(Why) Does Order Flow Forecast Exchange Rates?*

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Abstract

We investigate the predictive information content of order flow for exchange rate returns, using a unique dataset on daily end-user transactions in nine exchange rates across four customer types from 2001 to 2011. The results show that a multi-currency trading strategy based solely on end-customer order flow strongly outperforms the popular carry trade strategy. We also demonstrate that the excess returns generated from conditioning on order flow information can be largely replicated using a combination of strategies based on publicly available information. This is consistent with the notion that order flow aggregates disperse public information about economic fundamentals that are relevant to exchange rates.

Keywords: Order Flow; Foreign Exchange; Forecasting; Microstructure.

JEL Classification: F31; F41; G10.

1 Introduction

The analysis of exchange rates continues to generate widespread interest. At the heart of the excitement is the importance to understand currency movements for policy makers and for practitioners in both financial and commercial sectors. This is coupled with the well-documented difficulty to provide satisfactory explanations of developments in the foreign exchange (FX) market using traditional economic models of exchange rate determination (Engel, Mark and West, 2008; Evans, 2011).[1]

A particularly promising innovation in international finance over the last decade is the microstructure approach, pioneered by Evans and Lyons (2002). This strand of the literature argues that one problem with conventional theories of international finance is that they are 'common knowledge' models, meaning that all relevant information is not only public, but also fully and immediately known by all agents. Economic agents are all assumed to use the same model (or expectations formation mechanism) to process this publicly available information. The microstructure approach departs from these unrealistic assumptions and has recorded noticeable empirical success. Perhaps the most successful empirical contribution of the FX microstructure approach is the introduction of 'order flow', defined as the net of buyer- and seller-initiated currency transactions, i.e. a measure of net buying pressure for a particular currency. Notably, Evans and Lyons (2002) document that order flow can explain a large proportion of the daily variation in two major nominal US dollar exchange rates, when standard exchange rate models can explain virtually none. This result has been confirmed in a number of subsequent studies (e.g. Payne, 2003; Killeen, Lyons and Moore, 2006). Similarly, simple order flow models can forecast exchange rates out-of-sample with much more accuracy than it is typically recorded from economic variables (Evans and Lyons, 2005a; Rime, Sarno and Sojli, 2010). Froot and Ramadorai (2005) report evidence that flows impact on exchange rate returns up to one month ahead, although the predictability is related to transitory departures from the relationship between exchange rates and fundamentals. However, these results have been challenged by other studies, which do not find evidence of forecasting power in order flow (e.g. Sager and Taylor, 2008; Gradojevic and Neely, 2009; Danielsson, Luo and Payne, 2011).

A key problem currently faced by this literature is that theory has run ahead of measurement. Specifically, a key barrier is lack of order flow data that is long enough to establish stylized facts

[1] The disconnect between exchange rates and the macroeconomy is particularly apparent to those scholars with direct interactions with practitioners; e.g. Goodhart, while working as an academic advisor at the Bank of England, notes "I could not help but observe that some of the features of the foreign exchange [...] market did not seem to tally closely with current theory... [T]here appeared to be a number of discrepancies between economic theory in this field and the beliefs and views of practitioners" (1988, p. 437).

with the desired precision and robustness. To make further progress in this literature, it is necessary to study order flow data for a broad set of currency pairs and an extended sample period. Part of the problem is that electronic trading has only been in existence for a relatively short period and data from the main spot FX trading platforms (e.g. Electronic Broking Systems and Reuters) only have substantial liquidity since the late 1990s. This is coupled with the reluctance of electronic trading platforms to make the data easily available. Moreover, data from electronic platforms is highly dominated by inter-bank dealing, which is perhaps less desirable than proprietary customer data from the major banks. The customer data is available to banks with additional information that allows categorizing agents into fundamentally different types, e.g. commercial versus financial customers, or insurance companies versus hedge funds. A unique element of our paper is that it employs high-quality data for daily order flow representing the transactions of customers of one of the major players in the FX market, UBS. The dataset spans from 2001 to 2011 and covers nine currency pairs, disaggregated across four different segments of the FX market: asset managers, hedge funds, corporate clients, and private clients.

Using these data, we are able provide evidence on two fundamental issues in currency markets. First, we provide robust evidence that there is forecasting power in order flow for future exchange rate returns, at both daily and monthly frequencies. With four different segments of the FX market, a longer sample and more exchange rates in our dataset relative to previous studies in this context, our results uncover that the predictive information embedded in order flow is economically valuable. This conclusion is reached by evaluating the performance of simple models that condition solely on order flow in order to allocate wealth dynamically, in a portfolio that comprises nine bonds denominated in foreign currency.[2] We compare the performance of this portfolio allocation to the analogous allocation carried out on the basis of the carry trade strategy, which borrows in low-interest rate currencies and lends in high-interest rate currencies. The carry trade is an obvious benchmark as it is the most popular trading strategy in currency markets and is heavily studied in recent academic research (e.g. Lustig, Roussanov and Verdelhan, 2011; Burnside, Eichenbaum, Kleshchelski and Rebelo, 2011; Menkhoff, Sarno, Schmeling and Schrimpf, 2011). Moreover, the plain version of the carry trade is based on the assumption that the spot exchange rate follows a random walk process, which is the benchmark in the literature on exchange rate forecasting ever since the seminal paper of Meese and Rogoff (1983).

[2] The easiest way to think of this exercise is that we ask whether a dealer can profit, when trading on her own account, from observing the order flow of her customers when acting as a broker.

We find that an investor who pursues an out-of-sample investment strategy based solely on end-customer order flow outperforms the carry trade or random walk strategy over the sample, and this is generally true for every customer type in our dataset. However, the results also indicate that the predictive information in the order flow of hedge funds leads consistently to large gains relative to the random walk at both daily and monthly rebalancing frequencies, while the order flow of private clients is particularly powerful at the daily frequency and the order flow of asset managers (real money investors) is especially powerful at the monthly frequency. Given the heterogeneity of the order flows of different customer types, we also explore a strategy that conditions on the order flow of all customer types jointly, and find that this strategy consistently provides large gains both in-sample and out-of-sample relative to the random walk benchmark.

Second, we relate order flow to the state of the economy in a simple but innovative way, in order to provide evidence on how order flow is related to publicly available information. We analyze whether the excess returns generated by the strategy that uses order flow information - taken as a direct measure of the predictive information content in order flows - are related to the excess returns generated both by popular trading strategies (e.g. carry, purchasing power parity, momentum) and more elaborate strategies (e.g. models based on monetary fundamentals, Taylor rule fundamentals, a model based on cyclically adjusted international financial positions, and a spot-forward regression that allows the relationship between depreciation rates and forward premia to vary over time). This is a reasonable set of strategies that employ publicly available data and mimic what currency investors do in practice. Using standard regression analysis applied to these excess returns, we find that the excess returns generated from the order flow strategies are strongly related to and can be largely replicated using a broad combination of strategies based on public information. Put another way, information in interest rates, past values of exchange rates, inflation and output gaps is key in determining the net demand for currencies that is observed in FX order flow and can account for over 70 percent of the excess returns generated by models conditioning on order flow information. In some sense, we are able to uncover which public information is relevant to generate currency orders and, in turn, becomes 'price relevant'. We also find evidence that there is strong variation in the relative importance of different strategies in driving order flows both across customer types and over time, and this is particularly apparent in samples pre- and post-crisis. For example, while exposure to the carry trade was quite dominant during the pre-crisis period, after the crisis erupted in June 2007 and the carry trade collapsed, returns generated by order flows were much more strongly driven by strategies based on purchasing power parity and other economic fundamentals. Overall,

we interpret this evidence as suggesting that the information content in order flow is economically important and derives from aggregating disperse public information about economic fundamentals that are relevant to exchange rates.

The reminder of the paper proceeds as follows. Section 2 describes the data used for the empirical work, with specific attention to the UBS dataset for FX order flows. Section 3 provides a brief review of the related literature and the theoretical background of models that link order flow, exchange rates and the macroeconomy. Section 4 describes the models based on public information that we consider in this paper. Section 5 describes the framework used for measuring economic value in a dynamic international asset allocation context. Section 6 provides the empirical results from estimating the forecasting models conditioning on order flow and comparing their performance to the performance of the carry trade strategy. It also presents empirical results where we relate the excess returns generated by the information in order flow to the excess returns obtained from public information models. Section 7 briefly summarizes the key results and concludes. The Appendix reports further technical details and additional empirical results.

2 Data and Preliminaries

2.1 Data Sources

The empirical analysis uses customer order flows, spot and forward rates, interest rates and a set of macro variables for nine exchange rates relative to the US dollar (USD): the Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), Euro (EUR), British pound (GBP), Japanese yen (JPY), Norwegian kroner (NOK), New Zealand dollar (NZD) and Swedish kronor (SEK). The dataset ranges from January 2001 to May 2011 and covers 2618 daily observations after removing holidays and weekends.

The order flow data come from proprietary daily transactions between end-user segments and UBS, one of the world's largest player in the foreign exchange (FX) market with an average daily turnover larger than 10%.[3] These data are disaggregated into four segments: trades executed between UBS and asset managers (AM), hedge funds (HF), corporates (CO) and private clients (PC). The asset managers segment comprises real money investors such as mutual funds and pension funds unless they have an excessive amount of leverage or pursue an aggressive investment strategy. Leveraged traders and asset managers not included in the previous group (leverage ratio > 2) are classified

[3] Table 1 in Appendix B displays the overall market share for the top 10 leaders in the FX market from 2001 to 2011 using the Euromoney FX Survey.

as hedge funds. Clearly, the criterion for being labeled a hedge fund is simply that the investment is sufficiently leveraged. The corporates group includes non-financial corporations that export and import products and services around the world or have a complex international supply chains. Treasury units of large non-financial corporations are always treated as corporates unless they pursue an aggressive investment strategy. In the latter case, they are classified as hedge funds. The final category, private clients, includes wealthy clients with in excess of about $3 million in investible liquid assets. They primarily trade for financial reasons and with their own money.

The flow data are assembled as follows. Each transaction booked in the UBS's execution system at any of its world-wide offices is tagged with a client type. At the end of each business day, transactions are extracted and then aggregated across segments regardless of where they were collected (global transactions). The flow data measure in billions of US dollars the imbalance between the value of purchase and sale orders for foreign currency initiated by clients against UBS quotes. Specifically, let V_i be the dollar value of a transaction initiated by a customer at time i. The transaction is recorded with a positive (negative) sign if UBS fills a purchase (sale) order of foreign currency.[4] Over time, order flow is measured as the cumulative flow of buyer-initiated and seller-initiated orders. Each transaction is signed positively or negatively depending on whether the initiator of the transaction (the non-quoting counterparty) is buying or selling, respectively. It follows that a positive order flow indicates net demand of foreign currency while a negative order flow means net supply of foreign currency.

The dataset we use in this study is unique in many respects. Firstly, order flow is a proximate driver of prices because it conveys information that financial markets need to aggregate. Evans and Lyons (2002) suggest that uncertain demand shocks of investors, such as shocks to hedging demands, shocks to liquidity demands and differential interpretation of news, causally change currency prices if supply is less than perfectly elastic. In contrast, most of the empirical studies focus on interdealer data rather than customer order flow. This evidence is consistent with investor demand being the source of information shocks if the dealer flow maps one-to-one with customer demand shocks as in the portfolio shifts model of Evans and Lyons (2002). However, if dealers have private information, then dealers will trade strategically and make the aggregate order flow informative of price changes.

[4] It is important to remark that order flow is distinct from transaction volume. Order flow is transaction volume that is signed. Microstructure theory defines the sign of a trade depending on whether the initiator is buying or selling. The dealer posting the quote is the passive side while the trader is the active side of the transaction. Consider, for example, a sale of 10 units by a trader acting on a dealer's quotes. Then transaction volume is 10, but order flow is –10 (Lyons, 2001).

Put it differently, since the interdealer order flow is a combination of customer and dealer information, the empirical studies based on interdealer data are unable to disentangle the primitive component due to investor demand. Identification of customer demand shocks is also critical for testing agent-based macro models since asset prices are assumed to aggregate information shocks of individual agents. Secondly, most of the empirical studies use the number and not the dollar value of buyer-initiated and seller-initiated transactions to measure order flow (e.g., Evans and Lyons, 2002; Rime, Sarno and Sojli, 2010). Thirdly, our dataset spans more than 11 years of daily observations across four end-users for nine currency pairs and it comes from a major FX market leader. The existing datasets on customer order flows suffers from a number of limitations as they cover a relatively short period of time, fewer currency pairs or a limited number of end-user segments. For instance, Marsh and O'Rourke (2005) use three years of data for six currency pairs from Royal Bank of Scotland. Evans and Lyons (2008) and Evans (2010) employ six years of data for one currency pair from Citibank. Cerrato, Sarantis and Saunders (2011) uses six years of data for nine currency pairs from UBS but differently from this paper they only have access to weekly data. Froot and Ramadorai (2005) use seven year of data for eighteen currency pairs from State Street, a global custodian bank. These are flow data with primarily institutional investors for which they only have aggregated data. As a consequence, they cannot capture the same diversity in currency demand as in the UBS's end-user segments. In short, we have observations on a substantial share of global FX spot trading over a period by far longer and richer than any earlier data set. Finally, our dataset comprises raw data with a minimal amount of filtering. For instance, data are adjusted to take into account for large merger and acquisition deals which are pre-announced months or weeks in advance. Cross-border merger and acquisitions involve large purchases of foreign currency by the acquiring company to pay the cash component of the deal. These transactions are generally well-published so market participants are already aware of and have adjusted to the flow. Also, FX reserve managers, UBS proprietary (prop) traders and small banks not participating in the interbank market are excluded from the dataset. Flows from FX reserve managers are stripped out due confidential issues, flows from prop traders because they trade with UBS's own money, while non-market making banks often have non-financial customers behind them.

The exchange rates are Thomson Reuters data obtained through *Datastream*. Specifically, we use daily spot and spot-next forward rates for the daily exercise, and end-of-month spot and one-month forward rates for the monthly analysis. Mid-quotes are used throughout the analysis; bid and ask quotes are used to construct transaction costs as detailed in Section 5. The exchange rate is defined

as the US dollar price of a unit of foreign currency so that an increase in the exchange rate implies a depreciation of the US dollar. As interest rates, we use daily (end-of-month) spot-next (one-month) Eurodeposit rates from *Datastream.*

Turning to macroeconomic data, we obtain the narrow money index (M1) as a proxy for money supply, the industrial production index (IPI) as a proxy for real output, and the consumer price index (CPI) from the OECD statistics. These data are generally available at monthly frequency, except IPI for Australia, New Zealand and Switzerland, and CPI for Australia and New Zealand for which data are published at quarterly frequency. As inflation rate, we use an annual measure computed as the 12-month log difference of CPI. For the output gap, we construct the deviations from the Hodrick and Prescott (1997) filter as in Molodtsova and Papell (2009).[5] We mimic as closely as possible the information set available to the central banks using quasi-real time data: although data incorporate revisions, we update the Hodrick and Prescott (1997) trend each period so that ex-post data is not used to construct the output gap. In other words, at time t we only use data up to $t-1$ to construct the output gap.[6] From OECD statistics, we also obtain yearly data on the purchasing power parity (PPP) spot exchange rate. From the *International Financial Statistics* (IFS) database, we obtain quarterly data on external assets and liabilities, exports and imports of goods and services, and GDP.[7]

We convert all data but interest rates and order flows by taking logs. Throughout the rest of the paper, the symbols s_t, f_t, x_t, i_t, m_t, π_t, y_t and $\overline{y}_t$ refer to transformed spot exchange rate, interest rate, money supply, inflation rate, real output and output gap, respectively. We use an asterisk to denote the transformed data (i_t^*, m_t^*, π_t^*, y_t^* and $\overline{y}_t^*$) for the foreign country. The log of the PPP spot rate defines the log price level differential $p_t - p_t^*$. As in Gourinchas and Rey (2007), we construct a global measure of cyclical external imbalances, labelled nxa_t, as a linear combination of detrended (log) exports, imports, foreign assets, and liabilities relative to GDP.[8]

[5] While Orphanides (2001) stresses the importance of using real-time data to estimate Taylor rules for the United States, Orphanides and van Norden (2002) show that most of the difference between fully revised and real-time data comes from using ex post data to construct potential output and not from the data revisions themselves.

[6] The output gap for the first period is computed using real output data from January 1990 to January 2001. In the HP filter, we use a smoothing parameter equal to 14,400 as in Molodtsova and Papell (2009).

[7] Unadjusted data are seasonally adjusted using dummy-variable regressions. Note that in the out-of-sample analysis, we perform the adjustment in a recursive fashion to avoid any look-ahead bias.

[8] Following GR closely, we filter out the trend component in (log) exports, imports, foreign assets, and liabilities relative to GDP using the Hodrick-Prescott filter. We then combine these stationary components with weights reflecting the (trend) share of exports and imports in the trade balance, and the (trend) share of foreign assets and liabilities in the net foreign assets, respectively. These time-varying weights are replaced with their sample averages to minimize the impact of measurement error. Finally, note that the Hodrick-Prescott filter and the constant weights are based on the full-sample information for the in-sample analysis. In the out-of-sample, however, we perform the Hodrick-Prescott filter and compute the weights only using information available at the time of the forecast. This is to avoid any

Macroeconomic variables are only available at monthly or lower frequency. We construct daily observations by fixing the latest available observations until a new data point is again available.

2.2 Preliminary Analysis

Table 1 reports the market share by customer type for UBS and its rank relative to the top 10 leaders in the FX market from 2001 to 2011. We collect data from the Euromoney annual survey of the FX industry. This table reveals that UBS has been at the top of the list for both the overall market and end-user segments. Three of the UBS groups (asset managers, hedge funds and corporates) match quite closely with the segments defined by Euromoney (real money, leveraged funds and non-financial corporations).[9] The BIS triennial survey of the FX markets reports that for many developed economies the trading of financial customers is often twice as big as that of non-financial customers. However, as we have no data on daily volume, it is difficult to speculate with any precision on the relative importance of each group. Since 2003 Euromoney has surveyed the market share of end-user segments. According to this survey, UBS is particularly active with real-money investors with an average market share of 11%. In the leveraged funds sector the average market share is approximately 9% with a peak of 14.63% in 2010. The nonfinancial corporation segment is likely the one in which UBS is less active as the average market share is about 6%. Overall, UBS is among the top two banks trading against asset managers, among the top five banks for hedge funds, and among the top ten banks with non-financial corporations.

Tables 2 presents descriptive statistics for daily log exchange rate returns and flows across the four end-user segments for the nine currency pairs from January 2001 to May 2011. The trading of asset managers and hedge funds is the most volatile suggesting that they are financially motivated market participants. The corporates group is typically the least volatile. This fits with the view that corporate clients trade mostly for import and export reasons, while private clients are more financially oriented. Table 3 breaks down the key summary statistics across calendar years. Interestingly, the unwinding of the carry trade strategies displays a different timing for asset managers and hedge funds. For instance, hedge funds have begun unwinding their long positions in AUD and NZD since 2004, while asset managers only at the beginning of the crisis in 2007. This pattern simply confirms that hedge funds are more leveraged than asset managers.

look-ahead bias.

[9] Euromoney also have a group called Banks, which covers so-called non-market making banks, often small banks, that do not find it worthwhile to have presence in the interbank market but rather trade with other banks as their customer. There is no similar group in the UBS definitions, but these "customer-banks" often have non-financial customers behind them.

