Carry Trades, Order Flow and the Forward Bias Puzzle[*]

Francis Breedon

Queen Mary, University of London[†]

Dagfinn Rime

BI Norwegian Business School[‡]

Paolo Vitale

University Gabriele d'Annunzio[§]

October 2015

[†]School of Economics and Finance, Queen Mary, University of London, Mile End Road, London E1 4NS (United Kingdom); telephone: +44-(0)20-7882-8845; webpage: `http://www.econ.qmul.ac.uk`; e-mail: `f.breedon@qmul.ac.uk`.

[‡]Department of Finance, BI Norwegian Business School, Nydalveien 37, N-0484, Oslo (Norway); telephone: +47-46410507; webpage: `http://home.bi.no/dagfinn.rime`; e-mail: `dagfinn.rime@bi.no`.

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

ABSTRACT

We investigate the relation between foreign exchange (FX) order flow and the forward bias. We outline a decomposition of the forward bias according to which a negative correlation between interest rate differentials and order flow creates a time-varying risk premium consistent with that bias. Using ten years of data on FX order flow we find that more than half of the forward bias is accounted for by order flow — with the rest being explained by expectational errors. We also find that carry trading increases currency-crash risk in that order flow generates negative skewness in FX returns.

1   INTRODUCTION

The uncovered interest rate parity (UIP) condition states that, under risk neutrality, the gain from borrowing a low interest rate currency and investing in a higher interest rate one will, in equilibrium, be matched by an equally large expected loss by a depreciation of the high interest rate currency. This condition, combined with the hypothesis of rational expectations, implies that the forward rate should be an unbiased estimator of the corresponding future spot rate. But an extensive empirical literature documents that this is not the case and that high interest rate currencies systematically appreciate when the forward rate implies a depreciation. This is termed the forward bias, and, despite the large range of alternative explanations put forward, there is no general consensus on why this bias persists. Much like the whereabouts of the mythological Phoenix in Metastasio's citation, the forward bias arguably remains an unresolved puzzle.

From a market participants point of view the systematic bias in the forward rate means that an investor that borrows in low interest rate currencies and invests in high interest rate ones has a legitimate hope to profit both from the interest rate differential and the exchange rate variation. Such a strategy is called the carry trade. The following quote

from the Wall Street Journal from May 2007 reveal how market participants view the carry trade: "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."[1] This quotation suggests that market participants believe it is the very activity of carry trading that "lifts" high interest rate currencies, but also realize that there is significant risk of a dramatic reversal connected to carry trading.[2]

In this paper we explore both of these themes. Using data on foreign exchange (FX) order flow,[3] we study how carry trading "lifts" high interest rate currencies but also increases the probability of a dramatic reversal. Furthermore, using data on market participants' forecasts of future currency values, we can decompose the forward bias into one part associated with time-varying risk premia as a function of order flow, and one part associated with forecast errors.

We find that order flow can account for a substantial portion of the forward bias — particularly for currency pairs typically associated with carry trading. The basic idea, from the seminal paper by Evans and Lyons (2002) on the microstructure approach to FX, is that carry trading is a portfolio shift that requires a change in risk premia in order to be willingly accommodated by counterparties. Furthermore, we see that order flow predicts (in sample) shifts in the skewness of FX returns so that carry trading also leads to increased risk of sudden reversals.

Our empirical approach combines the Reuters survey of market participants' forecasts of future currency values and FX transactions data from Electronic Broking Services (EBS), for euro, yen and sterling against US dollars, over a period of ten 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, Burnside, Eichenbaum, and Rebelo (2009),

2

which also applies a microstructure approach to the forward bias puzzle, use indicative bid-ask quotes released by a large FX dealer. In our paper 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. Compared to other studies using data on FX order flow this is the longest data set to date. Compared to 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 order flow and survey forecasts and shows how the forward bias is large and significant and only partially due to forecast errors. Based on these preliminary results, Section 4 decomposes the forward bias into two components, one related to forecast errors, the other to a risk premium that is a function of order flow. In Section 5 we investigate the role of carry trade activity in generating FX order flow and how the carry trade increases the risk of large reversals. In the last Section we offer some final remarks.

2   A BRIEF LITERATURE REVIEW

The Forward Rate Unbiasedness (FRU) condition is a cornerstone in the study of the FX market. This condition states that in a risk-neutral (informationally) efficient market, the gain from borrowing at a low rate in one currency and lending at a high rate in another equals, on average, the loss on the exchange rate. Via the covered interest rate parity condition (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 condition is usually tested by regressing FX returns, $s_{t+1} - s_t$, on the forward

premium, $f_t - s_t$, (the so-called Fama regression) and checking if $\alpha = 0$ and $\beta = 1$,[45] in the linear relation

$$s_{t+1} - s_t = \alpha + \beta (f_t - s_t) + \epsilon_{t+1}. \tag{1}$$

However, in a multitude of studies (Lewis, 1995; Engel, 1996; Burnside, Eichenbaum, and Rebelo, 2009, among others), Fama's β is found to be significantly smaller than 1 and usually negative. The overview article by Froot and Thaler (1990) reports that the average value of the coefficient β across 75 published estimates is -0.88.

Although most studies have focussed on the role of time-varying risk premia in explaining this result, some of the strongest results on the forward premium puzzle have come from the analysis of market expectations derived from survey data. In an early contribution, Froot and Frankel (1989) estimated the contribution of forecast errors on Fama's β 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 (Frankel and Chinn, 1993; Chinn and Frankel, 2002; Cavaglia, Verschoor, and Wolff, 1994; Bacchetta, Mertens, and van Wincoop, 2008; Chinn, 2011) who have considered alternative survey data, covering longer periods and more currency pairs. For example, Bacchetta, Mertens, and van Wincoop (2008) employ monthly surveys of 3-, 6- and 12-month forecasts for seven exchange rates over the period between August 1986 and July 2005. The estimated contribution from forecast errors to the coefficient β ranges from -3.62 to -0.76 across the seven exchange rates and the three horizons.

Although systematic forecast errors may seem irrational, several mechanisms have been suggested in the literature. Lewis (1989a,b), Evans and Lewis (1995) and Burnside, Eichenbaum, and Rebelo (2011) study how learning or a peso problem can create forecast errors. Furthermore, slow reaction to news, through either ambiguity aversion (Ilut,

4

2012) or infrequent portfolio adjustments, induced by rational inattention combined with random walk expectations (Bacchetta and van Wincoop, 2010), may also generate forecast errors and a negative Fama's β. Importantly, the majority of these studies find that even after using survey data on expectations to control for forecast errors, there is still a significant deviation from the UIP condition, indicating a role for time-varying risk premia (Jongen, Verschoor, and Wolff, 2008).

