8
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, $s_{t+k} - s^k_{t,e} = \alpha^k_{ee} + \beta^k_{ee} fd^k_t + \lambda^k_{ee} o_{t,k} + \varepsilon_{t+k}$ ($k = 1, 3, 6, 12$ 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 brackets. Sample: Jan 1997 - Apr 2007.

	EUR/USD		USD/JPY		GBP/USD	
	FD	OF	FD	OF	FD	OF
1 Month	-2.41	-0.10	-0.11	-0.15	-2.34	0.03
	(-2.62)	(-1.23)	(-0.14)	(-2.43)	(-3.09)	(0.46)
3 Month	-4.86	-0.10	-2.24	-0.35	-2.54	0.28
	(-2.89)	(-0.55)	(-1.85)	(-2.98)	(-2.06)	(1.10)
6 Month	-6.49	-0.20	-4.05	-0.42	-2.53	0.21
	(-3.86)	(-1.06)	(-4.03)	(-6.65)	(-1.96)	(1.15)
1 Year	-5.15	0.20	-3.67	-0.29	-2.04	0.42
	(-3.40)	(1.17)	(-3.99)	(-2.64)	(-1.92)	(1.68)

Table 9
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,

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

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	0.01	0.30	0.61	0.84
	(0.22)	(2.92)	(2.90)	(2.54)
USD/JPY	0.12	1.02	1.59	1.75
	(1.19)	(3.39)	(2.61)	(1.75)
GBP/USD	0.15	0.13	0.25	0.63
	(3.45)	(1.30)	(1.66)	(3.24)

Table 10
Decomposition of Fama's Beta: Alternative Order Flow Definitions

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).

	EUR/USD			USD/JPY			GBP/USD		
	Implied	OF	ExpE	Implied	OF	ExpE	Implied	OF	ExpE
Panel A: Volume indicator									
1 Month	-4.09	-3.19	-1.90	1.18†	-0.36	0.54	-1.44	-0.09	-2.35
	[0.49]	(-2.38)	(-2.20)	[0.03]	(-0.54)	(0.68)	[0.46]	(-0.09)	(-3.05)
3 Month	-5.09	-1.51	-4.58	-1.41	-1.27	-1.14	-2.04†	-0.39	-2.66
	[0.84]	(-2.27)	(-3.62)	[0.18]	(-1.69)	(-0.79)	[0.32]	(-0.58)	(-1.83)
6 Month	-5.65	-0.45	-6.19	-1.80	-1.35	-1.45	-2.13†	-0.21	-2.92
	[0.51]	(-0.47)	(-4.40)	[0.99]	(-1.96)	(-1.09)	[0.34]	(-0.40)	(-1.81)
1 Year	-5.78	-0.21	-6.57	-1.49	-1.57	-0.92	-2.72	0.36	-4.08
	[0.51]	(-0.21)	(-4.64)	[0.37]	(-3.57)	(-0.99)	[0.17]	(0.73)	(-2.62)
Panel B: Dispersion of forecasts									
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
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, $s_{t+k} - s^k_{t,e} = \alpha^k_{ee} + \beta^k_{ee}\, fd^k_t + \lambda^k_{ee}\, o_{t,k} + \varepsilon_{t+k}$ ($k = 1, 3, 6, 12$ 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, 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 brackets. Sample: Jan 2000 – Apr 2007 in Panel A and Jan 1997 – Apr 2007 in Panel B.

	EUR/USD		USD/JPY		GBP/USD	
	FD	OF	FD	OF	FD	OF
Panel A: Volume indicator						
1 Month	-2.00	0.00	-0.34	-0.40	-2.34	0.03
	(-2.18)	(-0.08)	(-0.42)	(-3.29)	(-2.97)	(0.35)
3 Month	-4.35	-0.30	-2.97	-0.69	-2.32	0.46
	(-2.55)	(-1.90)	(-2.65)	(-3.26)	(-1.78)	(1.54)
6 Month	-6.28	-0.49	-4.79	-0.46	-1.65	0.18
	(-4.76)	(-3.74)	(-4.84)	(-1.85)	(-1.35)	(0.84)
1 Year	-5.35	-0.32	-5.75	-0.74	0.24	0.54
	(-3.74)	(-1.71)	(-5.88)	(-6.43)	(0.20)	(1.95)
Panel B: Dispersion of forecasts						
1 Month	-2.58	-0.14	0.81	0.02	-2.32	-0.02
	(-2.75)	(-2.67)	(0.82)	(0.78)	(-2.98)	(-0.50)
3 Month	-4.65	-0.05	-0.33	-0.06	-2.61	0.27
	(-2.93)	(-0.51)	(-0.21)	(-0.94)	(-2.13)	(1.44)
6 Month	-6.01	-0.09	-1.26	0.00	-2.65	0.23
	(-4.05)	(-1.00)	(-0.86)	(-0.20)	(-2.10)	(1.68)
1 Year	-5.64	0.11	-1.56	-0.04	-2.49	0.22
	(-4.47)	(1.08)	(-1.40)	(-0.83)	(-2.29)	(0.69)