Table 4 presents the contemporaneous cross correlations between flows and returns: while asset managers and hedge funds are positively correlated with the exchange rate returns, corporate and private clients are typically negatively correlated. These results are consistent with the previous empirical evidence reported by Evans and Lyons (2002) and Sager and Taylor (2006). Specifically, asset managers and hedge funds are informed traders (push customers) while corporate and private clients act as overnight liquidity providers (pull customers).

3 Related Literature and Predictive Regression for the Order Flow Model

At a theoretical level, Evans and Lyons (2007) formalize the notion that order flow conveys fundamental information about exchange rates in a dynamic general equilibrium model where information is first manifested at the micro (agent) level and is not symmetrically observed among agents. The model essentially combines a number of classical ingredients of the new open-economy macroeconomics literature with the insights of the FX microstructure literature, predicting an exchange rate behavior that matches several empirical facts. In a related theoretical paper, Bacchetta and van Wincoop (2006) show the existence of a close relation between order flow and exchange rates in a stylized dynamic rational expectations model. The information about macroeconomic fundamentals is assumed to be dispersed across agents, which generates heterogeneity of beliefs. This heterogeneity generates a large impact of currency trades associated with non-fundamental information (e.g. hedging trades); thus a disconnect between exchange rates and fundamentals arises in the short run. However, the relation between order flow and exchange rates is strong at both short and long horizons. In essence, these papers provide significant steps towards understanding the theoretical linkages between macroeconomic fundamentals, order flow and exchange rate fluctuations. Also, this literature clarifies how order flow may be seen as a vehicle for aggregating both differences in interpretation of news and changes in heterogeneous expectations about the future state of the economy (Evans and Lyons, 2005a).

Given the observed strong contemporaneous link between exchange rates and order flow, it is intriguing to ask whether order flow also has predictive power for future exchange rate returns. Evans and Lyons (2005a, 2006) argue that customer order flow is discovered slowly by the market, but the same argument can be applied for several other banks that have an informative clientele. Thus, it can be argued that the whole market will take some time to uncover the heterogeneous information embedded in order flow. These delays in information processing are, at first glance,

in contrast with canonical microstructure models such as those of Kyle (1985) and Glosten and Milgrom (1985), where the market maker only responds to unexpected order flow. However, not all assumptions of these models are true in a partially decentralized market with a complex information structure like the FX interbank market. For example, Easley and O'Hara (1992) examine the adverse selection problem that arises from the repeated trades of informed traders. Their model shows that trading volume affects the speed of price adjustment to information and that the efficiency of price adjustment to new information depends on the specific market structure. In market structures that have richer informational problems than described in the canonical microstructural models, asset prices do not necessarily reflect all new information instantaneously.

Not surprisingly, several banks have invested in technology that captures order flow information for forecasting purposes (e.g. Citi, UBS, Royal Bank of Scotland and HSBC). The microstructure literature has used some of these data (e.g. Evans and Lyons, 2005a; Sager and Taylor, 2008) as well as data constructed from electronic platforms, Reuters and EBS (e.g. Evans, 2002; Payne, 2003; Berger *et al.*, 2008; Rime, Sarno and Sojli, 2010) to investigate the existence of forecasting power in order flow for exchange rate returns. However, the evidence is scant and mixed. On the one hand, Evans and Lyons (2005a, 2006) use six years of proprietary disaggregated customer data on US dollar-euro from Citi and find that the forecasts based on an order-flow model outperform the random walk at various forecast horizons ranging from 1 to 20 trading days. Similarly, forecasting power is recorded by Rime, Sarno and Sojli (2010), albeit on a very short sample of data for Reuters inder-dealer trading over 12 months. On the other hand, Sager and Taylor (2008) and Danielsson, Luo and Payne (2011) find no evidence of better forecasting ability in order flow models relative to a random walk benchmark for several major exchange rates and different forecast horizons.[10] Hence, the existence of predictive power in order flow is awaiting further empirical tests with alternative data sources.

We are interested in comparing the performance of a model that conditions on the UBS order flow data relative to the carry trade or random walk strategy. We evaluate performance using several criteria: the Sharpe ratio, arguably the most common measure of performance evaluation among market practitioners; the Sortino ratio, which takes specifically into account downside risk; the maximum drawdown; and the performance fee that a risk-averse investor would be willing to pay to switch from a random walk strategy to an active management strategy based on an alternative

[10] Similarly, Killeen, Lyons and Moore (2006) estimates a partial adjustment (error correction) model for the effect of order flow on exchange rate returns and finds that the speed of convergence to the long-run equilibrium is very fast, implying that the predictive information content in order flow decays rapidly.

model that conditions on order flow. We choose to perform both one-day and one-month ahead forecasts because these are horizons that are relevant to the customers we study in this paper, with one-day horizons more likely to be relevant for hedge funds and private clients, and one-month horizons possibly more relevant for asset managers and corporate clients.

Consider an investor who forecasts exchange rate returns using currently available order flow information at a fixed rebalancing period and allocates wealth across currencies. The investor estimates a linear predictive regression of the form

$$\Delta s_t = \alpha + \beta x_{t-1}^s + \varepsilon_t, \tag{1}$$

where $\Delta s_t = s_t - s_{t-1}$ is the log-exchange rate return at time t; x_{t-1}^s indicates end-user order flow with s denoting asset managers (AM), hedge funds (HF), corporates (CO) and private clients (PC), respectively; α and β are parameters to estimate, and ε_t is a normal error term. The above regression can be used to generate exchange rate forecasts out-of-sample by re-estimating recursively each period as a new observation for order flow becomes available. In addition to predictive regressions only based on invidividual end-user flows, we also consider the impact of heterogeneous information flows by estimating a predictive regression that jointly uses disaggregate flows (ALL)

$$\Delta s_t = \alpha + \sum_{s=1}^{4} \beta_s x_{t-1}^s + \varepsilon_t \tag{2}$$

in contrast to a predictive regression that only conditions on aggregate order flow (TOT)

$$\Delta s_t = \alpha + \beta \sum_{s=1}^{4} x_{t-1}^s + \varepsilon_t. \tag{3}$$

4 Predictive Regressions for Public Information Models

We estimate a battery of predictive regressions for exchange rate returns, consistent with conventional empirical approaches used to test the present value model of exchange rates (e.g. Mark, 1995; Engel and West, 2005). All predictive regressions have the following linear structure:

$$\Delta s_t = \alpha + \beta x_{t-1} + \varepsilon_t, \tag{4}$$

where Δs_t is the log-exchange rate return at time t, x_{t-1} is a predictive variable, α and β are constants to be estimated, ε_t is a normal error term. The empirical models differ in the way they specify the predictive component x_t that is used to forecast exchange rate returns.

4.1 Random Walk

The first specification is the driftless or naive random walk (RW) model that sets $\alpha = \beta = 0$. Since the seminal contribution of Meese and Rogoff (1983), this model has become the benchmark in assessing exchange rate predictability. The RW model captures the prevailing view in international finance research that exchange rates are unpredictable and forms the basis of the widely used carry trade strategy in active currency management (e.g. Burnside, Eichenbaum, Kleshchelski and Rebelo, 2011; Menkhoff, Sarno, Schmeling and Schrimpf, 2011). The RW model is the benchmark to which we compare the model that conditions on order flow information. However, we also estimate a number of other predictive regressions that mimic other strategies commonly used by currency managers, and use them in the empirical work when we attempt to shed light on the drivers of the net demand for currencies across customer types that is captured by the UBS order flow data.

4.2 Forward Premium

The second specification uses the forward premium (FP) as a predictor

$$x_t = f_t - s_t. \tag{5}$$

where f is the one-period log-forward exchange rate. The predictive regression using FP as conditioning information captures the deviations from uncovered interest rate parity (UIP) condition. Under risk neutrality and rational expectations, UIP implies that $\alpha = 0$, $\beta = 1$, and the error term is serially uncorrelated. However, empirical studies consistently reject the UIP condition and it is a stylized fact that estimates of β often display a negative sign (e.g. Evans, 2011, Ch. 11). This implies that high-interest rate currencies tend to appreciate rather than depreciate over time.[11]

4.3 Purchasing Power Parity

The third regression is based on the purchasing power parity (PPP) condition and sets

$$x_t = p_t - p_t^* - s_t$$

where p (p^*) is the log of the domestic (foreign) price level. This is equivalent to a trading strategy that buys undervalued currencies and sells overvalued currencies over time. The PPP hypothesis states that national price levels should be equal when expressed in a common currency and is typically

[11] Note that we implicitly assume that covered interest parity (CIP) holds, so that the interest rate differential is equal to the forward premium, $f_t - s_t = i_t - i_t^*$. In this case, testing UIP is equivalent to testing for forward unbiasedness in exchange rates (Bilson, 1981). For recent evidence supporting the validity of CIP at the frequencies we are interested in, see Akram, Rime and Sarno (2008).

thought of as a long-run condition rather than holding at each point in time (e.g., Rogoff, 1996; and Taylor and Taylor, 2004).

4.4 Monetary Fundamentals

The fourth regression conditions on monetary fundamentals (MF):

$$x_t = (m_t - m_t^*) - (y_t - y_t^*) - s_t. \tag{6}$$

where m (m^*) is the log of the domestic (foreign) money supply and y (y^*) is the log of the domestic (foreign) real output. The relation between exchange rates and fundamentals defined in Equation (6) suggests that a deviation of the nominal exchange rate from its long-run equilibrium level determined by current monetary fundamentals requires the exchange rate to move in the future so as to converge towards its long-run equilibrium. The empirical evidence on the relation between exchange rates and fundamentals is mixed. On the one hand, short-run exchange rate variability appears to be disconnected from the underlying monetary fundamentals (Mark, 1995) in what is commonly referred to as the "exchange rate disconnect puzzle." On the other hand, there is growing evidence that exchange rates and monetary fundamentals are cointegrated (e.g. Groen, 2000; Rapach and Wohar, 2002), which requires that the exchange rate and/or the fundamentals move in such a way to restore and equilibrium relation between them over time.

4.5 Taylor Rule

The fifth specification uses the Taylor (1993) rule defined as

$$x_t = 1.5\,(\pi_t - \pi_t^*) + 0.1\,(\overline{y}_t - \overline{y}_t^*) + 0.1\,(s_t + p_t^* - p_t)\,. \tag{7}$$

where π (π^*) is the domestic (foreign) inflation rate, and $\overline{y}$ ($\overline{y}^*$) is the domestic (foreign) output gap measured as the percent deviation of real output from an estimate of its potential level, computed using the Hodrick and Prescott (1997) filter.[12] The Taylor rule postulates that the central bank raises the short-term nominal interest rate when output is above potential output and/or inflation rises above its desired level. The parameters on the inflation difference (1.5), output gap difference (0.1) and the real exchange rate (0.1) are fairly standard in the literature (e.g., Engel, Mark and West, 2007; Mark, 2009; Molodtsova and Papell, 2009).

[12] Note that in estimating the Hodrick-Prescott trend out of sample, at any given period t, we only use data up to period $t-1$. We then update the trend every time a new observation is added to the sample. This captures as closely as possible the information available at the time a forecast is made.

4.6 Cyclical External Imbalances

The sixth model employs a bilateral measure of cyclical external imbalances between the US and the foreign country as a predictive variable. As in Gourinchas and Rey (2007), we construct nxa_t, a global measure of cyclical external imbalances, which linearly combines detrended (log) exports, imports, foreign assets, and liabilities relative to GDP. The bilateral measure of cyclical external imbalances between the US and a foreign country is then constructed using a two-stage least squared estimator as in Della Corte, Sarno and Sestieri (2011). We firstly regress the global nxa_t for the US on a constant term and the global nxa_t for the foreign country, and then use the fitted value from this contemporaneous regression as x_t representing the proxy for the bilateral measure of cyclical external imbalances between the US and the foreign country.

4.7 Momentum

The final specification uses the one–year rolling exchange rate return as a conditional mean. This is equivalent to setting $E_t[\Delta s_{t+1}] = \sum_{i=1}^{d} \Delta s_{t+1-i}$ where $d = 252$ (12) indicates the number of trading periods in a year for daily (monthly) returns. This strategy creates a long exposure to the currencies which are trending higher, and a short exposure to the currencies that are trending lower.

5 Asset Allocation and Performance Evaluation

This section describes the framework for evaluating the performance of an asset allocation strategy that exploits predictability in exchange rate returns.

5.1 The Dynamic FX Strategy

We design an international asset allocation strategy that involves trading the US dollar vis-á-vis nine major currencies: the Australian dollar, Canadian dollar, Swiss franc, Deutsche mark\euro, British pound, Japanese yen, Norwegian kroner, New Zealand dollar and Swedish kronor. Consider a US investor who builds a portfolio by allocating her wealth between ten bonds: one domestic (US), and nine foreign bonds (Australia, Canada, Switzerland, Germany, UK, Japan, Norway, New Zealand and Sweden). The yield of the bonds is proxied by eurodeposit rates. At the each period $t+1$, the foreign bonds yield a riskless return in local currency but a risky return r_{t+1} in US dollars, whose expectation at time t is equal to $E_t\left[r_{t+1}\right] = i_t + \Delta s_{t+1|t}$. Hence the only risk the US investor is exposed to is FX risk.

Every period the investor takes two steps. First, she uses each predictive regression to forecast the one-period ahead exchange rate returns. Second, conditional on the forecasts of each model, she dynamically rebalances her portfolio by computing the new optimal weights. This setup is designed to assess the economic value of exchange rate predictability by informing us which empirical exchange rate model leads to a better performing allocation strategy.

5.2 Mean-Variance Dynamic Asset Allocation

Mean-variance analysis is a natural framework for assessing the economic value of strategies that exploit predictability in the mean and variance. Consider an investor who has a one-period horizon and constructs a dynamically rebalanced portfolio. Computing the time-varying weights of this portfolio requires one-step ahead forecasts of the conditional mean and the conditional variance-covariance matrix. Let r_{t+1} denote the $K \times 1$ vector of risky asset returns at time $t+1$, $r_{t+1|t} = E_t\left[r_{t+1}\right]$ the conditional expectation of r_{t+1}, $V_{t+1|t} = E_t[(r_{t+1} - r_{t+1|t})(r_{t+1} - r_{t+1|t})']$ the $K \times K$ conditional variance-covariance matrix of r_{t+1}, τ_{t+1} be a $K \times 1$ vector of proportional transaction costs, and $\tau_{t+1|t} = E_t\left[\tau_{t+1}\right]$ the conditional expectation of τ_{t+1}. The maximum expected return strategy consists of solving, at each period t, the following problem for a given target conditional volatility

$$\begin{aligned} \max_{w_t} \quad & r_{p,t+1|t} &= w_t' r_{t+1|t} + \left(1 - w_t'\iota\right) r_f - \phi\left(w_t, \tau_{t+1|t}\right) \\ \text{s.t.} \quad & \sigma_p^* &= \left(w_t' V_{t+1|t} w_t\right)^{1/2} \end{aligned} \tag{8}$$

where $r_{p,t+1}$ is the portfolio return, $r_{p,t+1|t} = E_t[r_{p,t+1|t}]$ is the conditional expectation of $r_{p,t+1}$, σ_p^* is the target conditional volatility of the portfolio returns, r_f is the riskless rate, and

$$\phi\left(w_t, \tau_{t+1|t}\right) = \sum_{i=1}^{K} \tau_{i,t+1|t} \left| w_{i,t} - w_{i,t}^- \right|$$

is the sum of transaction costs associated with each trade with $w_{i,t}^- = w_{i,t-1}\left(1 + r_{i,t}\right) / \left(1 + r_{p,t}\right)$. The optimal solution is not available in closed-form solution but obtained via numerical optimization.[13] Finally, the return on the investor's portfolio is defined as

$$r_{p,t+1} = w_t' r_{t+1} + \left(1 - w_t'\iota\right) r_f - \phi\left(w_t, \tau_{t+1}\right).$$

[13] We use a linear transaction cost function as it can be solved globally and efficiently as a convex portfolio optimization problem. In practice, transaction costs may be a concave rather than a convex function of the amount traded. This happens, for example, when an additional fixed component is considered. The total transaction costs decrease as the amount traded increases. This nonconvex portfolio optimization problem cannot be solved directly via convex optimization (see Lobo, Fazel and Boyd, 2007).

For simplicity, we model the proportional transaction cost for asset i as

$$\tau_{i,t} = \overline{\tau}_i + \eta_{i,t}$$

such that $\tau_{i,t+1|t} = \overline{\tau}_i$. Note that we assume that $\Sigma_{t+1|t} = \overline{\Sigma}$, where $\overline{\Sigma}$ is the unconditional covariance matrix of exchange rate returns. In other words, we do not model the dynamics of FX return volatility and correlation. Therefore, the optimal weights will vary across the empirical exchange rate models only to the extent that the predictive regressions produce better forecasts of the exchange rate returns.

5.3 Proportional Transaction Costs

The excess return from holding foreign currency, buying foreign currency at time t in the forward market while reversing the position in spot market at time $t+1$, can be computed net of the bid-ask spread as follows

$$er_{t+1}^{net} = s_{t+1}^{b} - f_t^{a}$$

where s_{t+1}^{b} is the bid-quote for the spot rate and f_t^{a} is the ask-quote for the forward rate. We can rewrite the above expression using mid-quotes and obtain

$$\begin{aligned} er_{t+1}^{net} &= \left(s_{t+1} - \frac{s_{t+1}^{a} - s_{t+1}^{b}}{2}\right) - \left(f_t + \frac{f_t^{a} - f_t^{b}}{2}\right) \\ &= (s_{t+1} - f_t) - c_{t+1} \end{aligned}$$

where s_{t+1} and f_t are the mid quotes for spot and forward exchange rates while $c_{t+1} = \left(s_{t+1}^{a} - s_{t+1}^{b} + f_t^{a} - f_t^{b}\right)/2$ represents the round-trip proportional transaction cost from entering a foreign currency at time t and exits the strategy at time $t+1$. In our setup, we define as $\tau_{t+1} = c_{t+1}/2$ the proportional transaction cost for increasing or decreasing the portfolio weight at time $t+1$ on a given foreign currency.

5.4 Performance Measures

We evaluate the performance of the exchange rate models using the Goetzmann, Ingersoll, Spiegel and Welch (2007) manipulation-proof performance measure defined

$$M(r_p) = \frac{1}{(1-\delta)} \ln \left\{ \frac{1}{T} \sum_{t=0}^{T-1} \left(\frac{1 + r_{p,t+1}}{1 + r_f} \right)^{1-\delta} \right\} \tag{9}$$

where $M(R_p)$ is an estimate of the portfolio's premium return after adjusting for risk, and can be interpreted as the certainty equivalent of the excess portfolio returns. This is an attractive criterion

since it is robust to the distribution of the portfolio returns and does not require the assumption of any particular utility function to rank portfolios. We build on this criterion and consider the difference between manipulation-proof performance measures for competing portfolios as follows:

$$\mathcal{P} = M(r_p^*) - M(r_p). \tag{10}$$

We interpret $\mathcal{P}$ as the maximum performance fee an investor will pay to switch from the RW to the alternative (e.g., UIP) strategy. In other words, this utility-based criterion measures how much a mean-variance investor is willing to pay for conditioning on better exchange rate forecasts. The performance fee will depend on δ, which is the investor's degree of relative risk aversion (RRA). We report $\mathcal{P}$ in annualized basis points (*bps*).