If perfect capital substitutability does *not* hold, a risk premium enters into the uncovered interest rate relation. If this risk premium is *time-varying*, and *negatively* correlated with the forward premium, then the Fama-regression has a missing variable bias and the β can turn out to be smaller than 1. Investigating such a risk premium has been a very active 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 β in the Fama regression. Lustig and Verdelhan (2007) find a role for consumption risk, whilst Bansal and Shaliastovich (2013), Verdelhan (2010), and Moore and Roche (2010) all have some success explaining the puzzle with either recursive (Epstein-Zin) preferences (Bansal and Shaliastovich, 2013) or habit-based (Campbell-Cochrane) preferences (Verdelhan, 2010; Moore and Roche, 2010).

Given that the empirical evidence suggests that the β coefficient in the Fama regression typically is significantly smaller than zero, an investment that borrows in low interest rate currencies and invests in high interest rate ones (carry trade) should on average generate positive returns. In fact, a number of recent empirical studies document the profitability of the carry trade (see Galati, Heath, and McGuire, 2007; Burnside, Eichenbaum, and Rebelo, 2007, 2009, 2011; Jylhä and Suominen, 2011; Lustig, Roussanov, and Verdelhan, 2011).

The literature on the asset pricing approach to foreign exchange has suggested various risk factors that can account for the cross-section of carry trade returns. In a pioneering work, Lustig, Roussanov, and Verdelhan (2011) construct a global carry portfolio whose return accounts for most of the cross sectional variation in carry portfolios, while Menkhoff, Schmeling, Sarno, and Schrimpf (2012) find that a global FX volatility risk factor can explain the cross-section of returns of carry portfolios. Interestingly, Menkhoff et al. (2012) find that high interest rate currencies are shown to be negatively related to such risk factor and to yield low returns during periods of increased uncertainty.[6] In a recent survey, Burnside (2012) considers several alternative risk factors and argues that the most successful one in explaining carry trade returns is associated with currency skewness.

Currency skewness is an important risk factor in that it captures that carry trade is subject to reversal risk as indicated by Breedon (2001) and Brunnermeier, Nagel, and Pedersen (2009). According to Brunnermeier, Nagel, and Pedersen (2009) carry trade activity drives exchange rate dynamics till market liquidity dries up and a currency crash ensues. In other words, carry trade activity generates the risk of a currency crash that justifies the positive returns it gains on average. Jurek (2007) provides confirmation of this thesis, as he shows that returns from a crash neutral carry trade strategy are statistically not different from zero.

The recent microstructure approach to exchange rates (see *inter alia* Evans and Lyons, 2002; Payne, 2003; Bjönnes and Rime, 2005; Danìelsson and Love, 2006; Killeen, Lyons, and Moore, 2006; Berger, Chaboud, Chernenko, Howorka, and Wright, 2008) suggests that the key variable in studying exchange rate dynamics is the so called order flow, i.e. the net initiated buying pressure of a currency. As argued by Breedon and Ranaldo (2013) and Breedon and Vitale (2010), order flow affects the FX risk premium through a

portfolio-balance effect, so that this new strand of research can also be used to shed light on the forward bias and the profitability of carry trade.

Burnside, Eichenbaum, and Rebelo (2007) apply a microstructure framework whereby the forward bias arises through adverse selection mechanisms, while Mancini, Ranaldo, and Wrampelmeyer (2013) and Jylhä and Suominen (2011) also find a role for illiquidity in explaining the puzzle.

Our study follows this line of research, as we aim to measure the time-varying risk premium directly using data on order flow in FX markets. The intuition is that order flow can be thought of as a portfolio shift, and with risk averse market participants this gives rise to changes in the risk premia in order for the portfolio shift to be willingly accomodated. Our approach to identifying factors influencing the risk premium can be seen as a complement to the asset pricing approaches pursued by e.g. Menkhoff, Schmeling, Sarno, and Schrimpf (2012) and Lustig, Roussanov, and Verdelhan (2011).

3 DATA AND PRELIMINARY ANALYSIS

3.1 The Data

This study employs two unique data sets to explore the link between expectations, risk premia and order flow. The first is a detailed transactions data set from EBS, created on a one-second timeslice basis, covering the period from the beginning of 1997 to April 2007 for trading in euro (Deutsche mark prior to 1999), yen and pound against the US dollar (i.e., the USD/EUR, USD/JPY, and USD/GBP exchange rates).[7] For USD/EUR and USD/JPY we estimate that EBS covers close to half of all spot transactions, though for USD/GBP its coverage is poor (less than 5%). To our knowledge this is the longest data set of order flow from the foreign exchange market to date.

Although our EBS data represents a significant share of total order flow over an extended sample period it has the possible drawback that it is dominated by inter-dealer trading rather than trading between dealers and customers. However, the so-called "hot-potato" trading described in Lyons (1997), where inter-dealer order flow is generated by laying off customer trades short after they occur, would suggest that the two types of order flow would be closely related. However, *if* the laying-off process was accomplished using aggressive limit orders, instead of market orders, we would have a reversed picture of the initiation of trades in the inter-dealer transactions compared to the customer transactions (since the counterparty that places the market order is designated as the trade initiator). Nonetheless, we believe that this is not a problem for the following reasons: First, Björnnes and Rime (2005) find that dealers indeed use market orders after having large imbalances in their inventory. Second, Table B.1 shows that, in the case of USD/EUR and USD/JPY, there is a strong correlation between EBS order flow and customer order flow received by a representative market maker.[8]

The second dataset is a detailed monthly 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 the same exchange rates at the 1-, 3-, 6- and 12-month horizon. 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. 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 forecasts for 1, 3, 6 and 12 months ahead, 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, and the contributors thus have a strong incentive to take the survey seriously.[9]

In addition, we also have data on interest rates and (at-the-money-forward) implied volatilities for the same horizons as the forecasts. We construct monthly data (the frequency of the survey forecasts) by measuring all market values (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 monthly observations.

3.2 The Forward Bias

The starting point for almost all studies of the forward bias is Fama's forward premium regression. In Panel A of Table 1 we show OLS estimates of Fama style regressions on monthly observations of spot returns on forward premia for four different horizons (1 month, 3 months, 6 months and one year) for USD/EUR, USD/JPY, and USD/GBP,[10]

$$s_{t+1} - s_t \;\; = \;\; \alpha \; + \; \beta \left(f_t \, - \, s_t \right) \; + \; \epsilon_{t+1} \, ,$$

where f_t and s_t is the log forward and spot rate, respectively.

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 FRU.

This result is also consistent with the existence of profitable carry trades where purchasing high interest rate currencies and selling low interest rate ones generates excess returns on average.

[Table 1 about here.]

In Panel B, we follow Froot and Frankel (1989) and report results from similar regressions using the expected return, $s_{t,e} - s_t$, constructed from the Reuters survey ($s_{t,e}$ is the median value in month t of the, e.g., 1-month ahead exchange rate forecasts contained in the Reuters survey), as dependent variable. 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 premium is partially 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 USD/EUR and USD/JPY exchange rates, are significantly so. This suggests that part of the forward bias is not explained by forecast errors, leaving room for an expected risk premium.[11]

4   A MICROSTRUCTURE-BASED DECOMPOSITION OF THE FORWARD BIAS

The deviation of the β-coefficient in the Fama regression from unity can be due to violations of the key assumptions underlying the FRU condition, namely risk neutrality and rational expectations. This may lead to a omitted variable bias in the Fama regression. If these omitted variables are negatively correlated with the forward premium then the estimates of β from the Fama regression will be lower than unity. This is the key idea behind the suggestion by Froot and Frankel (1989) to decompose the β-coefficient into

it's hypothesized value of 1 and deviations caused by the existence of risk premia and forecast errors that are correlated with the forward premium.

To fix ideas, say the US is the domestic economy and Japan is the foreign economy, and let the spot exchange rate measure the JPY needed to buy 1 US dollar (USD is base currency). Then, the log excess return on holding US dollar is given by $er_{t+1} = s_{t+1} - s_t - (i_t - i_t^*)$, where i and i^* are Japanese and US (here, one-period) nominal interest rates. The FX risk premium is then defined as the expected excess return, $\rho_t = E_t[er_{t+1}]$, where the expectation is conditioned on period t information. Hence, we have

$$E_t\left[s_{t+1}\right] - s_t = (i_t - i_t^*) + \rho_t. \tag{2}$$

Considering the definition of forecast error, $u_{t+1} = s_{t+1} - E_t\left[s_{t+1}\right]$, and using the CIP condition, $(i_t - i_t^*) = f_t - s_t$, we get

$$\Delta s_{t+1} = (f_t - s_t) + \rho_t + u_{t+1}. \tag{3}$$

Thus, as suggested by Froot and Frankel (1989), the β-coefficient in the Fama regression, $\Delta s_{t+1} = \alpha + \beta(f_t - s_t) + \epsilon_{t+1}$, differs from 1 if the forward premium is correlated either with the forecast error, u_{t+1}, or the risk premium ρ_t.

Unfortunately, until recently it has proven difficult to find variables that enable us to measure directly FX risk premia and estimate in any satisfactory way their contribution to the forward bias. However, the recent microstructure approach to exchange rates suggests that FX risk premia can be related to the trading process in the inter-dealer FX market. This idea is derived from inventory models developed in the 1970s and 1980s within the market microstructure theory literature. Stoll (1978) and Ho and Stoll (1981, 1983), among others, formulate models of dealership markets where the transaction price

differs from the expected liquidation value of the traded asset by a time-varying risk compensation imposed by risk-averse dealers to cover their inventory costs. Importantly, in all these models this risk compensation is shown to increase with the dealers' risk aversion, the size of their transactions, and the asset's variance.

In a similar vein, Lyons (1997), Evans and Lyons (1999), Killeen, Lyons, and Moore (2006) and Breedon and Vitale (2010) formulate market microstructure models of the FX market where order flow affects currency values via a portfolio-balance effect. In particular, in the portfolio-shift model of Evans and Lyons, since a shock to order flow must be willingly held, a risk premium on the base currency emerges to compensate investors for the extra risk they are forced to absorb.

In these market microstructure models it is shown that the FX risk premium, ρ_t, is an increasing function of inter-dealer order flow and the conditional variance of the future spot rate. Importantly, in such models these two factors enter *multiplicatively* into the FX risk premium, ρ_t. The intuition is as follows: First, if there is no uncertainty about the future spot rate, the foreign currency is not a risky asset and FX investors can absorb all FX order flow without the need to impose a risk premium. As uncertainty about future spot rates increases, the compensation needed to accept the risk in a portfolio shift of a given size also increases. Second, if there is no order flow imbalance, FX investors do not bear any risk and hence a risk premium is not required. As the imbalance increases, the compensation needed to induce investors to willingly hold the imbalance also increases.

Accordingly, in these market-microstructure-based models the UIP must be modified as follows

$$E_t\left[\,s_{t+1}\,\right] - s_t = (i_t - i_t^*) + \breve{o}_t\,, \tag{4}$$

12

where $\check{o}_t$ is the modified order flow variable, $\check{o}_t = \sigma_t^2 \cdot o_t$. Thus, the expected devaluation of the domestic currency in period t, $E_t \left[s_{t+1} \right] - s_t$, is equal to the sum of the interest rate differential, $(i_t - i_t^*)$, plus a *time-varying* risk premium. This time-varying risk premium, consistently with the models above, is given by the product of the inter-dealer order flow, o_t, and the conditional uncertainty over next period spot rate, σ_t^2.

Combining the modified UIP in (4) with the definition of the forecast error u_{t+1} and the CIP, it can be shown that the following decomposition of Fama's β applies,

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

$$\beta_o \;=\; \frac{\text{cov}\left(\check{o}_t, f_t - s_t\right)}{\text{var}(f_t - s_t)} \quad \text{and} \quad \beta_u \;=\; \frac{\text{cov}\left(u_{t+1}, f_t - s_t\right)}{\text{var}(f_t - s_t)}.$$

While analogous to the decomposition of Fama's β provided by Froot and Frankel (1989), ours gives more substance to the interpretation of the time-varying risk premium, which is now a function of order flow, o_t, and the conditional variance σ_t^2. Thus, unlike traditional attempts to explain the forward bias via the portfolio-balance approach, we use transaction data to measure directly deviations from the UIP condition due to the risk premium and pin down their impact on Fama's β.

4.1   Decomposing Fama's Beta

With our transaction and forecast data we can estimate the contribution from risk premia — the coefficient β_o — and forecast errors — the coefficient β_u — on Fama's β (see equation (5)). The coefficient β_o can be estimated by running a linear regression of a modified order flow variable, $\check{o}_t$, on the forward premium, $f_t - s_t$, which allows us to

identify the relation between the risk premium generated by the flow of orders and the forward premium. Similarly, recalling that $s_{t,e}$ denotes the median value of the survey expectations for period $t + 1$ exchange rate formulated at time t, β_u can be estimated by regressing the forecast error, $s_{t+1} - s_{t,e}$, on the forward premium. We estimate these jointly in the following system,

$$s_{t+1} - s_t \quad = \quad \alpha \ + \ (1 + \beta_o + \beta_u)\,(f_t - s_t) \ + \ \epsilon_{t+1}, \tag{5}$$

$$\check{o}_t \quad = \quad \alpha_o \ + \ \beta_o\,(f_t - s_t) \ + \ \epsilon_t^o, \tag{6}$$

$$s_{t+1} - s_{t,e} \quad = \quad \alpha_u \ + \ \beta_u\,(f_t - s_t) \ + \ \epsilon_{t+1}^u. \tag{7}$$

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 matching the maturity, i.e., $(t-1, t)$ in case of a 1-month contract.[12] As a proxy for the conditional variance that enters in the modified order flow we employ the implied volatility from FX options of the appropriate maturity observed at the beginning of period $t - 1$ (for the case of a 1-month contract), divided by its mean value over the entire sample (i.e., $\check{o}_t = o_t \cdot \frac{\sigma_t^2}{avg(\sigma_t^2)}$).[13,14]

[Table 2 about here.]