In the context of mean-variance analysis, perhaps the most commonly used measure of economic value is the Sharpe ratio ($\mathcal{SR}$). The realized $\mathcal{SR}$ is equal to the average excess return of a portfolio divided by the standard deviation of the portfolio returns. It is well known that because the $\mathcal{SR}$ uses the sample standard deviation of the realized portfolio returns, it overestimates the conditional risk an investor faces at each point in time and hence underestimates the performance of dynamic strategies (e.g., Marquering and Verbeek, 2004; Han, 2006). We also compute the Sortino ratio ($\mathcal{SO}$), which measures the excess return to "bad" volatility. Unlike the $\mathcal{SR}$, the $\mathcal{SO}$ differentiates between volatility due to "up" and "down" movements in portfolio returns. It is equal to the average excess return divided by the standard deviation of only the negative returns. In other words, the $\mathcal{SO}$ does not take into account positive returns in computing volatility because these are desirable. A large $\mathcal{SO}$ indicates a low risk of large losses. Finally, we also report the maximum cumulative loss from a market peak to the following trough. It is generally defined as maximum drawdown ($\mathcal{MDD}$) and measures how sustained one's losses can be. As large drawdowns usually lead to fund redemptions, it follows that a reasonably low $\mathcal{MDD}$ is critical to the success of any fund.

5.5 Portfolios Based on Combined Forecasts

Our analysis has so far focused on evaluating the performance of individual empirical exchange rate models relative to the random walk benchmark. Considering a large set of alternative models that capture different aspects of exchange rate behavior without knowing which model is "true" (or best) inevitably generates model uncertainty. In this section, we explore whether portfolio performance of net order flows can be replicated by combining the forecasts arising from the full set of competing predictive regressions. Even though the potentially superior performance of combined forecasts is

known since the seminal work of Bates and Granger (1969), applications in finance are only recently becoming increasingly popular (Timmermann, 2006; Rapach, Strauss and Zhou, 2010).[14]

Recall that we estimate $N = 6$ competing predictive regressions each of which provides an individual forecast $\Delta\widehat{s}_{i,t+1}$ for the one-step ahead exchange rate return, where $i \leq N$. We define the combined forecast $\Delta\widehat{s}_{c,t+1}$ as the weighted average of the N individual forecasts $\Delta\widehat{s}_{i,t+1}$:

$$\Delta\widehat{s}_{c,t+1} = \sum\nolimits_{i=1}^{N} \omega_{i,t}\Delta\widehat{s}_{i,t+1}, \tag{11}$$

where $\{\omega_{i,t}\}_{i=1}^{N}$ are the ex ante combining weights determined at time t. The combining methods we consider differ in how the weights are determined and can be organized into two classes. The first class uses simple averaging schemes: mean, median, and trimmed mean. The mean combination forecast sets $\omega_{i,t} = 1/N$ for $i = 1, \ldots, N$ in Equation (11), the median combination forecast is the median of $\{\Delta\widehat{s}_{i,t+1}\}_{i=1}^{N}$, and the trimmed mean combination forecast sets $\omega_{i,t} = 0$ for the individual forecasts with the smallest and largest values and and $\omega_{i,t} = 1/(N-2)$ for the remaining individual forecasts in Equation (11). These combined forecasts disregard the historical performance of the individual forecasts. The second type of combined forecasts is based on Bates and Granger (1969) and Stock and Watson (2004), and uses statistical information on the past performance of each individual model. In particular, we compute the MSE forecast combination by setting the following weights:

$$\omega_{i,t} = \frac{MSE_{i,t}^{-1}}{\sum_{j=1}^{N} MSE_{j,t}^{-1}}, \quad MSE_{i,t} = T^{-1}\sum\nolimits_{t=1}^{T}\left(\Delta s_t - \Delta\widehat{s}_{i,t}\right)^2. \tag{12}$$

Following Welch and Goyal (2008), we also consider a "kitchen sink" (KS) model that incorporates all economic variables into a multiple predictive regression model

$$\Delta s_{t+1} = \alpha + \sum_{i=1}^{6} \beta_i x_t^i + \varepsilon_{t+1} \tag{13}$$

where $i = \{FP, TR, PPP, MF, NXA, MOM\}$. Finally, we consider a 'Fund of Funds' (FoF) strategy that equally invests in the portfolio strategy based on the RW, FP, TR, PPP, MF, NXA, and MOM model, respectively.

6 Empirical Results

6.1 Preliminary Regressions on Exchange Rates and Order Flow

As a preliminary assessment of the exchange rate-order flow relationship, we estimate the contemporaneous relation between order flow and FX excess returns using ordinary least squares (OLS). We

[14] For a Bayesian approach to forecast combinations see Avramov (2002), Cremers (2002), Wright (2008), and Della Corte, Sarno and Tsiakas (2009).

regress the FX excess returns on order flow alone to investigate its explanatory power, and estimate the regression separately for each of the nine exchange rates and each customer type; we also estimate the regression for the aggregated, total order flow, and for the full set of four customer order flows available. The results are presented in Table 5 for daily data and in Table 6 for aggregated monthly data.[15]

Starting from Table 5, the estimated order flow coefficients are always positively signed for asset managers (AM) and for hedge funds (HF), while they are generally negatively signed for corporate clients (CO) and private clients (PC). The positive sign for AM and HF implies that net buying pressure for the foreign currency will lead to a positive FX excess returns. In contrast, the negative sign for CO and PC suggests that in a contemporaneous setting these customers may act as liquidity providers. However, it is important to note that the coefficients are not always statistically significant at conventional significance levels; for example, even at the 10 percent significance level, 7 out of 36 coefficients in the regressions for individual customer types are statistically insignificantly different from zero. The R^2 ranges from virtually zero to 12 percent for GBP in the regression for private clients. The regressions using total order flow - the sum of the order flow of the four customer types - record in each case a statistically significant, positively signed coefficient on order flow, although the R^2 remains low, which may not be particularly surprising given that we are only using data for one bank. The strongest results are obtained when we estimate a regression of FX excess returns on the order flow of all customers at the same time. We find that, when statistically, significant, the coefficients on the flows for AM and HF have a positive sign and the ones on CO and PC have a negative sign, but the R^2 now increases, in some cases dramatically, reaching over 20 percent for the EUR.

Turning to Table 6, we find that the results for monthly data are qualitatively identical, except that the R^2 is now higher and even for the regressions with just one customer type we observe an R^2 of, for example, 14.6 percent for EUR with AM flows and 20 percent for JPY excess return with PC flows. The regression which involves all four customer flows generates an average R^2 just above 16 percent, and the largest R^2 is 30 percent for CHF.

Next we calculate the simple correlation between currency order flows and FX returns at different

[15] Note that Evans and Lyons (2002a) and all subsequent papers after them uses FX excess returns rather than FX excess returns on the left hand side of this regression. We report results for FX excess given that our focus in this paper is on the evaluation of predictive models used for allocating wealth across international bonds, for which FX excess returns are the appropriate concept. Nevertheless it is obvious that the information content of order flow is associated largely with FX returns and hence the results are qualitatively identical when using FX returns as the dependent variable (results available upon request).

horizons, as in Froot and Ramadorai (2005, pp. 1548-9). We report the average correlation across the G-10 currencies in Figure 1, where the horizon is reported in log-scale on the horizontal axis, running from the 1-day horizon (10^0 days) to 252 days ($> 10^2$). In essence, this calculation gives a measure of the flow-return correlation for a variety of relevant horizons in our data set, across different customer types. The figure also shows the 90th percentile confidence intervals, estimated by generating $10,000$ replications under the null hypothesis that flows and FX returns are each i.i.d., with a contemporaneous correlation given by the actual observed value. As expected in light of the results discussed earlier, the correlation start off positive at the 1-day horizon for AM and HF flows, and negative for CO and PC flows. For AM flows, the correlations increase markedly with horizon up to about 2.5 months, and are statistically significant almost up to a year. For HF flows, the correlations increase slightly with horizon up to one month before decreasing, but they stay positive for all horizons. However, the HF correlations display much weaker evidence of statistical significance than for AM flows. For both CO and PC flows, the initial 1-day correlations are statistically significant and decrease (i.e. the correlations increase in absolute size) with horizon before weakening and becoming insignificant just after the 1-month horizon. However, the pattern in terms of both magnitude and significance is stronger for PC flows than for CO flows. Overall, this simple preliminary correlation analysis provides some first evidence that flows must either anticipate FX returns or follow recent returns.

Overall, this preliminary analysis suggests some evidence of a contemporaneous association between FX excess returns with customer flows, and that combining the four flows in the same model greatly stengthens the empirical relationship. It also shows that the correlation extends to relatively long horizons and that, therefore, it is empirically plausible that flows contain predictive information content for future FX (excess) returns. However, the analysis at this point has been intentionally simple and designed to explore the basic properties of the bivariate relationship between flows and returns. Ultimately, we are interested in whether the information content in order flow has predictive power for future FX excess returns in the context of a standard dynamic asset allocation context. We now turn to this exercise.

6.2 The Predictive Information Content in Order Flow

In our setting, the investor obtains the forecast of exchange rate returns for next day or next month, conditioning on order flow information available at the time of the forecast; he then chooses investment weights using the mean-variance framework discussed in the previous section for an annual

target volatility of $\sigma_p^* = 0.10$ and assuming that the coefficient of relative risk aversion $\gamma = 6$.[16] The portfolio weights are rebalanced at fixed intervals (every day or every month in our analysis).

We carry out the forecasting and portfolio optimization both in-sample and out-of-sample. The in-sample prediction is the fitted value of the exchange rate return, using the predictive regression model described in Section 3 estimated over the full dataset available to us from January 2001 and May 2011. However, the main focus is on out-of-sample analysis, where we first estimate the predictive model over the sample period from January 2001 to December 2003 and then re-estimate recursively for the rest of the sample period till May 2011, conditional on information available at the time of the forecast. The performance results include realized excess returns and their descriptive statistics (standard deviation, skewness and kurtosis), the Sharpe ratio and the Sortino ratio (both calculated in the standard way and also adjusting for serial correlation in returns), the maximum drawdown and the performance fee, calculated as discussed in Section 4. The results are presented in Tables 5 (daily rebalancing) and 6 (monthly rebalancing). All results reported in Tables 7-9 are net of transaction costs, and we assume 50% of the quoted spread. The benchmark model is the random walk or carry trade strategy.

Starting from the in-sample results in the daily rebalancing exercise (Table 7), we observe that the carry trade strategy has not performed particularly well over our sample. This is not surprising given that the crisis period that begins in June 2007 saw a collapse of carry trade strategies. In the context of the long sample analyzed in the work of Lustig, Roussanov and Verdelhan (2001), Burnside, Eichenbaum, Kleshchelski and Rebelo (2011) and Menkhoff, Sarno, Schmeling and Schrimpf (2011), the carry trade losses that characterize the 2007-8 period have relatively little impact on the average carry trade returns, but over our shorter 10-year period they reduce the in-sample Sharpe ratio to 0.13 at the daily frequency. Further trimming the sample period as in the out-of-sample exercise leads to a negative Sharpe ratio of -0.17. It is also clear that the maximum drawdown of the random walk model is very large. However, the question here is whether the order flow model does better than carry trades, and the answer is positive. The Sharpe ratios at the daily frequency ranges between 0.63 for AM flows and 1.0 for the model that uses all of the order flow series available. The results are qualitatively identical when examining the Sortino ratio.

In Table 8, we report results for the same exercise where the predictive regression is estimated using a robust estimator, discussed in Appendix A. The core results in Table 7 are robust to this

[16] Note also that robustness checks where we experimented with other values of the risk aversion coefficient γ (e.g. $\gamma = 2, 8$) do not qualitatively change any of our conclusions.

change of estimator and in fact they generally become marginally stronger. Moreover, the results are also robust to the change in the rebalancing period, as can be seen in Table 9 for the case of monthly rebalancing. In fact, we note that the Sharpe ratios increase when rebalancing monthly for all strategies, which is plausible since we are calculating returns and performance measures net of costs. Finally the returns in terms of performance fees calculations corroborate that a risk-averse investor would be willing to pay a large performance fee to switch from a random walk strategy to a strategy that conditions on order flow information, with the maximum in-sample performance fee reaching 983 basis points for the case where we use all order flow series jointly at the monthly frequency. These results provide *prima facie* evidence of the predictive power of order flow information as compared to the random walk benchmark. However, the analysis discussed until this point is in sample, while we are ultimately interested in the economic value of order flow as a conditioning variable out of sample.

The out-of-sample results, again reported in Tables 7-9, are generally consistent qualitatively with the in-sample results but also reveal several further interesting results. First note that the excess returns decrease for all strategies, and that returns volatility overshoots the target of 10 percent, largely because of the well-documented spike in the volatility of all exchange rates that occurs since June 2007 with the beginning of the subprime crisis. Also, this is a period all risky assets generated large negative returns. The Sharpe ratios generally decline but it is still the case that, both at the daily and monthly rebalancing frequencies, the models conditioning on order flow outperform the random walk benchmark by a significant margin. There is only one exception, which is the model using PC flows at the monthly frequency. The outperformance of order flow models is best seen from inspection of the performance fees. However, the results also indicate that the predictive information in the order flows of private clients (841 basis points) and hedge funds (744 basis points) are particularly powerful at the daily frequency, while the order flows of asset managers (877 basis points) and again hedge funds (561 basis points) are especially powerful at the monthly frequency. Given the heterogeneity of the order flows of different customer types, however, we also explore a strategy that conditions on the order flows of all customer types jointly, and find that this strategy consistently provides large gains both in-sample and out-of-sample relative to the random walk benchmark, with performance fees of 717 and 800 at the daily and monthly rebalancing frequencies respectively.[17]

[17] Again the results are qualitatively identical when examing other performance measures (e.g. the Sortino ratio) and when using a robust estimator rather than OLS (Table 8).

To provide a visual illustration of the these portfolio results, we present in Figure 2 the evolution of wealth for the four order flow models relative to the random walk benchmark, for the case of daily rebalancing. From this graph, we notice that the cumulative wealth is higher for each of the four order flow types, that the order flow for PC and HF performs better than AM and CO for this frequency, and that the outperformance relative to the random walk model is especially marked after the eruption of the subprime crisis in 2007. In fact, there appears to be a strong comovement of the wealth evolution for the random walk model and each of the four order flow models until the crisis, possibly suggesting that much of the order flow prior to the crisis was driven by carry positions. This changes with the beginning of the crisis when, not surprisingly, the unwinding of carry trades should have reduced the exposure to carry substantially. While this discussion is deliberately speculative, we now turn to a formal regression analysis of the drivers of the excess returns of the predictive models that condition on order flow information.

6.3 What Drives Customer Order Flow?

In the last part of the empirical analysis, we relate order flow to the state of the economy in a simple but innovative way, in order to provide evidence on how the information in order flow is related to publicly available information. Specifically, we analyze whether the excess returns generated by the strategies that use order flow information - taken as a direct measure of the predictive information content in order flows - are related to the excess returns generated both by popular trading strategies (e.g. carry, purchasing power parity, momentum) and more elaborate strategies (e.g. models based on monetary fundamentals, Taylor rule fundamentals, a model based on cyclically adjusted international financial positions, and a spot-forward regression that allows the relationship between depreciation rates and forward premia to vary over time). This is a reasonable set of strategies that employ publicly available data and mimic what currency investors do in practice. We implement these strategies using the predictive regressions described in Section 4, and then using the forecasts of FX returns generated by these models using the same mean-variance asset allocation framework employed earlier. These calculations deliver a set of realized FX excess returns, net of transaction costs, which are used as explanatory variables to attempt the replication of the realized excess returns of the order flow strategies. In essence, we are interested in shedding light on questions such as: What drives order flow? What strategies do different customers follow? Can the predictive information content in order flow be replicated using public information, or does it contain additional private information that cannot be recovered even with elaborate combinations of public data?

This set of questions are important in at least two contexts. First, they can help us understand better the behavior of FX traders, and the models or information that different customers employ when deciding what assets to buy and sell over time. This is therefore related to the broad literature that studies the behavior of FX currency managers, their performance and their exposures (e.g. Pojarlev and Levich, 2008). The main difference is that this literature tends to focus on directly observed returns of, say asset managers and hedge funds, in an attempt to replicate them and assess if they provide 'alpha' due to skill or superior information. In contrast, in our study we can observe the actual trading decisions of different customers, order flow, and therefore use order flow to generate returns that stem from its predictive power. Second, the recent theoretical literature (e.g. Evans and Lyons, 2007; Bacchetta and van Wincoop, 2006) formalize the notion that order flow conveys fundamental information about exchange rates, and hence order flow essentially aggregates dispersed economic information. This implies that order flow ought to be related to macroeconomic information empirically, and that it effectively summarizes it.

Using standard regression analysis, we find that the excess returns generated from the order flow strategies are strongly related to and can be largely replicated using a combination of the seven strategies based on public information examined (Tables 10 and 11). Starting from the results in Table 10, note that we run regressions for each customer type using in-sample realized excess returns. Also, we run four regressions, one for each customer type: one regression involves the excess returns from all seven strategies, and the other three regressions only include five returns as explanatory variables where we include just one of the returns from the random walk model, the spot-forward regression and the Taylor rule model. This is because for the latter three models the key piece of predictive information for excess returns is the interest rate differential, and hence the returns from these three strategies are highly correlated; this also means that in the larger regression that involves all seven strategies, the exposure to carry (interest rate differential) is perhaps better judged as the sum of the coefficients on the returns from these three strategies. In general, the regression we estimate is of the form:

$$\left(r^s_{p,t} - r_{f,t}\right) = \alpha + \sum_i \beta_i \left(r^i_{p,t} - r_{f,t}\right) + \varepsilon_t \tag{14}$$

where $r_{p,t}$ is the portfolio return of the order flow strategy with daily rebalancing and $r_{f,t}$ is the daily riskless return. $r^s_{p,t}$ indicates a strategy conditioning on the currency order flows of Asset Managers (AM), Corporates (CO), Hedge Funds (HF), and Private Clients (PC), respectively. $r^i_{p,t}$ refers to a strategy using the Random Walk (RW), Forward Premium (FP), Purchasing Power Parity

(PPP), Monetary Fundamentals (MF), Taylor Rule (TR), Global Imbalances (NXA) and Momentum (MOM), respectively. The portfolio returns are computed net of the effective bid-ask spread, which is assumed to be equal to 50% of the quoted spread. We compute bootstrapped standard errors and p-values obtained by resampling 10,000 times the portfolio weights by means of moving block bootstrap (Gonçalves and White, 2005).

Examining the results in Table 10, we note that: (i) the exposure to interest rate differentials (RW, FP and TR) is generally the largest judged by the size of the coefficients. (ii) Generally all of the strategies enter significantly in most regressions for all customer types. (iii) All strategies enter with the expected positive coefficient with the exception of momentum, which enters with a negative sign in the regressions for AM flows. This is indicative that over this sample AM flows were driven by contrarian strategies that buy currencies that have depreciated in the past and sell currencies that have appreciated in the past, whereas other customers' flows generally load positively on momentum. (iv) The $\overline{R}^2$ is generally very high, ranging from about 60 percent to 75 percent, suggesting that these strategies capture well the net demand for currency manifested in the order flows at our disposal. (vi) There is no evidence of positive 'alpha' in the order flow strategies, indicating that there is no additional positive excess returns generated by the order flow strategies in sample, over and above what can be generated by combining the set of strategies examined here.[18]

While the regressions are estimated over the full sample period with constant parameters, it is unlikely that these parameters are indeed constant. In fact, it is quite likely that the customers change the weight they assign to different fundamentals (strategies), which is a well-documented practice in currency markets.[19] We investigate in more detail this possibility by estimating the above regressions using a rolling window of one year. Figures 3-6 report the rolling estimates of the coefficients associated with each of the seven strategies as well as the $\overline{R}^2$, for each of the four customer types. The figures show clear evidence of instability in the parameters, as expected, and make apparent how all of the customers reduced their exposure to carry (interest rate differentials) in the second part of the sample period and especially after 2007.