From the system (5) to (7) we obtain the six orthogonality conditions (that the residuals in the three equations are uncorrelated with the forward discount and possess zero mean) and five coefficients α, α_o, α_u, β_o and β_u. We thus estimate the system using GMM that allows us to exploit the over-identification of the system (5) to (7) which results from our decomposition's of Fama's beta. The results from such GMM estimation are presented in Table 2. The Table reports for USD/EUR, USD/JPY and USD/GBP the estimated

values for the forecast error and the order flow coefficients, β_u and β_o, alongside the implied Fama β-coefficient, $1 + \beta_o + \beta_u$, and in parentheses the corresponding t-statistics. Separate columns present the J-statistics for the test on the over-identifying orthogonality conditions and in squared brackets the corresponding p-values. Because we have one over-identifying restriction that $\beta = 1 + \beta_o + \beta_u$, the J-statistics indicates whether the restriction is accepted. The values reported in Table 2 for the J-statistic show that this restriction is never rejected, confirming the validity of our decomposition of Fama's β and suggesting that we capture a significant share of the bias. In addition, the estimated values for the forecast error and the order flow coefficients, β_u and β_o, reveal the following: on the one hand, the forecast errors contribute significantly to a negative bias in the forward premium for USD/EUR and USD/GBP, but not for USD/JPY. On the other hand, order flow contributes significantly to a negative bias for USD/EUR and USD/JPY, but not for USD/GBP.[15]

Indeed, taking average values of the coefficients across the four horizons, we see that for USD/EUR modified order flow explains roughly half of the deviation of β from 1, i.e. half of the forward bias, while the other half is explained by the forecast error (see Table 3). For USD/JPY nearly all the bias is explained by modified order flow. By contrast, for USD/GBP the proportion explained by modified order flow is about 20%. The results for USD/GBP may well reflect the fact that EBS has a very small market share for that cross (see Table B.1 in the Web Appendix) so that our transaction data are not representative. In addition, one should notice that even in other studies, notably Bacchetta, Mertens, and van Wincoop (2008), the contribution of the forecast errors to the forward bias is found to differ across currency pairs. Finally, as we present below, GBP appears to be the least carry trade-like currency among these three.

[Table 3 about here.]

Pre-multiplying inter-dealer order flow by the conditional variance of the spot rate to derive our measure of the time-varying risk premium is justified by the theoretical underpinning discussed in Section 4. However, it may be that the contribution of the modified order flow variable, $\breve{o}_t$, in explaining the forward bias is mostly due to the volatility measure, σ_t^2. In the Web Appendix, Table C.2, we estimate a modified version of the system (5) to (7) where order flow and volatility are kept distinct and where their individual impact on the forward bias is identified. Results of such an exercise suggest that the decomposition of Fama's β still holds and that raw order flow explains a significant part of the forward bias.

5 CARRY TRADES AND THE FORWARD BIAS

5.1 Carry Trades and the Decomposition

A key element of the decomposition presented in Table 2 is the relation between order flow and the forward premium (equation (6)), in that it links the forward premium to the time-varying risk premium via order flow imbalance. This relation has a natural interpretation as carry trade activity where trading is motivated by interest rate differentials. Recent literature (see Burnside, 2012, for an overview) suggests that in several FX markets a significant element of trading activity is motivated by carry, and in line with this literature Table 2 indicates that a negative forward premium, hence a higher US interest rate than the foreign one, goes together with a buying pressure for USD.

However, the results in Table 2 are only suggestive, as our decomposition requires a correlation between $f_t - s_t$ and $\breve{o}_t$ whilst the carry trading activity that might generate $\breve{o}_t$ should, in principle, be stimulated by $f_{t-1} - s_{t-1}$ (since $f_t - s_t$ is not observed until the end of period t). Hence, in order to interpret the relation in Table 2 as carry trading we

16

need significant positive autocorrelation in the forward premium. We elaborate on this below.

The following example shows how carry trading may imply a negative covariance between order flow and the forward premium. Let's assume that the US dollar yields more than the yen. Due to CIP this corresponds to a negative forward premium in the USD/JPY market. A negative forward premium in the USD/JPY market at time $t-1$, $f_{t-1} - s_{t-1} < 0$, generates positive order flow, $o_t > 0$, in the interval of time $(t-1, t)$, as carry traders expect positive profits from a long dollar– short yen strategy and sell the Japanese currency for the American one. We can illustrate this by assuming that in the presence of carry trading order flow is given by

$$o_t = -\mu \left(f_{t-1} - s_{t-1} \right) + n_t, \tag{8}$$

where μ is a positive constant which measures the intensity of carry trading while n_t is an autonomous component not related to the forward premium. As monetary policy is sticky and interest rate differentials present substantial inertia, we can assume that the forward premium follows an AR(1) process,[16] so that

$$(f_t - s_t) = (1/\theta)(f_{t-1} - s_{t-1}) + \epsilon_t^f,$$

where $\theta > 1$ and ϵ_t^f is a white noise process. Given that $\check{o}_t = o_t \cdot \sigma_t^2$, we immediately see that for σ_t^2 time-invariant, we get

$$\beta_o = \frac{\text{cov}\left(\check{o}_t, f_t - s_t \right)}{\text{var}(f_t - s_t)} = -\theta \mu \sigma^2,$$

17

so that carry trading implies that within our decomposition β_o takes a negative value and hence that Fama's β is smaller than 1. This result shows that even *if* FX dealers were rational, so that $\beta_u = 0$, Fama's β would be smaller than 1 since

$$\beta \;\; = \;\; 1 \;\; - \;\; \theta\mu\sigma^2\,.$$

Moreover, if carry trade activity were particularly intensive, i.e. if μ were large, β could actually take a negative value, as found in many empirical studies on the forward premium bias. The value for β_o reported in Table 2 for the USD/EUR and USD/JPY rates shows that the contribution of carry trade to the forward bias is large.[17]

Results for USD/GBP give a different picture. The coefficient β_o is neither negative nor significant, indicating that carry trading does not generate much order flow in this market. There are two main explanations for the weak results obtained for the USD/GBP rate. First, as discussed above, EBS is not the dominant electronic trading platform for this cross and our order flow measure is thus significantly less representative in this case. Second, USD/GBP is usually not considered a carry trading cross.

To summarize whether carry trading generates a significant component of order flow in the USD/EUR, USD/JPY and USD/GBP markets in Table 4 we report the results of linear regressions of modified order flow (Panel A) or raw order flow (Panel B) on the (lagged) forward premium,

$$o_t \;\; = \;\; \alpha_o \;+\; \beta_o\left(f_{t-1} - s_{t-1}\right) \;+\; \epsilon_t^o\,. \tag{9}$$

As for the USD/EUR and USD/JPY crosses the slope coefficients are negative for all horizons and significantly so in almost all cases. The corresponding R^2-values range from 0.01 to 0.27, hence the forward premium generates a significant component of order flow

in these two markets. On the contrary, for the USD/GBP rate the slope coefficients are not significant and the R^2-values are negligible, confirming our claim that this is not a carry trade cross.[18] As a result, we drop USD/GBP from the rest of our analysis.

[Table 4 about here.]

Further evidence of carry trading activity in the USD/EUR and USD/JPY crosses is presented in Panel B of Table 1. In a Fama-regression using expected return from our survey forecasts, the slope coefficient β_{er} on the forward premium is less than one, suggesting that the forecasters in our survey have expectations about spot movements that is consistent with carry trading being attractive. This is particularly evident for the yen, and clearly less the case for sterling.

Interestingly, the results presented in Table 2 and the further evidence of carry trade activity in both USD/EUR and USD/JPY shown above are consistent with Plantin and Shin's (2012) thesis 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 currency they drive down the value of the former and drive up that of the latter, so that their expectations are fulfilled. This happens because in Plantin and Shin's model order flow 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.

5.2 Carry Trade Activity and Currency Crash Risk

Carry trade profitability is popularly said to go "up the stairs and down by the lift". Brunnermeier, Nagel, and Pedersen (2009) argue that carry trading is subject to crash

risk, in that movements in currency returns consistent with carry trade profitability may suddenly change direction and entail large losses for carry trading positions.

In our sample, USD/EUR and USD/JPY daily returns display pronounced negative skewness. This reflects the fact that the dollar is generally the investment currency in the carry trade strategy whereas the euro and yen are funding currencies. Sudden reversals, i.e. currency "crashes", then show up as a pronounced negative skewness in the returns of USD/EUR and 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 flow of orders 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 order flow data (based on CFTC FX futures positions) is problematic.

A way to test their empirical implication using our data on FX transactions consists of regressing the skewness of FX returns on lagged order flow. In particular, if carry trading increases currency crash risk, then, as speculators accumulate dollars vis-à-vis the euro and the yen (as traders purchase more dollar than they sell against euro and yen) this should translate into a larger probability of negative skewness for the corresponding dollar return. Therefore, regressing the skewness of the FX returns on modified order flow should yield a significantly negative slope coefficient for both the USD/JPY and USD/EUR crosses. In order to compare our results with those of Brunnermeier, Nagel, and Pedersen (2009), we also include the forward premium and the implied volatility as controls.

[Table 5 about here.]

In Table 5 we report the results of the following regression,

$$\zeta_t \quad = \quad \alpha_s \, + \, \gamma_s \, \breve{o}_{t-1} \, + \, \beta_s \, (f_{t-1} - s_{t-1}) \, + \, \delta_s \, ImpVol_{t-1} \, + \, \epsilon_t^s \, , \qquad (10)$$

where ζ_t is the realized skewness of daily FX returns in the period $(t-1, t)$ and $ImpVol_{t-1}$ is the implied volatility in $t - 1$. The coefficient on modified order flow is correctly (negatively) signed and significant for all horizons except the 1- and 3-month horizons for USD/JPY. The forward premium is correctly signed for both exchange rates (in the sense that a high US interest rate, i.e. a positive carry and a negative forward premium, is a predictor of currency crashes), but significant only for USD/JPY. Interestingly, we find a significant relation between implied volatility and skewness at the 3-month horizon for USD/EUR and at the 6-month horizon and above for USD/JPY.[19] 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* relation between volatility and skewness, while we undertake a predictive regression. Furthermore, our result is consistent with that the carry trade typically is more attractive at lower levels of volatility. It is intriguing to note that for both USD/EUR and USD/JPY 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 USD/EUR and USD/JPY 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 bias and to the market microstructure approach to FX markets. Our study contributes to both by applying the insights of the microstructure literature to the forward bias puzzle. We find evidence, particularly strong for the USD/EUR and USD/JPY crosses, that order flow is related to the forward premium (probably via carry trade activity) and that this order flow affects expected risk premia that condition realized returns. This indicates that microstructural mechanisms contribute to the forward premium puzzle. Thus, according to our decomposition of Fama's β, the portfolio-balance effect of order flow explains roughly 50 percent of the forward bias for the USD/EUR rate, 90 percent for the USD/JPY rate but only about 20 percent for USD/GBP, with the remainder being explained by expectational errors.

Finally, we see that carry trading activity does not represent a *free lunch*, in that the positive profits it is expected to gain are offset, to some extent, by the currency crash risk it provokes.

APPENDIX

[Table Descriptive Statistics here.   ]

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.

Andrews, D.W.K. (1991) "Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation", *Econometrica*, 59, 817–858.

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, 406–426.

Bacchetta, P., and E. van Wincoop. (2010) "Infrequent Portfolio Decisions: A Solution to the Forward Discount Puzzle", *American Economic Review*, 100, 870–904.

Bansal, R., and I. Shaliastovich. (2013) "A Long-Run Risks Explanation of Predictability Puzzles in Bond and Currency Markets", *Review of Financial Studies*, 26, 1–33.

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, 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, 93–109.

Björnnes, G.H. and D. Rime. (2005) "Dealer Behavior and Trading Systems in Foreign Exchange Markets", *Journal of Financial Economics*, 75, 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. (2013) "Intraday Patterns in FX Returns and Order Flow", *Journal of Money, Credit and Banking*, 45, 953–965.

Breedon, F., and P. Vitale. (2010) "An Empirical Study of Portfolio-balance and Information Effects of Order Flow on Exchange Rates", *Journal of International Money and Finance*, 29, 504–524.

Brunnermeier, M.K., S. Nagel, and L.H. Pedersen. (2009) "Carry Trades and Currency Crashes", in *NBER Macroeconomics Annual 2008* edited by D. Acemoglu, K. Rogoff, and M. Woodford, pp. 313347. Cambridge, MA: MIT Press.