Our final exercise involves using forecast combinations to generate exchange rate forecasts from

[18] We also estimate these regressions using the out-of-sample excess retuns (not reported to conserve space) and confirm qualitatively the above results.

[19] This practice is documented for example in the survey evidence of Cheung and Chinn (2001), based on questionnaires sent to US FX traders. It is also the basis of the 'scapegoat' theory of Bacchetta and van Wincoop (2004), and consistent with the empirical evidence on time-varying exchange rate models of Sarno and Valente (2009).

our set of seven strategies. In other words, we estimate the following regression

$$\left(r_{p,t}^{s} - r_{f,t}\right) = \alpha + \beta_i \left(r_{p,t}^{i} - r_{f,t}\right) + \varepsilon_t \tag{15}$$

where $r_{p,t}$ is the portfolio return of the order flow strategy with daily rebalancing and $r_{f,t}$ is the daily riskless return. $r_{p,t}^{s}$ indicates a strategy conditioning on the currency order flows of AM, CO, HF and PC, respectively. $r_{p,t}^{i}$ refers to a strategy that combines the seven strategies based on public information data. The combination employs the average (AVE), median (MED), trimmed mean (TRI), and mean-squared error (MSE) of the forecasts, the 'kitchen sink' (KS) regression that incorporates all predictors into a multiple predictive regression, and the 'Fund of Funds' (FoF) strategy that equally invests in the underlying portfolio strategies. The portfolio returns are computed net of the effective bid-ask spread, which is assumed to be equal to 50% of the quoted spread. Again, we construct bootstrapped standard errors and p-values by resampling 10,000 times the portfolio weights by means of moving block bootstrap (see Gonçalves and White, 2005). The results, reported in Table 11, suggest that, with the exception of the KS approach, all other combinations appear to work well, generating high $\overline{R}^2$ for each customer type. The results also confirm that the evidence that there is no significant positive 'alpha' in the returns from the order flow strategy, and further sugegst that the slope parameters are in the range between 0.7 and 1.2.

Overall, the evidence in this section suggests that information in interest rates, past values of exchange rates, inflation and output gaps is key in determining the net demand for currencies that is observed in FX order flow and can account for over 70 percent of the excess returns generated by models conditioning on order flow information. In some sense, we are able to uncover which public information is relevant to generate currency orders and, in turn, becomes 'price relevant'. We also find evidence that there is strong variation in the relative importance of different strategies in driving order flows over the sample, and this is particularly apparent in samples pre- and post-crisis. For example, while exposure to the carry trade was quite dominant during the pre-crisis period, after the crisis erupted in June 2007 and the carry trade collapsed, returns generated by order flows were much more strongly driven by strategies based on purchasing power parity and other economic fundamentals. Overall, we interpret this evidence as suggesting that the information content in order flow is economically important and derives from aggregating disperse public information about economic fundamentals that are relevant to exchange rates.

7 Conclusions

In this paper we examine the predictive information content of order flow for future exchange rate returns using a unique dataset for daily order flow representing the transactions of customers of one of the major players in the FX market, UBS. The dataset spans from 2001 to 2011 and covers nine currency pairs, disaggregated across four different segments of the FX market: asset managers, hedge funds, corporate clients, and private clients.

The empirical analysis provides two key results: (i) a multi-currency trading strategy based solely on end-customer order flow strongly outperforms the popular carry trade strategy; (ii) the excess returns generated from conditioning on order flow can be largely replicated using a combination of strategies based on publicly available information, consistent with the notion that order flow aggregates disperse public information about economic fundamentals that are relevant to exchange rates.

Table 1: Market Share by Institution Type

The table displays the overall market share and the market share by institution type for UBS. The rank is with respect to the top 10 leaders in the foreign exchange (FX) market from 2001 to 2011. The data are collected from the Euromoney annual survey of the global FX industry. The market share by institution type (available from 2003) are presented for *real money, leveraged funds* and *non-financial corporations.*

	Overall		Real Money		Leveraged Funds		Non-financial Corporations	
	share(%)	rank	share (%)	rank	share (%)	rank	share (%)	rank
2001	3.55	7						
2002	10.96	2						
2003	11.53	1	11.25	1	13.03	1	6.38	4
2004	12.36	1	11.32	2	11.70	2	7.16	3
2005	12.47	2	11.60	1	8.57	3	8.41	3
2006	22.50	1	11.35	2	5.23	7	6.38	4
2007	14.85	2	13.73	1	5.96	6	5.65	6
2008	15.80	2	9.07	2	7.53	4	5.13	5
2009	14.58	2	10.96	2	6.94	4	7.43	5
2010	11.30	2	9.39	2	14.63	2	4.93	9
2011	10.59	3						

Table 2. Descriptive Statistics

The table reports descriptive statistics for log exchange rate returns and foreign currency order flows at daily frequency. The exchange rate is defined as the US dollar price of a unit of foreign currency so that an increase in the exchange rate implies a depreciation of the US dollar. Order flow is defined as the difference between the value of buyer-initiated and seller-initiated transactions for the foreign currency so that a positive (negative) order flow implies net foreign currency purchases (sales). Order flows are in billions of US dollars and classified into four customer segments: *asset managers*, *hedge funds*, *corporates* and *private clients*. Q_5 and Q_{95} are the 5th and 95th percentile, respectively. ρ_l is the autocorrelation coefficient for a lag of l trading days. The sample period comprises daily observations from January 2001 to May 2011. Exchange rates are from Thomson Reuters while customer order flows are proprietary data from UBS.

		$Mean$	$Sdev$	Min	Max	Q_5	Q_{95}	ρ_1	ρ_5	ρ_{21}
AUD	FX Returns (%)	0.0248	0.943	−7.627	8.219	−1.449	1.282	−0.077	−0.018	−0.040
	Asset Managers	−0.0017	0.146	−3.725	1.531	−0.151	0.144	−0.027	−0.006	−0.022
	Hedge Funds	−0.0052	0.118	−1.273	0.814	−0.175	0.154	0.073	0.041	−0.036
	Corporates	0.0035	0.048	−0.311	0.965	−0.035	0.050	0.172	0.109	0.041
	Private Clients	0.0002	0.092	−2.339	2.069	−0.067	0.072	−0.135	0.029	0.001
CAD	FX Returns (%)	0.0162	0.628	−3.298	3.770	−0.971	1.014	−0.027	−0.032	0.013
	Asset Managers	0.0035	0.136	−1.178	2.734	−0.136	0.149	0.096	0.010	0.022
	Hedge Funds	−0.0003	0.096	−0.754	1.162	−0.135	0.127	−0.007	0.020	−0.030
	Corporates	0.0048	0.056	−0.392	1.317	−0.042	0.051	0.172	0.106	0.034
	Private Clients	−0.0005	0.093	−4.023	1.043	−0.039	0.048	0.041	−0.021	−0.001
CHF	FX Returns (%)	0.0242	0.707	−2.873	5.038	−1.123	1.159	−0.058	−0.004	−0.052
	Asset Managers	−0.0033	0.199	−2.889	2.153	−0.266	0.228	0.032	0.048	0.005
	Hedge Funds	0.0091	0.207	−2.051	3.252	−0.261	0.288	−0.034	0.032	−0.009
	Corporates	0.0075	0.166	−5.702	3.572	−0.105	0.138	0.026	0.003	0.008
	Private Clients	0.0061	0.111	−1.348	2.597	−0.118	0.130	0.076	0.011	0.044
EUR	FX Returns (%)	0.0157	0.674	−3.173	3.733	−1.101	1.091	−0.022	0.009	−0.041
	Asset Managers	−0.0002	0.498	−12.803	3.981	−0.526	0.563	0.032	−0.001	−0.022
	Hedge Funds	−0.0267	0.391	−2.862	2.886	−0.590	0.580	−0.016	0.000	−0.008
	Corporates	−0.0490	0.166	−2.042	1.738	−0.296	0.169	−0.003	0.075	0.036
	Private Clients	0.0140	0.265	−2.122	4.240	−0.363	0.356	0.037	−0.004	0.000
GBP	FX Returns (%)	0.0036	0.618	−5.883	3.042	−0.986	0.949	0.026	−0.036	−0.037
	Asset Managers	0.0067	0.408	−8.289	9.102	−0.276	0.278	−0.130	0.024	0.019
	Hedge Funds	−0.0146	0.340	−13.162	3.183	−0.264	0.227	0.023	0.032	−0.004
	Corporates	0.0009	0.084	−0.914	1.815	−0.090	0.096	−0.009	0.046	−0.030
	Private Clients	0.0033	0.122	−1.698	1.321	−0.155	0.155	−0.004	0.006	−0.040
JPY	FX Returns (%)	0.0133	0.685	−6.203	3.706	−1.043	1.081	−0.054	0.013	−0.050
	Asset Managers	0.0090	0.306	−4.001	6.586	−0.326	0.329	0.127	−0.008	−0.008
	Hedge Funds	0.0127	0.280	−5.063	5.131	−0.327	0.352	−0.109	−0.001	−0.030
	Corporates	0.0050	0.061	−0.792	0.567	−0.078	0.089	0.037	−0.007	−0.030
	Private Clients	0.0004	0.102	−0.786	0.729	−0.144	0.136	0.014	0.014	−0.040
NOK	FX Returns (%)	0.0182	0.824	−4.709	5.625	−1.317	1.238	−0.019	−0.009	−0.051
	Asset Managers	0.0017	0.056	−0.638	0.605	−0.060	0.061	0.065	−0.037	0.014
	Hedge Funds	0.0001	0.040	−0.540	0.400	−0.051	0.050	0.074	0.051	0.024
	Corporates	0.0006	0.011	−0.112	0.127	−0.010	0.014	0.028	0.029	−0.006
	Private Clients	0.0003	0.010	−0.099	0.088	−0.012	0.012	0.061	−0.011	−0.004
NZD	FX Returns (%)	0.0233	0.911	−6.813	5.188	−1.546	1.351	−0.014	−0.015	−0.021
	Asset Managers	−0.0009	0.057	−1.171	0.672	−0.052	0.047	0.097	0.050	−0.012
	Hedge Funds	−0.0001	0.045	−0.440	0.633	−0.063	0.057	0.054	0.017	−0.007
	Corporates	−0.0014	0.015	−0.472	0.114	−0.014	0.010	0.183	−0.022	0.014
	Private Clients	−0.0001	0.019	−0.189	0.242	−0.023	0.026	0.062	0.004	−0.003
SEK	FX Returns (%)	0.0158	0.844	−5.379	5.243	−1.315	1.295	−0.029	0.007	−0.063
	Asset Managers	0.0001	0.057	−0.548	0.427	−0.078	0.081	−0.016	0.030	−0.016
	Hedge Funds	0.0006	0.044	−0.408	1.337	−0.044	0.045	0.032	0.068	−0.011
	Corporates	0.0005	0.018	−0.149	0.247	−0.018	0.020	0.049	−0.016	0.055
	Private Clients	0.0001	0.009	−0.102	0.145	−0.010	0.010	0.006	−0.038	0.021

Table 3. Descriptive Statistics Across Calendar Years

The table reports the means and the standard deviations of log exchange rate returns and foreign currency order flows across calendar years. The exchange rate is defined as the US dollar price of a unit of foreign currency so that an increase in the exchange rate implies a depreciation of the US dollar. Order flow is defined as the difference between the value of buyer-initiated and seller-initiated transactions for the foreign currency so that a positive (negative) order flow implies net foreign currency purchases (sales). Order flows are in billions of US dollars and classified into four customer segments: *asset managers*, *hedge funds*, *corporates* and *private clients*. The sample period comprises daily observations from January 2001 to May 2011. Exchange rates are from Thomson Reuters while customer order flows are proprietary data from UBS.

	AUD		CAD		CHF		EUR		GBP		JPY		NOK		NZD		SEK	
Year	*Mean*	*Sdev*	*Mean*	*Sdev*	*Mean*	*Sdev*	*Mean*	*Sdev*	*Mean*	*Sdev*	*Mean*	*Sdev*	*Mean*	*Sdev*	*Mean*	*Sdev*	*Mean*	*Sdev*
FX Returns (%)																		
2001	−0.037	0.830	−0.026	0.338	−0.014	0.782	−0.026	0.753	−0.013	0.507	−0.057	0.667	−0.010	0.669	−0.026	0.842	−0.043	0.784
2002	0.037	0.572	0.005	0.392	0.073	0.626	0.065	0.578	0.041	0.427	0.041	0.629	0.101	0.621	0.091	0.626	0.073	0.619
2003	0.117	0.637	0.077	0.555	0.043	0.736	0.073	0.661	0.041	0.506	0.040	0.519	0.015	0.739	0.089	0.664	0.075	0.718
2004	0.016	0.857	0.030	0.561	0.034	0.756	0.029	0.675	0.028	0.637	0.019	0.617	0.037	0.752	0.037	0.891	0.031	0.741
2005	−0.025	0.571	0.014	0.494	−0.057	0.616	−0.054	0.573	−0.043	0.514	−0.056	0.558	−0.041	0.654	−0.020	0.647	−0.070	0.646
2006	0.029	0.535	−0.001	0.450	0.030	0.555	0.043	0.488	0.052	0.485	−0.004	0.510	0.031	0.635	0.012	0.684	0.059	0.625
2007	0.041	0.794	0.062	0.611	0.029	0.448	0.040	0.394	0.005	0.438	0.027	0.621	0.055	0.599	0.034	0.911	0.023	0.552
2008	−0.084	1.799	−0.079	0.991	0.024	0.937	−0.017	0.899	−0.121	0.899	0.081	1.060	−0.097	1.236	−0.108	1.366	−0.075	1.154
2009	0.094	1.222	0.057	0.911	0.012	0.825	0.009	0.809	0.039	0.918	−0.010	0.828	0.072	1.164	0.085	1.287	0.035	1.332
2010	0.051	0.939	0.021	0.699	0.041	0.669	−0.027	0.755	−0.014	0.646	0.053	0.663	−0.002	0.880	0.029	0.913	0.025	0.906
2011	0.045	0.723	0.021	0.416	0.093	0.691	0.067	0.673	0.055	0.484	0.005	0.663	0.069	0.795	0.049	0.727	0.075	0.844
Asset Managers																		
2001	−0.002	0.027	−0.003	0.048	−0.004	0.090	0.002	0.163	0.001	0.090	0.004	0.127	0.000	0.013	0.000	0.008	0.000	0.018
2002	−0.004	0.070	0.000	0.042	0.010	0.074	−0.006	0.185	0.003	0.080	0.008	0.113	0.000	0.008	−0.001	0.007	−0.001	0.024
2003	−0.001	0.054	0.000	0.052	0.012	0.106	0.010	0.251	0.006	0.090	0.006	0.132	0.002	0.042	0.000	0.013	−0.001	0.022
2004	0.003	0.063	−0.001	0.065	0.006	0.141	0.022	0.228	0.004	0.143	0.031	0.356	0.001	0.018	0.002	0.017	−0.001	0.035
2005	0.007	0.090	−0.002	0.059	0.001	0.135	0.021	0.278	−0.002	0.107	0.021	0.202	0.002	0.032	−0.001	0.020	−0.003	0.051
2006	0.012	0.137	0.005	0.140	−0.015	0.297	0.075	0.568	−0.009	0.619	−0.005	0.407	−0.007	0.067	0.003	0.054	0.001	0.072
2007	−0.010	0.231	−0.014	0.173	−0.006	0.351	0.015	0.483	0.059	0.938	0.054	0.430	0.003	0.095	−0.009	0.122	−0.004	0.082
2008	−0.023	0.295	0.012	0.216	−0.005	0.298	−0.027	0.643	−0.028	0.559	0.015	0.528	0.001	0.084	−0.003	0.083	0.003	0.088
2009	0.009	0.099	0.027	0.237	−0.013	0.124	−0.029	0.695	0.005	0.215	−0.033	0.224	0.012	0.055	0.000	0.044	0.000	0.058
2010	−0.005	0.156	0.016	0.131	−0.005	0.138	−0.096	0.897	0.030	0.202	−0.008	0.253	0.004	0.048	−0.005	0.052	0.006	0.059
2011	−0.014	0.115	−0.010	0.140	−0.037	0.182	0.033	0.357	0.005	0.203	0.005	0.207	0.002	0.088	0.010	0.070	0.004	0.077

(Continued)

Table 3. Descriptive Statistics Across Calendar Years *(continued)*

	AUD		CAD		CHF		EUR		GBP		JPY		NOK		NZD		SEK	
Year	*Mean*	*Sdev*	*Mean*	*Sdev*	*Mean*	*Sdev*	*Mean*	*Sdev*	*Mean*	*Sdev*	*Mean*	*Sdev*	*Mean*	*Sdev*	*Mean*	*Sdev*	*Mean*	*Sdev*
Hedge Funds																		
2001	0.000	0.019	0.002	0.084	0.003	0.102	0.006	0.214	0.002	0.053	0.001	0.153	0.002	0.009	0.000	0.005	0.000	0.004
2002	0.001	0.025	−0.005	0.065	0.006	0.134	−0.014	0.212	−0.006	0.103	0.001	0.237	0.000	0.012	0.000	0.010	0.000	0.022
2003	0.002	0.061	−0.005	0.075	0.006	0.155	−0.040	0.304	−0.004	0.093	0.009	0.162	0.001	0.017	0.000	0.013	0.000	0.010
2004	−0.011	0.129	−0.004	0.101	0.020	0.305	−0.043	0.557	0.005	0.185	−0.005	0.512	−0.002	0.029	−0.001	0.021	−0.001	0.024
2005	−0.003	0.066	0.003	0.076	−0.017	0.223	−0.044	0.379	0.001	0.133	0.011	0.165	−0.004	0.032	−0.002	0.033	−0.003	0.026
2006	−0.013	0.128	−0.001	0.133	0.023	0.329	−0.033	0.474	−0.036	0.418	0.028	0.307	−0.002	0.053	−0.001	0.057	0.006	0.097
2007	−0.005	0.173	0.007	0.111	0.016	0.245	−0.048	0.373	−0.025	0.300	0.028	0.311	0.002	0.058	−0.003	0.074	0.003	0.060
2008	−0.011	0.170	0.008	0.096	0.021	0.179	0.018	0.538	−0.050	0.902	−0.002	0.367	0.000	0.055	−0.002	0.060	−0.003	0.036
2009	0.004	0.113	−0.012	0.100	0.005	0.148	−0.031	0.337	−0.005	0.133	0.010	0.198	0.001	0.025	0.004	0.044	0.001	0.027
2010	−0.008	0.144	0.006	0.103	0.013	0.131	−0.020	0.373	−0.024	0.155	0.039	0.199	0.002	0.032	0.002	0.051	0.003	0.036
2011	−0.024	0.142	−0.004	0.097	0.001	0.176	−0.075	0.346	−0.021	0.123	0.030	0.198	0.005	0.037	0.007	0.043	−0.002	0.028
Corporates																		
2001	−0.002	0.017	0.016	0.117	−0.003	0.070	−0.022	0.128	0.007	0.061	0.001	0.062	0.001	0.007	0.000	0.003	0.001	0.023
2002	−0.003	0.021	0.002	0.019	−0.008	0.073	−0.030	0.095	0.003	0.049	0.000	0.035	0.001	0.005	−0.001	0.003	0.000	0.013
2003	−0.002	0.020	0.000	0.022	−0.009	0.096	−0.006	0.171	0.003	0.050	0.002	0.050	−0.001	0.006	−0.001	0.005	0.000	0.016
2004	0.003	0.017	0.006	0.026	0.001	0.063	−0.032	0.108	0.010	0.051	0.009	0.057	0.000	0.005	0.000	0.008	0.000	0.013
2005	0.020	0.108	0.007	0.028	0.021	0.089	−0.043	0.146	0.007	0.047	0.010	0.057	0.000	0.010	−0.002	0.008	0.001	0.011
2006	0.004	0.052	0.007	0.053	0.003	0.442	−0.037	0.154	−0.003	0.143	0.012	0.090	0.003	0.014	−0.003	0.036	0.004	0.035
2007	0.007	0.037	0.013	0.074	−0.009	0.148	−0.084	0.199	0.002	0.146	0.005	0.070	0.000	0.010	−0.002	0.015	−0.001	0.016
2008	0.007	0.043	0.003	0.036	0.031	0.162	−0.083	0.269	−0.004	0.069	0.010	0.079	−0.001	0.009	−0.001	0.008	0.001	0.018
2009	−0.001	0.028	0.003	0.069	0.020	0.067	−0.043	0.165	−0.010	0.051	0.003	0.041	0.001	0.014	−0.002	0.009	−0.001	0.012
2010	0.000	0.038	−0.009	0.044	0.022	0.063	−0.085	0.138	−0.003	0.100	0.000	0.050	0.001	0.015	−0.001	0.007	−0.001	0.010
2011	0.007	0.069	0.005	0.039	0.021	0.060	−0.107	0.154	−0.006	0.046	0.001	0.049	0.000	0.012	−0.002	0.010	−0.001	0.010
Private Clients																		
2001	0.001	0.015	−0.001	0.013	0.007	0.066	0.022	0.095	0.001	0.048	−0.002	0.073	0.001	0.005	0.000	0.004	0.000	0.004
2002	0.001	0.013	0.001	0.007	−0.002	0.053	0.013	0.084	0.001	0.025	−0.002	0.090	0.001	0.002	0.000	0.003	0.000	0.002
2003	0.006	0.027	0.000	0.023	−0.006	0.076	0.006	0.196	0.002	0.047	0.008	0.170	0.000	0.003	0.000	0.005	0.000	0.003
2004	−0.006	0.048	0.000	0.022	0.002	0.117	0.005	0.250	0.004	0.069	0.005	0.074	0.000	0.005	0.000	0.005	0.000	0.004
2005	0.001	0.035	−0.001	0.028	0.003	0.059	0.024	0.282	0.000	0.117	0.004	0.060	0.000	0.005	0.000	0.012	0.000	0.007
2006	0.003	0.121	0.002	0.073	0.002	0.107	0.046	0.523	−0.001	0.187	0.008	0.101	−0.001	0.017	−0.001	0.026	−0.002	0.018
2007	−0.002	0.068	−0.004	0.054	0.023	0.255	−0.010	0.273	0.002	0.174	−0.003	0.104	0.001	0.016	−0.002	0.040	0.000	0.017
2008	0.010	0.212	−0.007	0.265	0.021	0.129	0.021	0.347	0.017	0.156	−0.003	0.131	0.000	0.012	0.004	0.030	0.000	0.009
2009	0.001	0.083	0.001	0.087	0.007	0.049	0.033	0.165	0.003	0.166	−0.001	0.111	0.001	0.008	0.000	0.010	0.000	0.006
2010	−0.012	0.105	0.001	0.023	0.005	0.048	−0.012	0.177	0.004	0.103	−0.002	0.046	0.000	0.007	−0.001	0.012	0.000	0.008
2011	−0.004	0.060	0.004	0.022	0.002	0.032	−0.007	0.127	−0.001	0.075	−0.021	0.108	0.000	0.009	−0.001	0.021	0.000	0.004

Table 4. Cross Correlations

The table reports the cross correlations among log exchange rate returns and foreign currency order flows. The exchange rate is defined as the US dollar price of a unit of foreign currency so that an increase in the exchange rate implies a depreciation of the US dollar. Order flow is defined as the difference between the value of buyer-initiated and seller-initiated transactions for the foreign currency so that a positive (negative) order flow implies net foreign currency purchases (sales). Order flows are in billions of US dollars and classified into four customer segments: *asset managers*, *hedge funds*, *corporates* and *private clients*. The superscripts a, b, and c denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample period comprises daily observations from January 2001 to May 2011. Exchange rates are from Thomson Reuters while customer order flows are proprietary data from UBS.

		FX Returns	Asset Managers	Hedge Funds	Corporates	Private Clients
AUD	FX Returns	1.000				
	Asset Managers	0.061^c	1.000			
	Hedge Funds	0.200^c	-0.048^c	1.000		
	Corporates	-0.044^b	-0.008	-0.045^b	1.000	
	Private Clients	-0.051^c	-0.094^c	-0.087^c	0.022	1.000
CAD	FX Returns	1.000				
	Asset Managers	0.106^c	1.000			
	Hedge Funds	0.203^c	0.010	1.000		
	Corporates	-0.047^c	-0.071^c	-0.005	1.000	
	Private Clients	-0.092^c	-0.205^c	-0.225^c	-0.046^b	1.000
CHF	FX Returns	1.000				
	Asset Managers	0.149^c	1.000			
	Hedge Funds	0.312^c	0.003	1.000		
	Corporates	-0.072^c	-0.175^c	-0.041^b	1.000	
	Private Clients	-0.243^c	0.023	-0.110^c	0.047^b	1.000
EUR	FX Returns	1.000				
	Asset Managers	0.049^c	1.000			
	Hedge Funds	0.130^c	-0.186^b	1.000		
	Corporates	-0.056^c	0.038^b	-0.016^c	1.000	
	Private Clients	-0.348^c	-0.146	-0.027^c	0.010^c	1.000
GBP	FX Returns	1.000				
	Asset Managers	0.075^c	1.000			
	Hedge Funds	0.336^c	-0.039^c	1.000		
	Corporates	-0.079^c	-0.043^b	-0.089	1.000	
	Private Clients	-0.344^c	-0.007^c	-0.170	0.121	1.000
JPY	FX Returns	1.000				
	Asset Managers	0.103^c	1.000			
	Hedge Funds	0.227^c	0.022	1.000		
	Corporates	-0.050^c	-0.020	-0.009	1.000	
	Private Clients	-0.283^c	-0.115^c	-0.181^c	0.103^c	1.000
NOK	FX Returns	1.000				
	Asset Managers	0.068^c	1.000			
	Hedge Funds	0.083^c	0.011	1.000		
	Corporates	-0.030	-0.073^c	-0.074^c	1.000	
	Private Clients	0.147^c	0.016	0.048^b	-0.118^c	1.000
NZD	FX Returns	1.000				
	Asset Managers	0.114^c	1.000			
	Hedge Funds	0.132	-0.077^c	1.000		
	Corporates	0.013	-0.017	0.070^c	1.000	
	Private Clients	-0.014	-0.072^c	-0.023	0.036^a	1.000
SEK	FX Returns	1.000				
	Asset Managers	0.103^c	1.000			
	Hedge Funds	0.065^c	-0.079^c	1.000		
	Corporates	-0.007	-0.049^c	-0.027	1.000	
	Private Clients	0.086^c	0.032^a	0.066^c	-0.078^c	1.000

Table 5: Daily Excess Returns and Contemporaneous Order Flows

The table reports the estimates from regressions of daily excess returns on a constant (not reported) and foreign currency order flows. Order flow is defined as the difference between the value of buyer-initiated and seller-initiated transactions for the foreign currency so that a positive (negative) order flow implies net foreign currency purchases (sales). Order flows are classified into four customer segments: *asset managers*, *hedge funds*, *corporates* and *private clients*. *Ser* is the Breusch-Godfrey test for the null hypothesis of no first-order residual correlation. *Het* is the White test for the null hypothesis of homoskedasticity in the residuals. Robust standard errors are reported in parentheses and asymptotic p-values in brackets. The superscripts a, b, and c denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample period comprises daily data from January 2001 to May 2011. Exchange rates are from Thomson Reuters while customer order flows are proprietary data from UBS.

	Asset Managers				*Hedge Funds*				*Corporates*				*Private Clients*			
	β_{AM}	$\overline{R}^2(\%)$	*Ser*	*Het*	β_{HF}	$\overline{R}^2(\%)$	*Ser*	*Het*	β_{CO}	$\overline{R}^2(\%)$	*Ser*	*Het*	β_{PC}	$\overline{R}^2(\%)$	*Ser*	*Het*
AUD	0.0040^a	0.3	[< .01]	[< .01]	0.0160^c	3.9	[< .01]	[0.12]	-0.0087^c	0.2	[< .01]	[0.82]	-0.0052^a	0.2	[< .01]	[0.25]
	(0.0021)				(0.0020)				(0.0029)				(0.0032)			
CAD	0.0049^c	1.1	[0.13]	[0.01]	0.0132^c	4.1	[0.14]	[0.02]	-0.0052^c	0.2	[0.16]	[0.88]	-0.0062^a	0.8	[0.06]	[< .01]
	(0.0014)				(0.0015)				(0.0019)				(0.0035)			
CHF	0.0053^c	2.2	[< .01]	[0.11]	0.0107^c	9.7	[0.02]	[< .01]	-0.0030^a	0.5	[< .01]	[0.01]	-0.0154^c	5.9	[< .01]	[< .01]
	(0.0009)				(0.0016)				(0.0017)				(0.0056)			
EUR	0.0010^a	0.5	[0.06]	[< .01]	0.0058^c	11.3	[0.28]	[< .01]	-0.0032^c	0.6	[0.18]	[< .01]	-0.0088^c	11.8	[0.70]	[< .01]
	(0.0005)				(0.0004)				(0.0011)				(0.0011)			
GBP	0.0007	0.2	[0.22]	[< .01]	0.0024^b	1.7	[0.36]	[< .01]	-0.0041	0.3	[0.18]	[0.92]	-0.0177^c	12.1	[0.91]	[< .01]
	(0.0006)				(0.0011)				(0.0016)				(0.0024)			
JPY	0.0023^c	1.0	[< .01]	[0.04]	0.0055^c	5.1	[< .01]	[< .01]	-0.0056	0.2	[< .01]	[0.34]	-0.0189^c	8.0	[< .01]	[< .01]
	(0.0007)				(0.0015)				(0.0024)				(0.0021)			
NOK	0.0100^c	0.4	[0.32]	[0.89]	0.0181^b	0.7	[0.59]	[< .01]	-0.0241	0.1	[0.71]	[0.25]	0.1283^c	2.1	[0.62]	[0.41]
	(0.0031)				(0.0072)				(0.0183)				(0.0189)			
NZD	0.0184^c	1.3	[0.29]	[0.04]	0.0271^c	1.7	[0.08]	[0.85]	0.0083	0.1	[0.73]	[0.76]	-0.0066	0.1	[0.40]	[0.39]
	(0.0049)				(0.0051)				(0.0085)				(0.0090)			
SEK	0.0152^c	1.0	[0.05]	[0.98]	0.0126^b	0.4	[0.05]	[0.27]	-0.0035	0.1	[0.06]	[0.82]	0.0788^c	0.7	[0.11]	[0.32]
	(0.0029)				(0.0064)				(0.0103)				(0.0132)			

(Continued)

Table 5: Daily Excess Returns and Contemporaneous Order Flows *(continued)*

	Disaggregate Order Flows							*Total Order Flow*			
	β_{AM}	β_{HF}	β_{CO}	β_{PC}	$\overline{R}^2(\%)$	*Ser*	*Het*	β	$\overline{R}^2(\%)$	*Ser*	*Het*
AUD	0.0043^b	0.0160^c	-0.0068^b	-0.0026	4.5	[< .01]	[0.07]	0.0061^c	1.6	[< .01]	[< .01]
	(0.0022)	(0.0020)	(0.0031)	(0.0035)				(0.0021)			
CAD	0.0043^c	0.0127^c	-0.0046^b	-0.0021	5.3	[0.10]	[< .01]	0.0049^c	1.7	[0.22]	[< .01]
	(0.0014)	(0.0016)	(0.0019)	(0.0033)				(0.0010)			
CHF	0.0053^c	0.0098^c	-0.0010	-0.0136^c	16.4	[< .01]	[< .01]	0.0037^c	2.9	[< .01]	[< .01]
	(0.0010)	(0.0015)	(0.0013)	(0.0034)				(0.0007)			
EUR	0.0011^b	0.0050^c	-0.0006	-0.0075^c	20.4	[0.48]	[< .01]	0.0010^b	0.9	[0.07]	[< .01]
	(0.0005)	(0.0004)	(0.0009)	(0.0009)				(0.0004			
GBP	0.0004	0.0023^b	-0.0038^b	-0.0173^c	13.8	[0.78]	[< .01]	0.0005^a	0.1	[0.22]	[0.67]
	(0.0006)	(0.0010)	(0.0017)	(0.0024)				(0.0003)			
JPY	0.0016^c	0.0044^c	-0.0025	-0.0160^c	11.6	[< .01]	[< .01]	0.0025^c	2.2	[< .01]	[< .01]
	(0.0006)	(0.0013)	(0.0022)	(0.0021)				(0.0005)			
NOK	0.0062^a	0.0141^a	-0.0091	0.1232^c	2.9	[0.87]	[< .01]	0.0140^c	1.3	[0.14]	[0.04]
	(0.0033)	(0.0079)	(0.0176)	(0.0226)				(0.0031)			
NZD	0.0201^c	0.0274^c	0.0031	0.0007	3.2	[0.27]	[0.04]	0.0213^c	2.7	[0.15]	[< .01]
	(0.0053)	(0.0043)	(0.0095)	(0.0093)				(0.0036)			
SEK	0.0153^c	0.0134^b	0.0034	0.0768^c	2.3	[< .01]	[0.94]	0.0156^c	1.6	[0.05]	[0.19]
	(0.0029)	(0.0060)	(0.0104	(0.0132				(0.0029)			

Table 6: Monthly Excess Returns and Contemporaneous Order Flows

The table reports the estimates from regressions of monthly excess returns on a constant (not reported) and foreign currency order flows. Order flow is defined as the difference between the value of buyer-initiated and seller-initiated transactions for the foreign currency so that a positive (negative) order flow implies net foreign currency purchases (sales). Order flows are classified into four customer segments: *asset managers*, *hedge funds*, *corporates* and *private clients*. *Ser* is the Breusch-Godfrey test for the null hypothesis of no first-order residual correlation. *Het* is the White test for the null hypothesis of homoskedasticity in the residuals. Robust standard errors are reported in parentheses and asymptotic p-values in brackets. The superscripts a, b, and c denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample period comprises end-of-month (non-overlapping) data from January 2001 to May 2011. Exchange rates are from Thomson Reuters while customer order flows are proprietary data from UBS.

	Asset Managers				*Hedge Funds*				*Corporates*				*Private Clients*			
	β_{AM}	$\overline{R}^2(\%)$	*Ser*	*Het*	β_{HF}	$\overline{R}^2(\%)$	*Ser*	*Het*	β_{CO}	$\overline{R}^2(\%)$	*Ser*	*Het*	β_{PC}	$\overline{R}^2(\%)$	*Ser*	*Het*
AUD	0.0121	3.3	[0.24]	[< .01]	0.0095	1.4	[0.28]	[0.24]	−0.0101	0.1	[0.45]	[0.04]	−0.0370^c	18.4	[0.39]	[0.97]
	(0.0101)				(0.0075)				(0.0083)				(0.0073)			
CAD	0.0082^b	5.2	[0.34]	[0.09]	0.0106^a	1.8	[0.91]	[0.58]	−0.0081^b	0.5	[0.45]	[0.81]	−0.0218	9.7	[0.65]	[0.01]
	(0.0040)				(0.0065)				(0.0041)				(0.0139)			
CHF	0.0112^c	12.0	[0.77]	[0.27]	0.0090^c	6.9	[0.38]	[0.35]	−0.0109^b	8.0	[0.13]	[0.01]	−0.0216^c	9.0	[0.59]	[0.15]
	(0.0028)				(0.0030)				(0.0050)				(0.0068)			
EUR	0.0051^c	14.6	[0.56]	[< .01]	0.0036^a	3.8	[0.30]	[0.02]	−0.0043	0.8	[0.48]	[0.06]	−0.0054^b	3.7	[0.88]	[0.68]
	(0.0015)				(0.0020)				(0.0038)				(0.0027)			
GBP	0.0047^b	6.6	[0.09]	[0.90]	0.0038^c	5.2	[0.05]	[0.75]	−0.0030	0.1	[0.10]	[0.79]	−0.0196^c	15.3	[0.04]	[0.20]
	(0.0020)				(0.0010)				(0.0045)				(0.0054)			
JPY	0.0036^b	3.2	[0.63]	[< .01]	0.0051^b	4.8	[0.66]	[0.10]	−0.0132^a	1.5	[0.51]	[0.70]	−0.0261^c	20.0	[0.33]	[0.23]
	(0.0018)				(0.0023)				(0.0076)				(0.0056)			
NOK	0.0279^b	4.5	[0.59]	[0.21]	0.0487^c	7.3	[0.26]	[0.53]	−0.0693	0.4	[0.22]	[0.25]	0.1960^c	5.8	[0.40]	[0.03]
	(0.0125)				(0.0106)				(0.0460)				(0.0808)			
NZD	0.0216^a	1.7	[0.69]	[0.89]	0.0155	0.1	[0.69]	[0.33]	0.0270	0.1	[0.58]	[0.84]	−0.0749^b	2.3	[0.74]	[0.98]
	(0.0123)				(0.0210)				(0.0244)				(0.0364)			
SEK	0.0394^c	7.6	[0.50]	[0.67]	0.0421^c	4.3	[0.19]	[0.49]	−0.0942^b	3.1	[0.54]	[0.59]	0.0885^a	0.3	[0.38]	[0.34]
	(0.0106)				(0.0133)				(0.0478)				(0.0471)			

(Continued)

Table 6: Monthly Excess Returns and Contemporaneous Order Flows *(continued)*

	Disaggregate Order Flows							*Total Order Flow*			
	β_{AM}	β_{HF}	β_{CO}	β_{PC}	$\overline{R}^2(\%)$	*Ser*	*Het*	β	$\overline{R}^2(\%)$	*Ser*	*Het*
AUD	0.0074	−0.0009	−0.0094	−0.0354[c]	18.8	[0.38]	[0.00]	−0.0006	0.1	[0.37]	[0.06]
	(0.0085)	(0.0062)	(0.0066)	(0.0081)				(0.0052)			
CAD	0.0028	0.0054	−0.0069[b]	−0.0178	10.1	[0.70]	[0.00]	0.0044	0.7	[0.59]	[0.53]
	(0.0043)	(0.0068)	(0.0036)	(0.0138)				(0.0037)			
CHF	0.0108[c]	0.0077[c]	−0.0073[b]	−0.0171[c]	30.1	[0.83]	[0.31]	0.0029[b]	1.3	[0.50]	[0.36]
	(0.0024)	(0.0019)	(0.0034)	(0.0044)				(0.0016)			
EUR	0.0046[c]	0.0027[a]	−0.0013	−0.0053[b]	19.5	[0.32]	[0.05]	0.0025[c]	7.1	[0.36]	[0.47]
	(0.0014)	(0.0014)	(0.0028)	(0.0023)				(0.0009)			
GBP	0.0036[a]	0.0006	0.0027	−0.0172[c]	17.8	[0.02]	[0.60]	0.0024[c]	4.7	[0.07]	[0.83]
	(0.0021)	(0.0017)	(0.0054)	(0.0059)				(0.0006)			
JPY	0.0014	0.0011	−0.0037	−0.0230[c]	19.0	[0.27]	[0.01]	0.0027	2.5	[0.75]	[< .01]
	(0.0015)	(0.0024)	(0.0076)	(0.0056)				(0.0017)			
NOK	0.0197[a]	0.0345[c]	−0.0066	0.1468[a]	11.8	[0.65]	[0.12]	0.0302[c]	10.5	[0.53]	[0.57]
	(0.0119)	(0.0128)	(0.0412)	(0.0800)				(0.0083)			
NZD	0.0267[b]	0.0089	0.1014[c]	−0.0772[b]	4.3	[0.39]	[0.99]	0.0178[a]	1.3	[0.67]	[0.41]
	(0.0136)	(0.0188)	(0.0388)	(0.0386)				(0.0102)			
SEK	0.0333[c]	0.0326[b]	−0.0786	0.0115	12.3	[0.67]	[0.13]	0.0326[c]	9.1	[0.26]	[0.29]
	(0.0114)	(0.0130)	(0.0528)	(0.0601)				(0.0071)			