Burnside, C. (2012) "Carry Trades and Risk", in *The Handbook of Exchange Rates* edited by J. James, I. W. Marsh, and L. Sarno, pp. 283–312. New York: Wiley.

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

Burnside, C., M.S. Eichenbaum, and S. Rebelo. (2009) "Understanding the Forward Premium Puzzle: A Microstructure Approach", *American Economic Journal: Macroeconomics*, 1, 127–154.

———— (2011) "Carry Trade and Momentum in Currency Markets", *Annual Review of Financial Economics*, 3, 511–535.

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, 321–343.

Chinn, M. (2011) "(Almost) A Quarter Century of Currency Expectations Data: Interest Rate Parity and the Risk Premium", Manuscript, University of Wisconsin, Madison.

Chinn, M., and J.A. Frankel. (2002) "Survey Data on Exchange Rate Expectations: More Currencies, More Horizons, More Tests", in *Monetary Policy, Capital Flows and Financial Market Developments in the Era of Financial Globalization: Essays in Honor of Max Fry*, edited by W. Allen, and D. Dickinson, pp. 145–167. London: Routledge.

Christiansen, C., A. Ranaldo, and P. Söderlind. (2011) "The Time-Varying Systematic Risk of Carry Trade Strategies", *Journal of Financial and Quantitative Analysis*, 46, 1107–1125.

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

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

Engel, C. (1996) "The Forward Discount Anomaly and the Risk Premium: A Survey of Recent Evidence", *Journal of Empirical Finance*, 3, 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, 709–742.

Evans, M.D.D., and R.K. Lyons. (1999) "Order Flow and Exchange Rate Dynamics", NBER Working Paper 7317.

——— (2002) "Order Flow and Exchange Rate Dynamics", *Journal of Political Economy*, 110, 170–180.

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, 136–144.

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

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*, 27–41.

Ho, T., and H.R. Stoll. (1981) "Optimal Dealer Pricing Under Transactions and Return Uncertainty", *Journal of Financial Economics*, 9, 47–73.

——— (1983) "The Dynamics of Dealer Markets Under Competition", *Journal of Finance*, 38, 1053–1074.

Hodrick, R.J., 1989, Risk, Uncertainty and Exchange Rates, Journal of Monetary Economics, 23, 433459.

Ilut, C. (2012) "Ambiguity Aversion: Implications for the Uncovered Interest Rate Parity Puzzle", *American Economic Journal: Macroeconomics*, 4, 33–65.

Ito, T. (1990) "Foreign Exchange Rate Expectations: Micro Survey Data", *American Economic Review*, 80, 434–449.

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

Jurek, J. W. (2007) "Crash-Neutral Currency Carry Trades", Manuscript, Princeton University.

Jylhä, P., and M. Suominen. (2011) "Speculative Capital and Currency Carry Trade", *Journal of Financial Economics*, 99, 60–75.

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, 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, 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 *Handbook of International Economics*, edited by G.M. Grossman, and K. Rogoff, pp. 19131971. Amsterdam: North Holland.

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

Lustig, H.N., N.L. Roussanov, and A. Verdelhan. (2011), "Common Risk Factors in Currency Markets", *Review of Financial Studies*, 24, 3731–3777.

Lyons, R.K. (1997) "A Simultaneous Trade Model of the Foreign Exchange Hot Potato", *Journal of International Economics*, 42, 275–298.

——— (2001) *The Microstructure Approach to Exchange Rates*. Cambridge, MA: MIT Press.

Mancini, L., A. Ranaldo, and J. Wrampelmeyer. (2013) "Liquidity in the Foreign Exchange Market: Measurement, Commonality, and Risk Premiums", *Journal of Finance*, 68, 1805–1841.

Menkhoff, L., M. Schmeling, L. Sarno, and A. Schrimpf. (2012) "Carry Trades and Global Foreign Exchange Volatility", *Journal of Finance*, 67, 681–718.

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*, 29, 1151–1170.

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

Plantin, G., and H.H. Shin. (2012) "Carry Trades, Monetary Policy and Speculative Dynamics". Manuscript, Princeton University.

Stoll, H.R. (1978) "The Supply of Dealer Services in Securities Markets", *Journal of Finance*, 33, 1133–1151.

Tryon, R. (1979) "Testing for Rational Expectations in Foreign Exchange Markets", International Finance Discussion Papers 139, Board of Governors of the Federal Reserve System.

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

[1] From "Carry Trade Prompts Warnings" Wall Street Journal, 18 May 2007.

[2] It is well known that exchange rate changes can wipe out the gains from a positive interest rate differential. Indeed, carry trading profits are known to go "up by the stairs and down by the lift."

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

[4] The CIP condition states that $f_t - s_t = (i_t - i_t^*)$ where i and i^* denote domestic and foreign interest rates (for the same length as the forward contract). Akram, Rime, and Sarno (2008) show that the CIP condition holds for the purposes of this paper. There were signs of violations of the CIP during the financial crisis. Our data do however end in April 2007, well before the disruptions in the FX forward market.

[5] This regression also appeared in a paper by Tryon as early as 1979.

[6] Christiansen, Ranaldo, and Söderlind (2011) find qualitatively similar results using a regime-switching time-series approach.

[7] For convenience we use the USD as a base currency. This implies that an increase in s_t corresponds to an increase in the value of the US dollar vis-à-vis the foreign currency. Similarly, a positive order flow measures a buying pressure for USD.

[8] Berger, Chaboud, Chernenko, Howorka, and Wright (2008) present similar arguments.

[9] See the Appendix for some descriptive statistics. Additional descriptive statistics and graphs are available in the Web Appendix.

[10] All results in this paper are based on robust standard errors derived using Andrews' data-based bandwith selection method (Andrews, 1991) and a Bartlett kernel. All regressions presented in the text use a 1-month horizon as an example. As explained below, leads and lags (where appropriate) are chosen to match the horizon of the contract analyzed.

[11]Indeed, most other studies of survey data find that in most cases the hypothesis of perfect substitutability (i.e. the restriction $\alpha = 0$ and $\beta = 1$ in the regression of $s_{t,e} - s_t$ on $f_t - s_t$) is violated. In particular see Cavaglia, Verschoor, and Wolff (1994) and more recently Chinn (2011).

[12]For the 3-month horizon we aggregate order flow over $(t - 3, t)$, etc. This framework is obviously quite restrictive, but it captures in a parsimonious way the idea that in order to have a longer- horizon forecast one needs a longer-horizon tendency in order flow.

[13]Normalizing the conditional variance by its mean allows to directly compare the estimated coefficients in our regressions with those obtained using raw order flow in lieu of modified order flow.

[14]As an alternative estimate we consider the conditional variance of the next period exchange rate forecasts collected by Reuters at the beginning of period $t - 1$ in case of 1-month contract. These results are discussed in the Web Appendix, the variance-measure is observed at the beginning of the period for aggregation of order flow.