Table 7. The Economic Value of Daily Currency Order Flows

The table shows the in-sample and out-of-sample performance of currency strategies investing in the G-10 developed countries with daily rebalancing. The benchmark strategy employs a naïve random walk (RW) model. The competing strategies condition on lagged foreign currency order flow which is defined as the difference between the value of buyer-initiated and seller-initiated transactions. Order flows are classified into four customer segments: *asset managers* (AM), *hedge funds* (HF), *corporates* (CO) and *private clients* (PC). TOT indicates a strategy that conditions on aggregate customer order flows. ALL is a strategy that jointly uses disaggregate customer order flows. Using the exchange rate forecasts from each model, a US investor builds a maximum expected return strategy subject to a target volatility $\sigma_p^*= 10\%$ and proportional transaction. The strategy is daily rebalanced between a domestic bond and nine foreign bonds. For each strategy, we report the annualized mean (r_p) and volatility (σ_p), skewness (*Skew*), excess kurtosis (*Kurt*), annualized Sharpe ratio (*SR*) and Sortino ratio (*SO*), maximum drawdown (*MDD*), and performance fee ($\mathcal{P}$) a risk-averse investor is willing to pay to switch from the benchmark strategy to a competing strategy. For *Skew* and *Kurt*, we report both standard and robust measures (outliers) as in Kim and White (2004). For *SR* and *SO*, we report both standard and robust measures (serial correlation) as in Lo (2002). $\mathcal{P}$ is computed for $\gamma = 6$ and is expressed in annual basis points. The results are reported net of the effective bid-ask spread, which is assumed to be equal to *50%* of the quoted spread. The in-sample period comprises daily observations from January 2001 to May 2011. The out-of-sample analysis runs from January 2004 to May 2011. Exchange rates are from Thomson Reuters while customer order flows are proprietary data from UBS.

	r_p	σ_p	*Skew*		*Kurt*		$\mathcal{SR}$		$\mathcal{SO}$		$\mathcal{MDD}$	$\mathcal{P}$
Strategy	(%)	(%)	*std.*	*rob.*	*std.*	*rob.*	*std.*	*rob.*	*std.*	*rob.*	(%)	(*bps*)
					In-Sample Period: Jan 2001 - May 2011							
RW	2.9	9.6	−0.73	−0.06	11.11	1.17	0.13	0.13	0.16	0.15	37.0	
AM	8.5	10.8	−0.20	−0.03	6.03	0.62	0.63	0.77	0.87	1.05	19.6	484
HF	11.1	9.9	0.05	−0.01	2.22	0.47	0.95	0.96	1.45	1.46	14.7	804
CO	10.7	10.3	−0.18	−0.02	2.12	0.48	0.88	0.95	1.29	1.41	17.1	736
PC	9.0	10.2	−0.24	−0.02	2.43	0.54	0.72	0.81	1.05	1.18	22.2	570
TOT	9.1	10.3	−0.09	−0.03	3.19	0.60	0.73	0.81	1.05	1.17	19.9	583
ALL	12.1	10.5	−0.19	0.00	2.75	0.61	1.00	1.25	1.44	1.79	14.0	871
					Out-of-Sample Period: Jan 2004 - May 2011							
RW	−0.8	14.4	−0.72	−0.06	7.54	1.13	−0.17	−0.16	−0.20	−0.19	47.6	
AM	0.9	13.1	−0.52	−0.06	2.22	0.96	−0.06	−0.05	−0.08	−0.07	38.8	279
HF	4.9	12.3	−0.45	−0.04	1.96	0.69	0.26	0.22	0.36	0.29	37.9	744
CO	4.1	13.8	−0.58	−0.06	2.68	0.86	0.18	0.16	0.23	0.20	39.7	549
PC	6.8	13.5	−0.57	−0.06	2.54	0.93	0.38	0.38	0.50	0.50	35.5	841
TOT	3.8	12.7	−0.55	−0.06	2.67	0.84	0.17	0.15	0.22	0.20	35.3	600
ALL	4.5	12.1	−0.52	−0.04	2.82	0.64	0.23	0.20	0.32	0.26	38.6	717

Table 8. The Economic Value of Daily Currency Order Flows (M-estimator)

The table shows the in-sample and out-of-sample performance of currency strategies investing in the G-10 developed countries with daily rebalancing. The benchmark strategy employs a naïve random walk (RW) model. The competing strategies condition on lagged foreign currency order flow which is defined as the difference between the value of buyer-initiated and seller-initiated transactions. Order flows are classified into four customer segments: *asset managers* (AM), *hedge funds* (HF), *corporates* (CO) and *private clients* (PC). TOT indicates a strategy that conditions on aggregate customer order flows. ALL is a strategy that jointly uses disaggregate customer order flows. Using the exchange rate forecasts from each model, a US investor builds a maximum expected return strategy subject to a target volatility $\sigma_p^*= 10\%$ and proportional transaction. The strategy is daily rebalanced between a domestic bond and nine foreign bonds. For each strategy, we report the annualized mean (r_p) and volatility (σ_p), skewness (*Skew*), excess kurtosis (*Kurt*), annualized Sharpe ratio (*SR*) and Sortino ratio (*SO*), maximum drawdown (*MDD*), and performance fee ($\mathcal{P}$) a risk-averse investor is willing to pay to switch from the benchmark strategy to a competing strategy. For *Skew* and *Kurt*, we report both standard and robust measures (outliers) as in Kim and White (2004). For *SR* and *SO*, we report both standard and robust measures (serial correlation) as in Lo (2002). $\mathcal{P}$ is computed for $\gamma = 6$ and is expressed in annual basis points. The results are reported net of the effective bid-ask spread, which is assumed to be equal to *50%* of the quoted spread. The in-sample period comprises daily observations from January 2001 to May 2011. The out-of-sample analysis runs from January 2004 to May 2011. The parameter estimates for order flow strategies are computed using the M-estimator (see Appendix A). Exchange rates are from Thomson Reuters while customer order flows are proprietary data from UBS.

	r_p	σ_p	*Skew*		*Kurt*		$\mathcal{SR}$		$\mathcal{SO}$		$\mathcal{MDD}$	$\mathcal{P}$
Strategy	(%)	(%)	*std.*	*rob.*	*std.*	*rob.*	*std.*	*rob.*	*std.*	*rob.*	(%)	(*bps*)
					In-Sample Period: Jan 2001 - May 2011							
RW	2.9	9.6	−0.73	−0.06	11.11	1.17	0.13	0.13	0.16	0.15	37.0	–
AM	9.0	9.8	−0.44	−0.04	2.71	0.71	0.76	0.77	1.03	1.04	23.8	603
HF	9.7	10.0	−0.29	−0.04	2.85	0.57	0.81	0.78	1.14	1.09	26.7	662
CO	9.8	9.9	−0.39	−0.05	2.52	0.64	0.83	0.84	1.15	1.17	22.2	674
PC	8.9	9.9	−0.48	−0.05	3.11	0.55	0.73	0.71	1.00	0.97	23.6	582
TOT	8.8	9.9	−0.48	−0.04	3.43	0.75	0.72	0.72	0.97	0.97	24.7	573
ALL	10.7	9.9	−0.18	−0.02	2.90	0.75	0.92	0.84	1.30	1.20	23.9	767
					Out-of-Sample Period: Jan 2004 - May 2011							
RW	−0.8	14.4	−0.72	−0.06	7.54	1.13	−0.17	−0.16	−0.20	−0.19	47.6	–
AM	4.1	13.3	−0.50	−0.04	4.71	1.22	0.18	0.18	0.23	0.23	36.6	582
HF	6.5	12.9	−0.51	−0.04	2.77	1.01	0.38	0.34	0.49	0.44	35.9	861
CO	4.6	13.5	−0.64	−0.07	4.94	1.15	0.22	0.20	0.27	0.25	37.9	617
PC	9.6	13.2	−0.68	−0.07	3.68	0.89	0.60	0.63	0.76	0.79	34.7	1146
TOT	5.0	12.8	−0.62	−0.04	3.76	0.93	0.26	0.24	0.33	0.31	35.9	716
ALL	5.9	12.6	−0.43	−0.04	2.99	0.84	0.34	0.33	0.44	0.44	33.7	819

Table 9. The Economic Value of Monthly Currency Order Flows

The table shows the in-sample and out-of-sample performance of currency strategies investing in the G-10 developed countries with monthly rebalancing. The benchmark strategy employs a naïve random walk (RW) model. The competing strategies condition on lagged foreign currency order flow which is defined as the difference between the value of buyer-initiated and seller-initiated transactions. Order flows are classified into four customer segments: *asset managers* (AM), *hedge funds* (HF), *corporates* (CO) and *private clients* (PC). TOT indicates a strategy that conditions on aggregate customer order flows. ALL is a strategy that jointly uses disaggregate customer order flows. Using the exchange rate forecasts from each model, a US investor builds a maximum expected return strategy subject to a target volatility $\sigma_p^*= 10\%$ and proportional transaction. The strategy is daily rebalanced between a domestic bond and nine foreign bonds. For each strategy, we report the annualized mean (r_p) and volatility (σ_p), skewness (*Skew*), excess kurtosis (*Kurt*), annualized Sharpe ratio (*SR*) and Sortino ratio (*SO*), maximum drawdown (*MDD*), and performance fee ($\mathcal{P}$) a risk-averse investor is willing to pay to switch from the benchmark strategy to a competing strategy. For *Skew* and *Kurt*, we report both standard and robust measures (outliers) as in Kim and White (2004). For *SR* and *SO*, we report both standard and robust measures (serial correlation) as in Lo (2002). $\mathcal{P}$ is computed for $\gamma = 6$ and is expressed in annual basis points. The results are reported net of the effective bid-ask spread, which is assumed to be equal to *50%* of the quoted spread. The in-sample period comprises monthly (non-overlapping) observations from January 2001 to May 2011. The out-of-sample analysis runs from January 2004 to May 2011. Exchange rates are from Thomson Reuters while customer order flows are proprietary data from UBS.

	r_p	σ_p	*Skew*		*Kurt*		$\mathcal{SR}$		$\mathcal{SO}$		$\mathcal{MDD}$	$\mathcal{P}$
Strategy	(%)	(%)	*std.*	*rob.*	*std.*	*rob.*	*std.*	*rob.*	*std.*	*rob.*	(%)	(*bps*)
					In-Sample Period: Jan 2001 - May 2011							
RW	9.4	10.0	−0.26	0.02	0.04	0.12	0.70	0.58	1.11	0.92	−28.0	
AM	14.6	10.3	0.18	−0.05	1.68	1.50	1.18	0.96	1.91	1.55	−12.6	504
HF	15.5	9.6	0.11	−0.02	0.52	0.55	1.35	1.21	2.44	2.18	−9.2	626
CO	17.3	9.7	0.15	0.03	0.33	0.54	1.53	1.97	2.82	3.63	−5.6	806
PC	11.4	9.4	−0.39	−0.07	0.88	0.91	0.95	0.74	1.41	1.10	−17.3	229
TOT	15.0	10.4	0.21	−0.01	2.27	3.19	1.21	1.03	1.75	1.49	−11.1	539
ALL	19.5	10.5	0.38	0.10	0.87	0.79	1.63	1.26	3.07	2.37	−9.8	983
					Out-of-Sample Period: Jan 2004 - May 2011							
RW	5.2	13.4	−0.28	0.02	0.53	0.54	0.20	0.17	0.31	0.26	−40.2	
AM	13.3	12.9	0.05	0.01	0.57	0.07	0.84	0.74	1.45	1.28	−21.1	877
HF	10.5	13.0	−0.28	−0.12	0.61	1.21	0.61	0.57	0.92	0.85	−29.9	561
CO	10.4	15.4	−0.24	0.04	0.50	0.34	0.51	0.53	0.80	0.83	−33.0	343
PC	−5.0	17.2	−1.54	−0.11	4.56	3.40	−0.44	−0.27	−0.46	−0.28	−65.1	−1587
TOT	7.8	13.7	−1.21	−0.09	3.19	1.46	0.38	0.43	0.44	0.49	−28.4	180
ALL	13.1	13.5	−0.06	−0.03	1.02	0.81	0.79	0.76	1.22	1.18	−23.9	800

Table 10. Daily Order Flows and Driving Factors

The table displays the estimates of the following regressions $\left(r^s_{p,t} - r_{f,t}\right) = \alpha + \sum_i \beta_i \left(r^i_{p,t} - r_{f,t}\right) + \varepsilon_t$, where $r_{p,t}$ is the portfolio return of a currency strategy investing in the G-10 developed countries with daily rebalancing and $r_{f,t}$ is the daily riskless return. $r^s_{p,t}$ indicates a strategy conditioning on the currency order flows of *asset managers* (AM), *corporates* (CO), *hedge funds* (HF), and *private clients* (PC), respectively. $r^i_{p,t}$ refers to a strategy using the *random walk* (RW), *forward premium* (FP), *purchasing power parity* (PPP), *monetary fundamentals* (MF), *Taylor rule* (TR), *cyclical external imbalances* (NXA) and *momentum* (MOM), respectively. The portfolio returns are computed net of the effective bid-ask spread, which is assumed to be equal to *50%* of the quoted spread. The superscripts a, b, and c denote statistical significance at the 10%, 5%, and 1% level, respectively. Bootstrapped standard errors (in parentheses) and p-*values* are obtained by resampling 10,000 the portfolio weights by means of moving block bootstrap (see Gonçalves and White, 2005). The portfolio returns run from January 2001 to May 2011. Exchange rates are from Thomson Reuters while customer order flows are proprietary data from UBS. All other data are from Datastream, OECD and IFS.

	α	β_{RW}	β_{FP}	β_{TR}	β_{PPP}	β_{MFU}	β_{NXA}	β_{MOM}	$\overline{R}^2$(%)
				In-Sample Period: Jan 2001 - May 2011					
AM	−0.022	0.271^c			0.045^a	0.315^c	0.517^c	−0.059^b	62.1
	(0.021)	(0.027)			(0.025)	(0.035)	(0.047)	(0.026)	(1.60)
	−0.035		0.297^c		0.018	0.245^c	0.435^c	−0.134^c	61.0
	(0.022)		(0.032)		(0.027)	(0.039)	(0.049)	(0.030)	(2.00)
	−0.044^b			0.254^c	0.001	0.187^c	0.560^c	−0.057^b	60.6
	(0.021)			(0.025)	(0.025)	(0.037)	(0.046)	(0.029)	(1.80)
	−0.041^b	0.206^c	0.225^c	0.153^c	0.056^b	0.225^c	0.361^c	−0.048^a	66.1
	(0.020)	(0.026)	(0.031)	(0.025)	(0.023)	(0.037)	(0.042)	(0.024)	(1.60)
HF	0.014	0.202^c			0.102^c	0.373^c	0.363^c	0.037^b	66.9
	(0.018)	(0.019)			(0.024)	(0.032)	(0.033)	(0.016)	(1.40)
	0.003		0.246^c		0.083^c	0.318^c	0.286^c	−0.021	66.8
	(0.019)		(0.032)		(0.026)	(0.036)	(0.043)	(0.018)	(2.00)
	−0.002			0.175^c	0.067^c	0.283^c	0.399^c	0.035^a	65.5
	(0.018)			(0.021)	(0.024)	(0.036)	(0.034)	(0.017)	(1.60)
	0.001	0.155^c	0.197^c	0.094^c	0.112^c	0.310^c	0.233^c	0.039^b	69.8
	(0.017)	(0.022)	(0.032)	(0.022)	(0.024)	(0.036)	(0.038)	(0.018)	(1.60)
CO	0.009	0.187^c			0.132^c	0.337^c	0.415^c	0.045^b	67.5
	(0.018)	(0.021)			(0.022)	(0.025)	(0.033)	(0.017)	(1.60)
	0.001		0.204^c		0.113^c	0.289^c	0.359^c	−0.007	66.9
	(0.018)		(0.028)		(0.023)	(0.028)	(0.038)	(0.021)	(1.90)
	−0.011			0.239^c	0.102^c	0.226^c	0.429^c	0.061^c	68.3
	(0.018)			(0.022)	(0.022)	(0.030)	(0.034)	(0.019)	(1.80)
	−0.009	0.127^c	0.142^c	0.175^c	0.137^c	0.249^c	0.304^c	0.067^c	70.7
	(0.017)	(0.023)	(0.027)	(0.022)	(0.022)	(0.030)	(0.036)	(0.018)	(1.60)
PC	−0.017	0.178^c			0.072^c	0.433^c	0.390^c	0.021	71.0
	(0.017)	(0.019)			(0.021)	(0.029)	(0.028)	(0.014)	(1.40)
	−0.029		0.300^c		0.063^c	0.375^c	0.270^c	−0.034^b	73.2
	(0.017)		(0.024)		(0.022)	(0.032)	(0.038)	(0.015)	(1.50)
	−0.030^a			0.146^c	0.042^b	0.357^c	0.424^c	0.017	69.9
	(0.017)			(0.019)	(0.021)	(0.032)	(0.029)	(0.017)	(1.40)
	−0.030^a	0.131^c	0.262^c	0.060^c	0.087^c	0.375^c	0.227^c	0.011	75.0
	(0.016)	(0.019)	(0.024)	(0.020)	(0.021)	(0.033)	(0.034)	(0.015)	(1.30)

Continued

Table 11. Daily Order Flows and Combined Strategies

The table displays the estimates of the following regressions $\left(r^s_{p,t} - r_{f,t}\right) = \alpha + \beta_i \left(r^i_{p,t} - r_{f,t}\right) + \varepsilon_t$ where $r_{p,t}$ is the portfolio return of a currency strategy investing in the G-10 developed countries with daily rebalancing and $r_{f,t}$ is the daily riskless return. $r^s_{p,t}$ indicates a strategy conditioning on the currency order flows of *sset Managers* (AM), *corporates* (CO), *hedge funds* (HF), and *private clients* (PC), respectively. $r^i_{p,t}$ refers to a strategy that combines the *random walk* (RW), *forward premium* (FP), *purchasing power parity* (PPP), *monetary fundamentals* (MF), *Taylor rule* (TR), *cyclical external imbalances* (NXA) and *momentum* (MOM), respectively. The combination employs the average (AVE), median (MED), trimmed mean (TRI), and mean-squared error (MSE) of the forecasts, the 'kitchen sink' (KS) regression that incorporates all predictors into a multiple predictive regression, and the 'Fund of Funds' (FoF) strategy that equally invests in the underlying portfolio strategies. The portfolio returns are computed net of the effective bid-ask spread, which is assumed to be equal to *50%* of the quoted spread. The superscripts a, b, and c denote statistical significance at the 10%, 5%, and 1% level, respectively. Bootstrapped standard errors (in parentheses) and p-*values* are obtained by resampling 10,000 the portfolio weights by means of moving block bootstrap (see Gonçalves and White, 2005). The portfolio returns run from January 2001 to May 2011. Exchange rates are from Thomson Reuters while customer order flows are proprietary data from UBS. All other data are from Datastream, OECD and IFS.