[15]In Table C.4 of the Web Appendix we present OLS estimates of the three separate equations together with a Wald test of the implied coefficient $1 + \beta_o + \beta_u$ against the unrestricted estimate of β. Results are very similar at short horizons though we do get some rejections at the longer horizons.

[16]Simple graphical analysis shows that in our dataset the interest rate differentials indeed are positively serially correlated.

[17]Since β_o is based on the correlation between $f_t - s_t$ and $\breve{o}_t$ which itself relies on both these variables being driven by $f_{t-1} - s_{t-1}$, the Web Appendix offers alternative specifications of our decomposition using $f_{t-1} - s_{t-1}$ as an instrument for $f_t - s_t$ and using $f_{t-1} - s_{t-1}$ directly. The results reported in Table C.3 are similar to those shown in Table 2.

[18]The extent to which a currency is a "carry"-currency or not can be seen from its position in portfolio-formation based on forward premium, as in Lustig, Roussanov, and Verdelhan (2011). Using their approach we find that over our sample period sterling is rarely in either funding or investment portfolios, while the yen (in particular) and the euro are often in such portfolios (typically the funding portfolios). This analysis is available upon request.

[19]Similar results are obtained when using raw order flow in lieu of modified order flow.

Table 1
Fama Regression: Monthly Data

Panel A presents OLS estimates of β^k from the regression

$$s_{t+k} - s_t = \alpha^k + \beta^k (f_t^k - s_t) + \epsilon_{t+k},$$

(equation (1) in the text) where $s_{t+k} - s_t$ is the spot return over the next k months, $f_t^k - s_t$ is the corresponding forward premium, while f_t^k and s_t are the log of the forward rate (for maturity k) and the spot rate. Panel B presents OLS estimates of β_{er}^k from the regression

$$s_{t,e}^k - s_t = \alpha_{er}^k + \beta_{er}^k (f_t^k - s_t) + \epsilon_{t,k}^{er},$$

where $s_{t,e}^k - s_t$ is the expected return over the next k months the interval $(t, t+k)$ as $s_{t,e}^k$ denotes the median value in month t of the k months ahead exchange rate forecasts contained in the Reuters survey. The maturity k is equal to 1, 3, 6 and 12, while t-statistics, based on robust standard errors, are reported in parenthesis below coefficient estimates. Coefficient values indicated by † are significantly smaller than 1 at the 5%-level. Sample: Jan 1997 - Apr 2007. USD is the base currency in all cases.

	1 Month	3 Month	6 Month	12 Month
Panel A: Realized return				
USD/EUR	−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)
USD/GBP	−2.514	−2.040	−1.950†	−2.186†
	(−1.30)	(−1.23)	(−1.36)	(−1.90)
Panel B: Expected return				
USD/EUR	−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)
USD/GBP	−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 values of β_o^k and β_u^k from GMM estimation of the system

$$s_{t+k} - s_t = \alpha^k + (1+\beta_o^k+\beta_u^k)(f_t^k - s_t) + \epsilon_{t+k},$$

$$\breve{o}_{t,k} = \alpha_o^k + \beta_o^k(f_t^k - s_t) + \epsilon_{t,k}^o,$$

$$s_{t+k} - s_{t,e}^k = \alpha_u^k + \beta_u^k(f_t^k - s_t) + \epsilon_{t+k}^u.$$

(equations (5) to (7) in the text). The modified order flow variable $\breve{o}_{t,k}$ is cumulate order between month $t - k$ and t (divided by its standard deviation), pre-multiplied by the k months ahead exchange rate variance, measured by squared implied volatility at the end of month $t - k$; $f_t^k - s_t$ is the forward premium; f_t^k and s_t are the log of the forward rate (for maturity k) and the spot rate; $s_{t,e}^k$ denotes the median value in month t of the k months ahead exchange rate forecasts contained in the Reuters survey. For any currency the first, second and third columns in the Table report respectively the implied Fama's β ($1+\beta_o^k+\beta_u^k$), β_o^k and β_u^k and in parentheses the corresponding t-statistics, based on robust standard errors. The fourth column reports the J-statistic and the corresponding p- value in squared brackets. Sample: Jan 1997 - Apr 2007. USD is the base currency in all cases.

	USD/EUR				USD/JPY				USD/GBP			
	$1+\beta_o^k+\beta_u^k$	β_o^k	β_u^k	J-stat	$1+\beta_o^k+\beta_u^k$	β_o^k	β_u^k	J-stat	$1+\beta_o^k+\beta_u^k$	β_o^k	β_u^k	J-stat
1 Month	-4.42	-4.31	-1.11	0.0007	-2.18	-4.03	0.84	0.0014	-0.55	-0.03	-1.52	0.0173
	(-3.84)	(-3.68)	(-1.31)	[0.98]	(-2.53)	(-3.27)	(0.93)	[0.97]	(-0.41)	(-0.02)	(-2.18)	[0.90]
3 Month	-4.77	-3.34	-2.43	0.0218	-2.30	-2.75	-0.55	0.0087	-2.11	-0.62	-2.49	0.0084
	(-3.78)	(-3.50)	(-1.94)	[0.88]	(-2.78)	(-2.33)	(-0.35)	[0.93]	(-1.26)	(-0.90)	(-1.75)	[0.93]
6 Month	-5.46	-3.50	-2.96	0.0173	-2.95	-3.25	-0.70	0.0135	-1.87	-0.61	-2.26	0.0001
	(-4.02)	(-4.71)	(-2.43)	[0.90]	(-4.37)	(-2.45)	(-0.43)	[0.91]	(-1.17)	(-1.19)	(-1.63)	[0.99]
12 Month	-5.86	-3.56	-3.30	0.0157	-3.17	-4.01	-0.16	0.0130	-1.30	-1.07	-1.23	0.0174
	(-4.03)	(-4.56)	(-3.46)	[0.90]	(-3.48)	(-2.69)	(-0.12)	[0.91]	(-0.79)	(-2.65)	(-0.83)	[0.89]

33

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.

	USD/EUR		USD/JPY		USD/GBP	
	Forward bias	OF share	Forward bias	OF share	Forward bias	OF share
1 Month	-5.42	0.80	-3.18	1.27	-1.57	0.02
3 Month	-5.77	0.58	-3.30	0.83	-2.82	0.20
6 Month	-6.46	0.54	-3.95	0.82	-3.09	0.21
12 Month	-6.86	0.52	-4.17	0.96	-3.82	0.47
Mean	-6.13	0.61	-3.65	0.97	-2.46	0.22

Table 4
The Impact of the Forward Premium on Order Flow

This Table reports OLS-estimates of a linear regression of order flow OF, either the modified order flow ($\check{o}_{t,k}$) in Panel A or raw order flow ($o_{t,k}$) in Panel B, on the forward premium, $f_t^k - s_t$,

$$OF_{t,k} \;=\; \alpha_o^k \;+\; \beta_o^k \, (f_{t-k}^k - s_{t-k}) \;+\; \epsilon_{t,k}^o \,,$$

with $k = 1, 3, 6, 12$ months (equation (9) in the text). The modified order flow variable $\check{o}_{t,k}$ is cumulate order flow between month $t-k$ and t, divided by the standard deviation of order flow (to ease comparison across currency pairs), pre-multiplied by the k months ahead exchange rate variance, measured by squared implied volatility at the end of month $t - k$; the raw order flow is the same without the volatility adjustment; the forward premium is $f_t^k - s_t$, 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 (at survey date). t-statistics are based on robust standard errors. Sample: Jan 1997 - Apr 2007. USD is the base currency in all cases.

Currency	Hor.	A) Mod. order flow			B) Raw order flow		
		β_o^k	t-stat	adj.R^2	β_o^k	t-stat	adj.R^2
USD/EUR	1	-0.037	-3.58	0.17	-0.040	-4.45	0.23
	3	-0.039	-3.90	0.21	-0.041	-4.46	0.26
	6	-0.039	-3.94	0.22	-0.041	-4.29	0.27
	12	-0.039	-3.59	0.23	-0.040	-3.75	0.27
USD/JPY	1	-0.047	-2.23	0.06	-0.008	-0.84	0.01
	3	-0.055	-2.68	0.11	-0.011	-1.15	0.03
	6	-0.058	-3.09	0.14	-0.012	-1.33	0.05
	12	-0.064	-3.99	0.21	-0.016	-1.81	0.09
USD/GBP	1	0.005	0.39	-0.01	-0.004	-0.28	-0.01
	3	0.006	0.50	0.00	-0.002	-0.13	-0.01
	6	0.005	0.48	0.00	0.001	0.09	-0.01
	12	0.010	1.40	0.07	0.007	1.04	0.03

Table 5
The Impact of Order Flow on the Skewness of FX Returns

The Table reports the OLS-estimates from the regression of the average skewness of daily FX returns in the period $(t-k,t)$, ζ_t^k, on modified order flow, the forward premium and implied volatility,

$$\zeta_t^k \;=\; \alpha_{sk}^k \;+\; \gamma_{sk}^k \, \breve{o}_{t-k,k} \;+\; \beta_{sk}^k \, (f_{t-k}^k - s_{t-k}) \;+\; \delta_{sk}^k \, ImpVol_{t-k}^k \;+\; \epsilon_{t,k}^{sk},$$

with $k = 1,3,6, 12$ months. The modified order flow variable $\breve{o}_{t-k,k}$ is cumulate order flow between month $t-k$, and t (divided by its standard deviation), pre-multiplied by the k months ahead exchange rate variance, measured by squared implied volatility at the end of of month $t-k$; the forward premium is $f_t^k - s_t$, 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 implied volatility at the end of month t. Robust t-statistics are in parenthesis. Sample: Jan 1997 - Apr 2007. USD is the base currency in all cases.

	USD/EUR			USD/JPY		
	γ_{sk}^k	β_{sk}^k	δ_{sk}^k	γ_{sk}^k	β_{sk}^k	δ_{sk}^k
1 Month	-16.73	27.95	0.38	-4.88	50.60	0.23
	(-3.14)	(0.61)	(0.14)	(-0.94)	(2.11)	(0.11)
3 Month	-7.08	8.21	7.40	-3.09	32.32	3.52
	(-2.61)	(0.46)	(2.22)	(-1.30)	(3.60)	(1.61)
6 Month	-4.38	6.33	4.60	-2.67	23.79	6.45
	(-3.00)	(0.79)	(1.21)	(-3.15)	(5.91)	(4.27)
12 Month	-3.16	3.22	-0.09	-1.35	10.60	4.77
	(-4.26)	(0.94)	(-0.03)	(-5.51)	(6.44)	(4.21)

Descriptive Statistics

Table presents descriptive statistics on monthly data. Spot return is measured in yearly percentage points. A positive spot return is an appreciation of the USD. Order flow is standardized by its standard deviation to ease comparison, and a positive value corresponds to net USD buying. However, the reported standard deviations for order flow are for non-standardized series divided by its mean. Modified order flow is standardized order flow pre-multiplied by 100 times the 1 month ahead exchange rate variance, measured by squared implied volatility. The forecast error is the difference between the actual spot rate and the the median value in month $t-k$ of the k months ahead exchange rate forecasts from the Reuters survey. Sample: Jan 1997 - Apr 2007. USD is the base currency in all cases.

		Mean	Std.dev.	Skew.	Kurt.	p10	p90	Obs.
Spot return	USD/EUR	-0.50	35.91	-0.18	2.84	-51.49	45.88	123
	USD/JPY	0.28	39.88	-0.57	3.80	-49.87	49.34	123
	USD/GBP	-1.50	25.91	-0.24	2.94	-34.80	31.75	123
Order flow	EUR	-0.06	1.00	0.86	2.62	-1.03	1.54	124
	JPY	2.29	1.00	0.59	3.31	1.11	3.72	124
	GBP	-0.13	1.00	0.46	6.68	-1.19	0.93	124
Modified order flow	EUR	-0.15	1.16	0.63	3.05	-1.39	1.41	123
	JPY	2.52	2.62	2.54	9.76	0.72	5.01	123
	GBP	-0.14	1.01	-0.22	6.45	-1.11	0.91	123
Forecast error	EUR, 1M	1.96	11.36	0.84	5.36	-11.56	14.37	124
	EUR, 3M	11.7	56.22	0.02	2.59	-60.32	89.26	122
	EUR, 6M	26.75	86.9	0.22	2.51	-92.76	156.49	119
	EUR, 1Y	39.85	132.47	0.19	2.33	-135	209.09	113
	JPY, 1M	-0.73	13.82	-1.01	5.52	-15.02	15.96	124
	JPY, 3M	-1.17	63	-0.93	4.54	-84.67	70.1	122
	JPY, 6M	8.1	101.56	-0.62	3.2	-144.45	125.94	119
	JPY, 1Y	23.26	137.47	-0.05	2.01	-159.66	193.82	113
	GBP, 1M	0.09	8.37	0.32	3.08	-10.03	11.95	124
	GBP, 3M	-2.45	35.38	0.03	2.72	-45.45	45.69	122
	GBP, 6M	-7.46	53.07	0.23	3.04	-72.73	73.51	119
	GBP, 1Y	-16.94	79.98	0.44	2.6	-114	105.41	113