	α	β	$\overline{R}^2(\%)$	α	β	$\overline{R}^2(\%)$	α	β	$\overline{R}^2(\%)$
		AVE			MED			TRI	
AM	-0.019	0.732^c	48.5	-0.027	0.796^c	56.6	-0.045^b	0.849^c	60.9
	(0.024)	(0.027)	(3.30)	(0.023)	(0.024)	(2.50)	(0.021)	(0.02)	(2.00)
CO	0.006	0.741^c	58.9	0.005	0.746^c	58.9	-0.015	0.818^c	66.9
	(0.019)	(0.023)	(2.10)	(0.02)	(0.023)	(2.80)	(0.018)	(0.019)	(2.00)
HF	-0.001	0.763^c	57.7	-0.007	0.811^c	64.4	-0.024	0.857^c	67.9
	(0.021)	(0.025)	(2.50)	(0.019)	(0.02)	(2.10)	(0.018)	(0.019)	(1.90)
PC	-0.021	0.792^c	63.2	-0.025	0.822^c	67.0	-0.044^c	0.876^c	72.0
	(0.019)	(0.018)	(1.80)	(0.019)	(0.018)	(2.30)	(0.017)	(0.014)	(1.50)
		MSE			KS			FoF	
AM	-0.019	0.733^c	48.5	0.084^b	-0.162^c	2.4	-0.016	1.24^c	58.4
	(0.024)	(0.027)	(3.40)	(0.033)	(0.034)	(1.00)	(0.022)	(0.032)	(2.00)
CO	0.006	0.744^c	59.2	0.107^c	-0.128^c	1.8	0.012	1.216^c	66.6
	(0.019)	(0.023)	(2.10)	(0.031)	(0.026)	(0.80)	(0.018)	(0.028)	(1.30)
HF	-0.001	0.764^c	57.7	0.097^c	-0.071^b	0.4	0.003	1.283^c	68.5
	(0.021)	(0.025)	(2.50)	(0.032)	(0.03)	(0.50)	(0.018)	(0.022)	(1.60)
PC	-0.021	0.794^c	63.3	0.086^c	-0.128^c	1.6	-0.014	1.28^c	69.3
	(0.019)	(0.018)	(1.80)	(0.032)	(0.03)	(0.80)	(0.018)	(0.021)	(1.30)

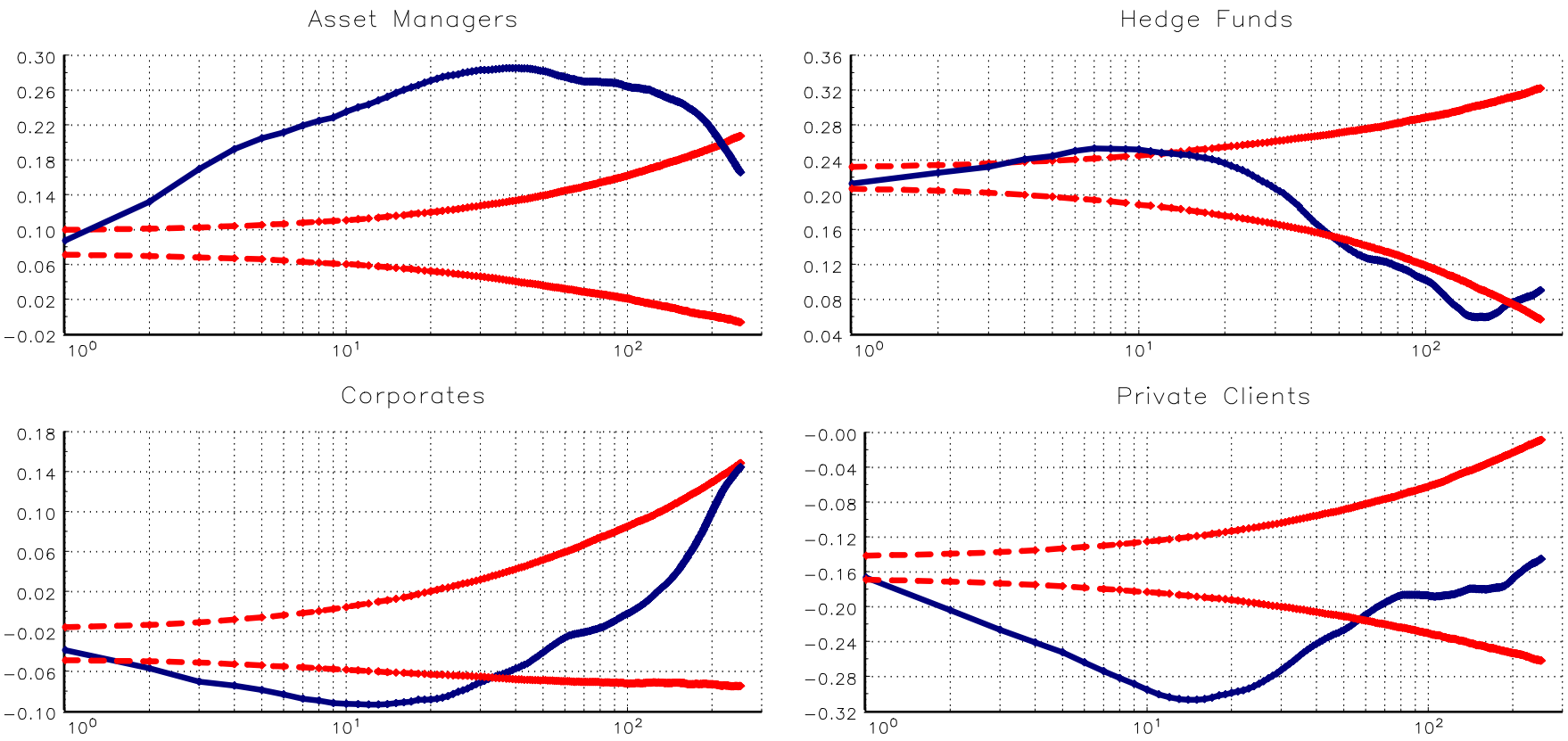

Figure 1. Contemporaneous Correlation of Currency Flows and Returns

This figure shows the evolution of the contemporaneous correlation coefficient between customer order flows and exchange rate returns (vertical axis) at different return horizon (horizontal axis, log scale in days) for the G-10 developed countries. The blue line is the in sample panel correlation coefficient computed using overlapping return windows from 1 (10^0) to 252 ($> 10^2$) trading days, while the red lines represent the 90th percentile bootstrap confidence intervals, estimated by generating 10,000 replications. The exchange rate is defined as the US dollar price of a unit of foreign currency so that an increase (decrease) in the exchange rate implies an appreciation (depreciation) of the foreign currency. The order flow is defined as the difference between the value of buyer-initiated and seller-initiated transactions for the foreign currency so that a positive (negative) order flow implies net foreign currency purchases (sales). Order flows are classified into four customer segments: *asset managers*, *hedge funds*, *corporates* and *private clients*. The sample period comprises daily data from January 2001 to May 2011. Exchange rates are from Thomson Reuters while customer order flows are proprietary data from UBS.

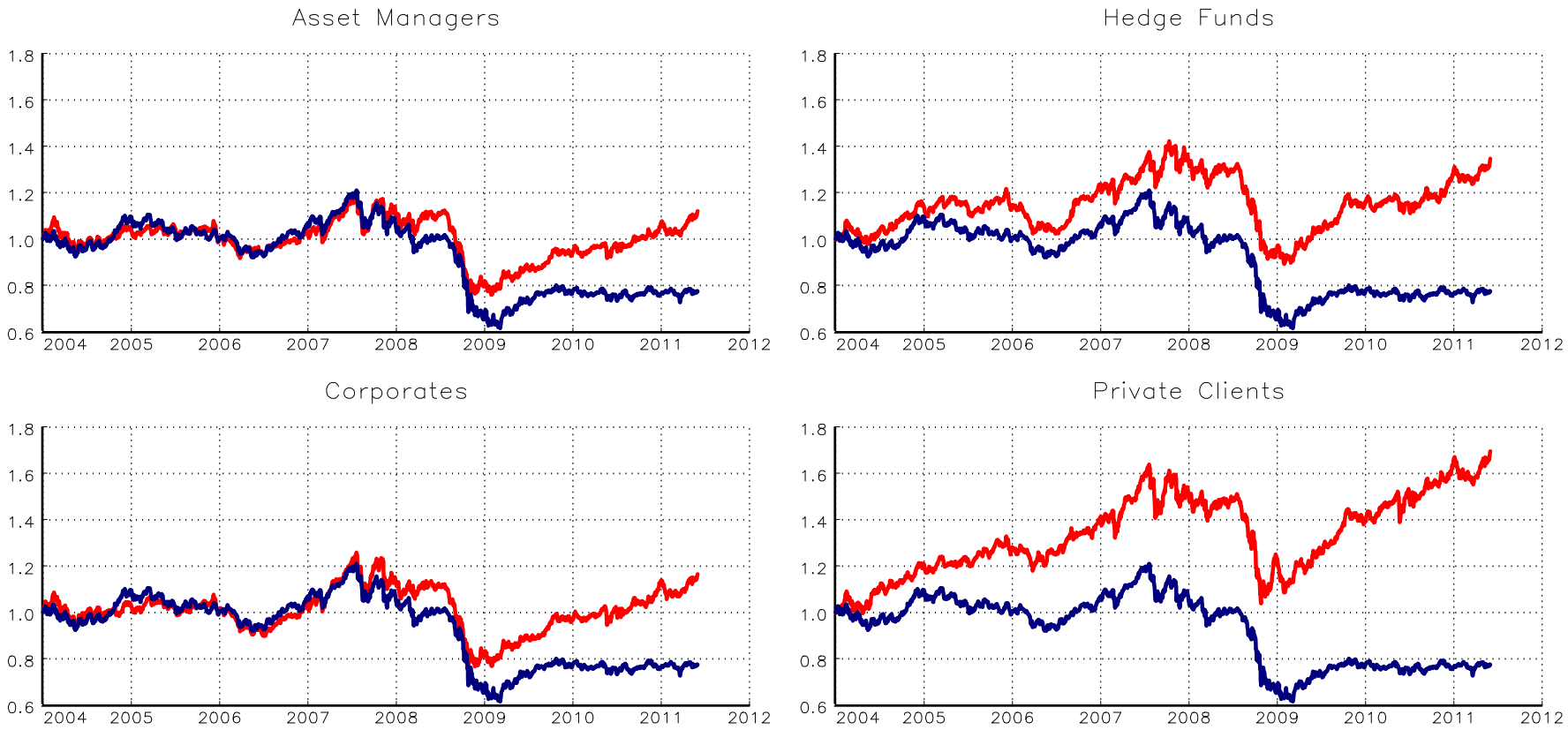

Figure 2. Daily Cumulative Wealth of Currency Flow Strategies

This figure displays the out-of-sample cumulative wealth of currency strategies investing in the G-10 developed countries with daily rebalancing. The blue line represents the benchmark strategy which employs a naïve random walk model. The red line indicates a strategy conditioning on foreign currency order flow, defined as the difference between the value of buyer-initiated and seller-initiated transactions. Order flows are classified into four customer segments: *asset managers*, *hedge funds*, *corporates* and *private clients*. Initial wealth is $1 growing at the portfolio return, net of transaction costs. The out-of-sample analysis runs from January 2004 to May 2011. Exchange rates are from Thomson Reuters while customer order flows are proprietary data from UBS.

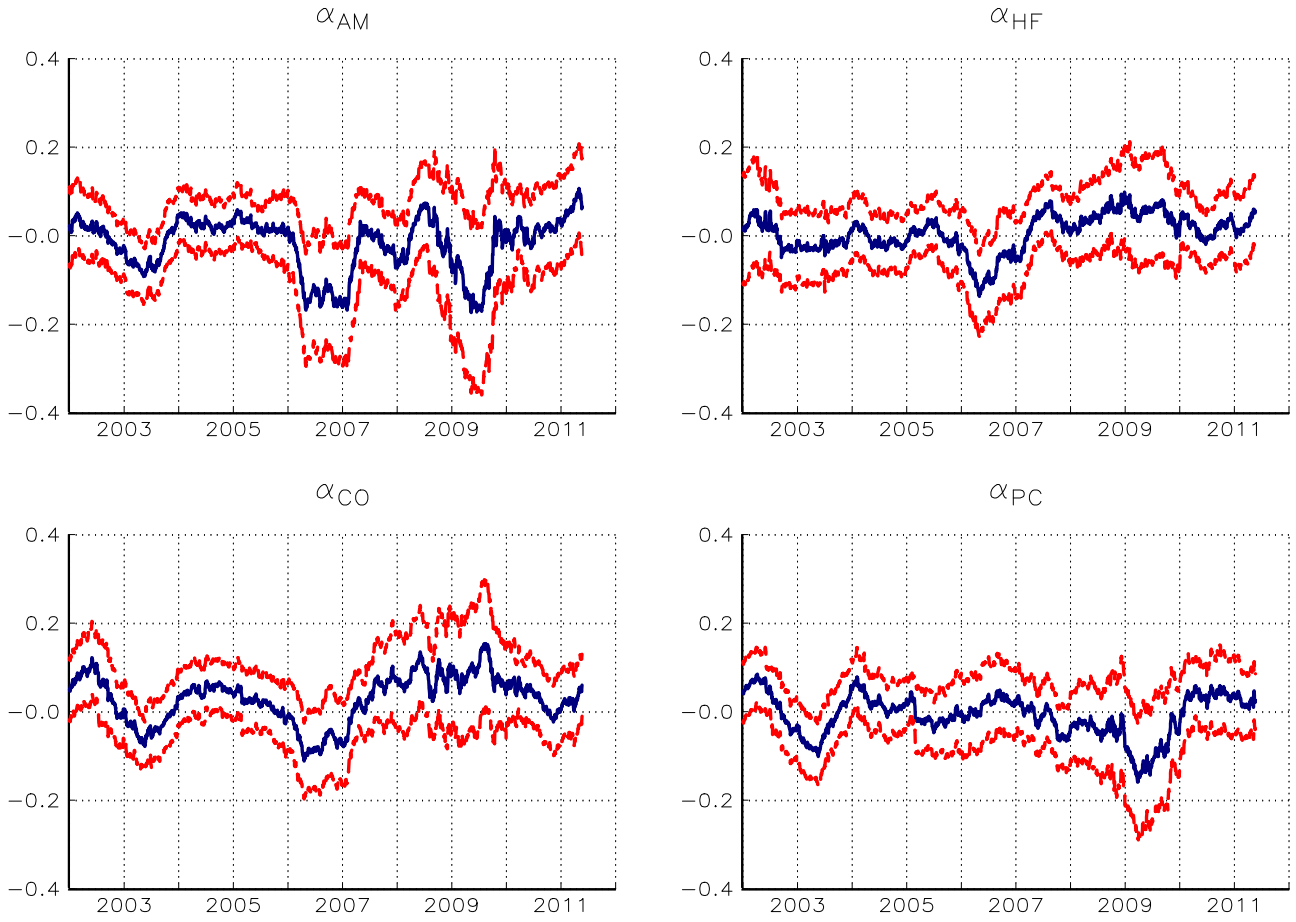

Figure 4. Rolling Estimates: the Alphas

The figure displays the one-year rolling estimate of α (solid line) and its 95% confidence interval (dashed lines) from the regression $(r^s_{p,t} - r_f) = \alpha + \sum_i \beta_i (r^i_{p,t} - r_f) + \varepsilon_t$, where $r_{p,t}$ is the portfolio return, net of transaction costs, of a currency strategy investing in the G-10 developed countries with daily rebalancing, and r_f is the riskless return. s indicates a strategy conditioning on the currency order flow of *asset managers* (AM), *hedge funds* (HF), *corporates* (CO) and *private clients* (PC), respectively. i refers to the *random walk* (RW), *forward premium* (FP), *Taylor rule* (TR), *purchasing power parity* (PPP), *monetary fundamentals* (MF), *cyclical external imbalances* (NXA) and *momentum* (MOM) strategy, respectively. The sample analysis runs from January 2001 to May 2011. Exchange rates are from Thomson Reuters while customer order flows are proprietary data from UBS.

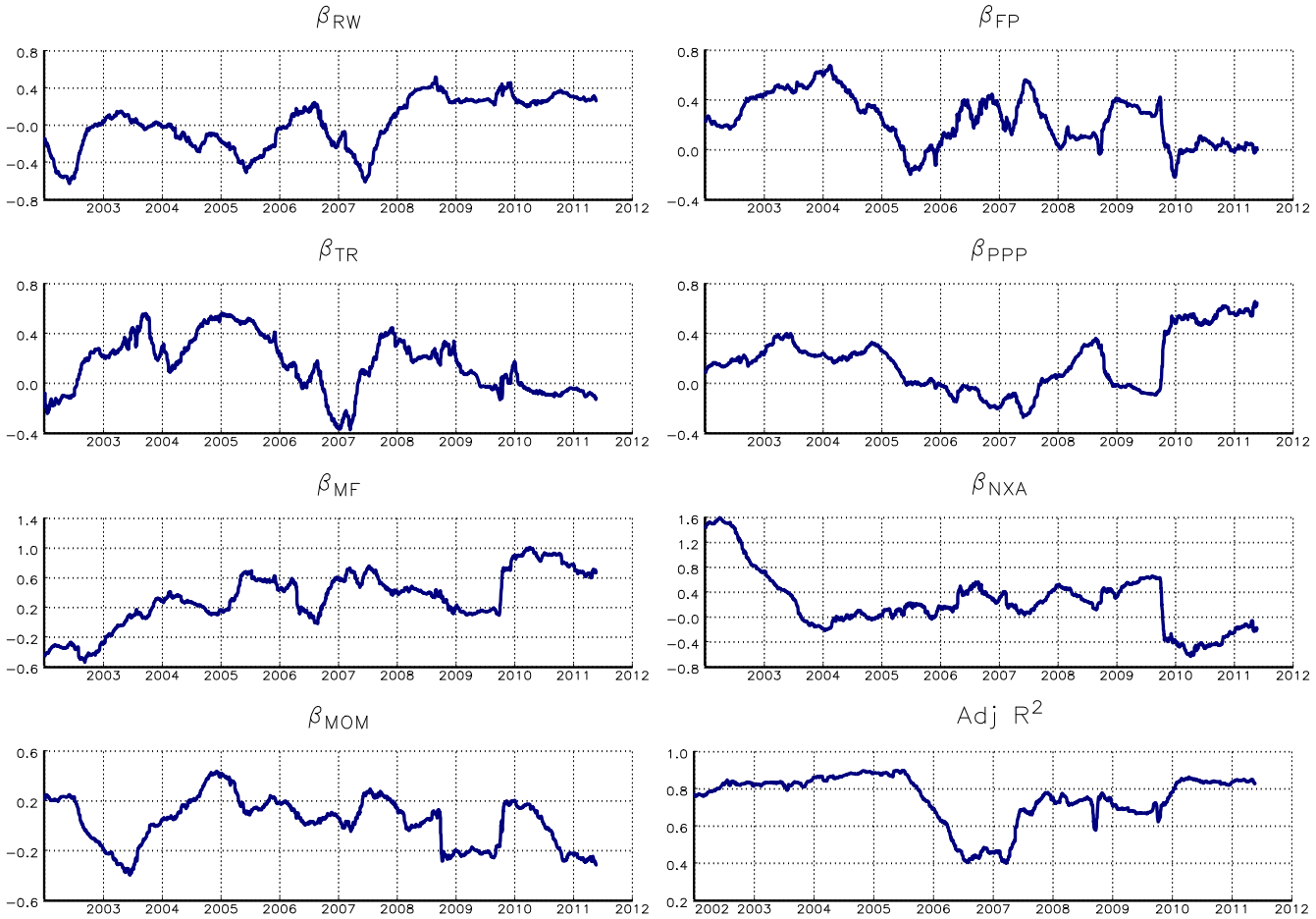

Figure 4. Rolling Estimates: Asset Managers

The figure displays the one-year rolling estimates of $(r_{p,t}^{AM} - r_f) = \alpha + \sum_i \beta_i (r_{p,t}^i - r_f) + \varepsilon_t$ where $r_{p,t}$ is the portfolio return, net of transaction costs, of a currency strategy investing in the G-10 developed countries with daily rebalancing, and r_f is the riskless return. AM denotes a strategy conditioning on the currency order flow of *asset managers*. i refers to the *random walk* (RW), *forward premium* (FP), *Taylor rule* (TR), *purchasing power parity* (PPP), *monetary fundamentals* (MF), *cyclical external imbalances* (NXA) and *momentum* (MOM) strategy, respectively. The sample analysis runs from January 2001 to May 2011. Exchange rates are from Thomson Reuters while customer order flows are proprietary data from UBS.

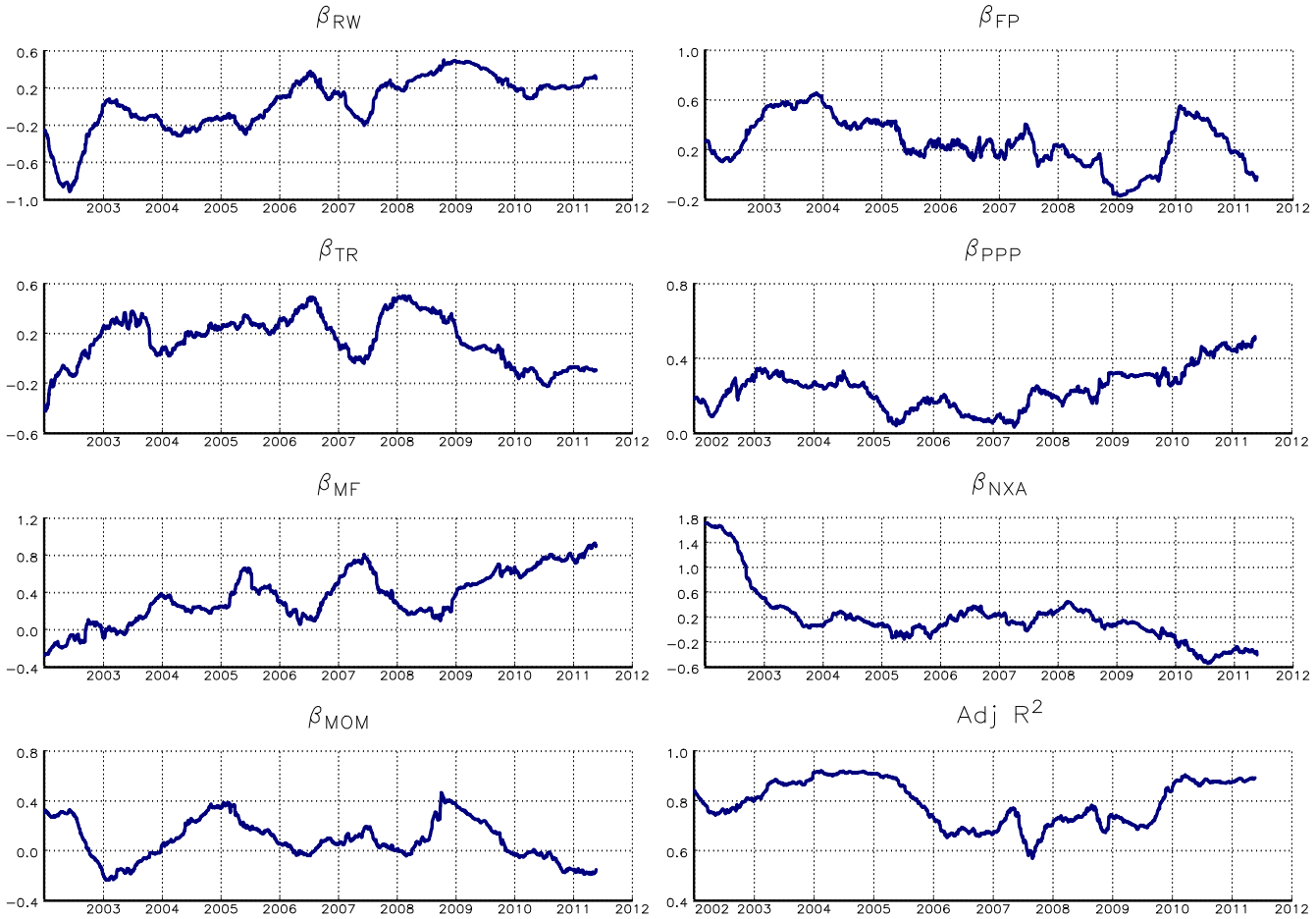

Figure 5. Rolling Estimates: Hedge Funds

The figure displays the one-year rolling estimates of $(r_{p,t}^{HF} - r_f) = \alpha + \sum_i \beta_i (r_{p,t}^i - r_f) + \varepsilon_t$ where $r_{p,t}$ is the portfolio return, net of transaction costs, of a currency strategy investing in the G-10 developed countries with daily rebalancing, and r_f is gross riskless return. HF denotes a strategy conditioning on the currency order flow of *hedge funds*. i refers to the *random walk* (RW), *forward premium* (FP), *Taylor rule* (TR), *purchasing power parity* (PPP), *monetary fundamentals* (MF), *cyclical external imbalances* (NXA) and *momentum* (MOM) strategy, respectively. The sample analysis runs from January 2001 to May 2011. Exchange rates are from Thomson Reuters while customer order flows are proprietary data from UBS.

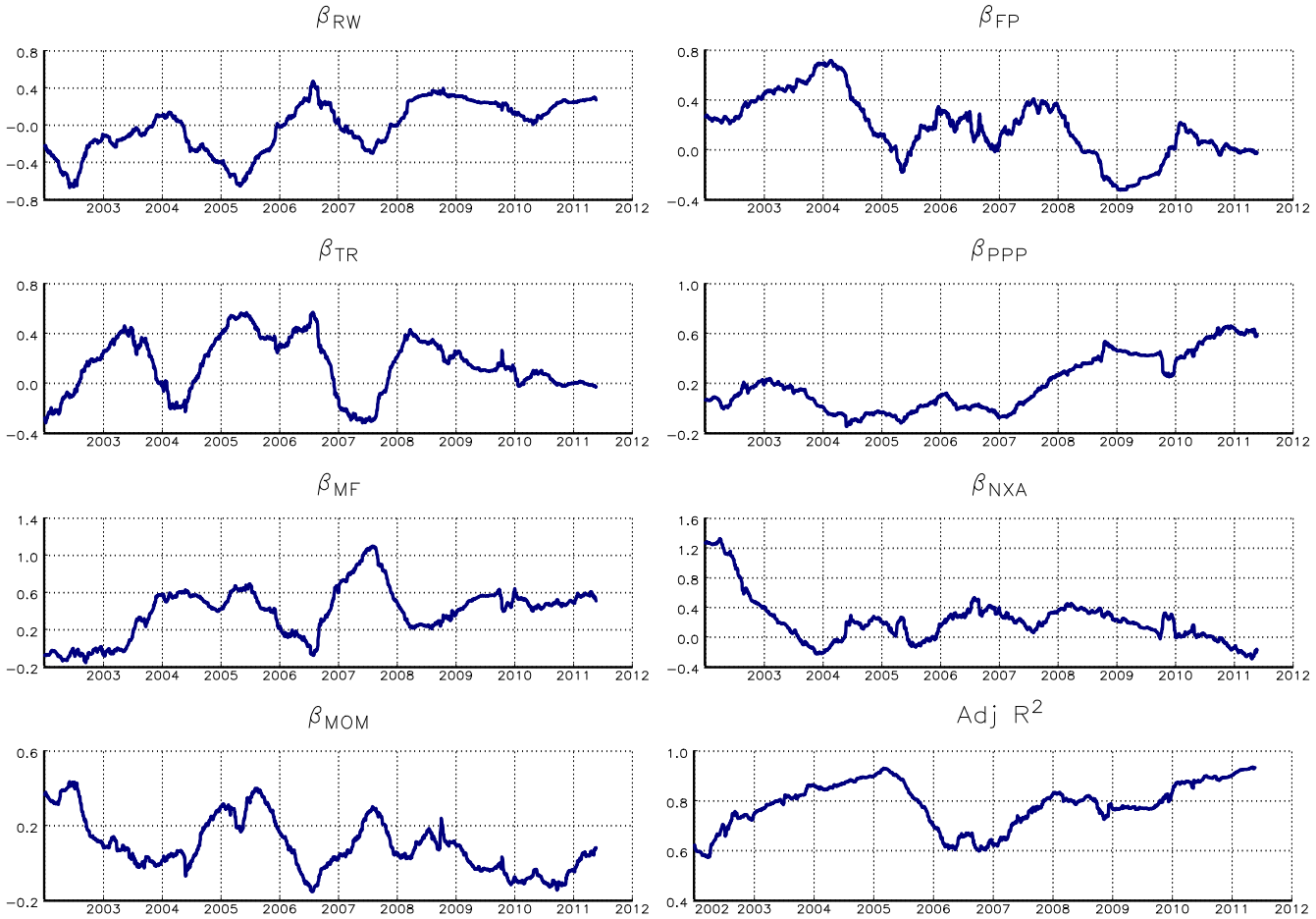

Figure 6. Rolling Estimates: Corporates

The figure displays the one-year rolling estimates of $(r_{p,t}^{CO} - r_f) = \alpha + \sum_i \beta_i (r_{p,t}^{i} - r_f) + \varepsilon_t$ where $r_{p,t}$ is the portfolio return, net of transaction costs, of a currency strategy investing in the G-10 developed countries with daily rebalancing, and r_f is the riskless return. CO denotes a strategy conditioning on the currency order flow of *corporates*. i refers to the *random walk* (RW), *forward premium* (FP), *Taylor rule* (TR), *purchasing power parity* (PPP), *monetary fundamentals* (MF), *cyclical external imbalances* (NXA) and *momentum* (MOM) strategy, respectively. The sample analysis runs from January 2001 to May 2011. Exchange rates are from Thomson Reuters while customer order flows are proprietary data from UBS.

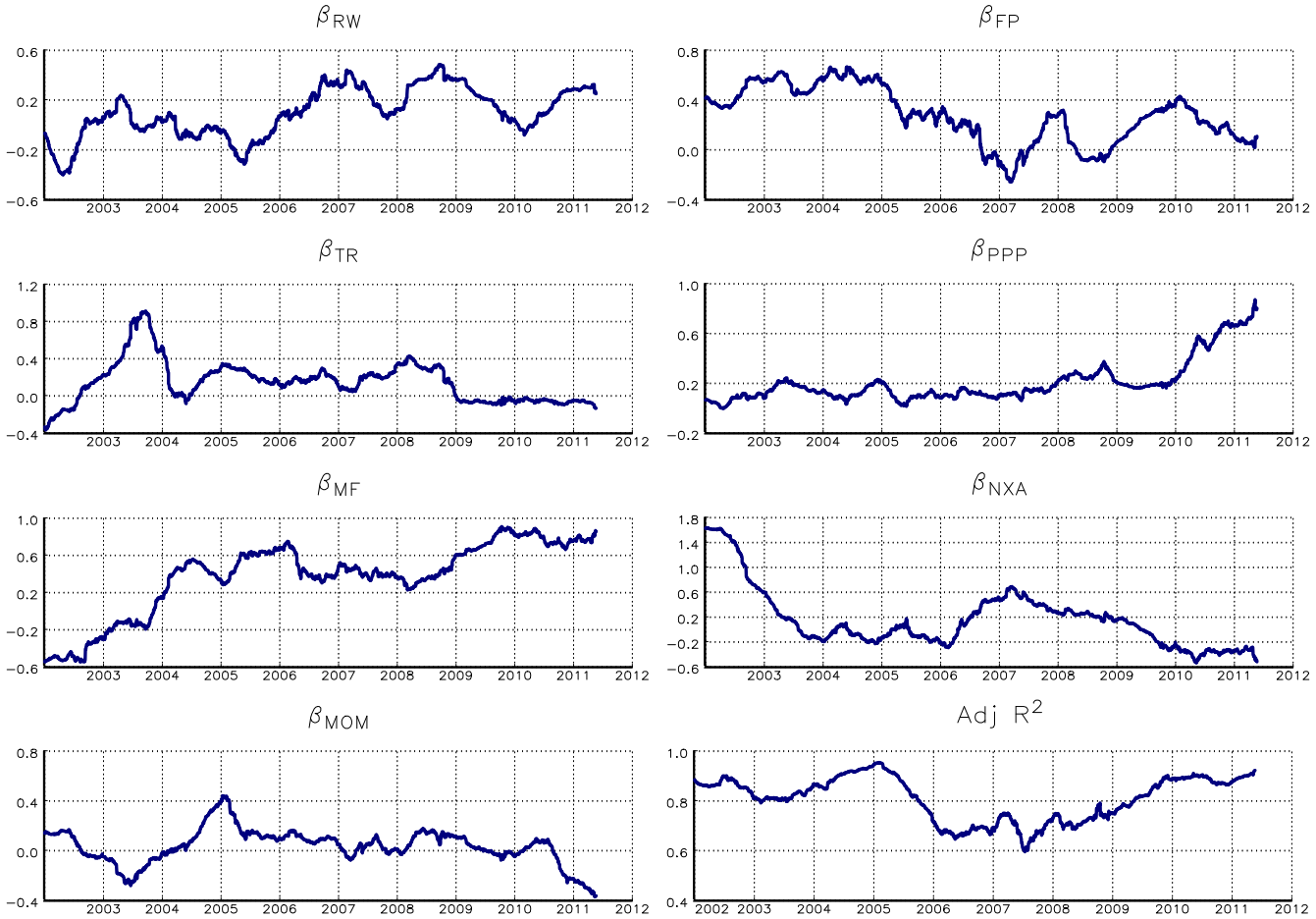

Figure 7. Rolling Estimates: Private Clients

The figure displays the one-year rolling estimates of $(r_{p,t}^{PC} - r_f) = \alpha + \sum_i \beta_i (r_{p,t}^i - r_f) + \varepsilon_t$ where $r_{p,t}$ is the portfolio return, net of transaction costs, of a currency strategy investing in the G-10 developed countries with daily rebalancing, and r_f is the gross riskless return. PC denotes a strategy conditioning on the currency order flow of *private clients*. i refers to the *random walk* (RW), *forward premium* (FP), *Taylor rule* (TR), *purchasing power parity* (PPP), *monetary fundamentals* (MF), *cyclical external imbalances* (NXA) and *momentum* (MOM) strategy, respectively. The sample analysis runs from January 2001 to May 2011. Exchange rates are from Thomson Reuters while customer order flows are proprietary data from UBS.

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A Appendix: Robust Regression

Daily order flow data may contain outliers. Standard least square estimates can behave badly when the error distribution is not normal and heavy-tailed. Removing outliers from the sample is not a meaningful solution as subjective outlier deletion or algorithms have the drawback of removing legitimate observations. Robust regression, instead, aims at obtaining parameter estimates that are not adversely affected by the presence of potential outliers (Hampel, Ronchetti, Rousseeuw and Stahel, 2005). The most common general method of robust regression is M-estimation introduced by Huber (1964).

In brief, consider the following linear model

$$y_t = x_t'\beta + \varepsilon_t.$$

Robust parameter estimates are the solutions to

$$\min_{\beta} \sum_{t=1}^{T} \rho\left(\frac{y_t - x_t'\beta}{\sigma}\right) \tag{16}$$

where σ is the scale of the error term, and $\rho(\cdot)$ is a bisquare function defined as

$$\rho(y) = \begin{cases} 1 - \left[1 - (y/k)^2\right]^3 & if \quad |y| \leq k \\ 1 & if \quad |y| > k. \end{cases}$$

The first order condition for the optimization problem in Equation (16) is

$$\sum_{t=1}^{T} \rho'\left(\frac{y_t - x_t'\widehat{\beta}}{\widehat{\sigma}}\right) x_t' = 0 \tag{17}$$

where

$$\rho'(y) = \begin{cases} 6y/k^2 - \left[1 - (y/k)^2\right]^2 & if \quad |y| \leq k \\ 0 & if \quad |y| > k. \end{cases}$$

is the derivative of $\rho(\cdot)$. In the bisquare function the constant $k = 4.685$ ensures 95% efficiency of $\widehat{\beta}$ when errors are normal. Computationally, the parameters are found using iteratively reweighed least squares with a weighting function corresponding to the bisquare function $\rho(y)$ and an initial estimate for the residual scale of $\widehat{\sigma} = MAR/0.6745$, where MAR is the median absolute residual. While least-squares assign equal weight to each residual, the weights of the bisquare estimator decline as soon as the residual departs from 0, and is 0 for $|y| > k$. Compared to standard least squares, by construction, robust regression estimates are less influenced by potential contamination in the data (Maronna, Martin and Yohai, 2006).

Table B1: Overall Market Share

The table displays the overall market share for the top 10 leaders in the foreign exchange (FX) market from 2001 to 2011. The data are collected from the Euromoney annual survey of the global FX industry (Euromoney FX Survey).

	FX Market in 2001	share (%)	FX Market in 2002	share (%)	FX Market in 2003	share (%)	FX Market in 2004	share (%)
1	Citigroup	9.74	Citigroup	11.17	**UBS**	11.53	**UBS**	12.36
2	Deutsche Bank	9.08	**UBS Warburg**	10.96	Citigroup	9.87	Deutsche Bank	12.18
3	Goldman Sachs	7.09	Deutsche Bank	9.79	Deutsche Bank	9.79	Citigroup	9.37
4	JP Morgan	5.22	Goldman Sachs	6.69	JPMorgan Chase	6.79	JPMorgan	5.78
5	Chase Manhattan Bank	4.69	JPMorgan Chase	5.86	Goldman Sachs	5.56	HSBC	4.89
6	Credit Suisse First Boston	4.10	Credit Suisse First Boston	4.62	Credit Suisse First Boston	4.23	Goldman Sachs	4.54
7	**UBS Warburg**	3.55	Morgan Stanley	3.70	HSBC	3.89	Barclays Capital	4.08
8	State Street Bank & Trust	2.99	ABN Amro	3.40	Morgan Stanley	3.87	Credit Suisse First Boston	3.79
9	Bank of America	2.99	SEB	2.76	Barclays Capital	3.84	RBS	3.51
10	Morgan Stanley Dean Witter	2.87	Barclays Capital	2.61	ABN Amro	3.63	Merrill Lynch	3.49

	FX Market in 2005	share (%)	FX Market in 2006	share (%)	FX Market in 2007	share (%)	FX Market in 2008	share (%)
1	Deutsche Bank	16.72	**UBS**	22.50	Deutsche Bank	19.30	Deutsche Bank	21.70
2	**UBS**	12.47	Deutsche Bank	20.06	**UBS**	14.85	**UBS**	15.80
3	Citigroup	7.50	Citigroup	10.59	Citigroup	9.00	Barclays	9.12
4	HSBC	6.37	RBS	6.53	RBS	8.90	Citigroup	7.49
5	Barclays Capital	5.85	Barclays Capital	4.53	Barclays Capital	8.80	RBS	7.30
6	Merrill Lynch	5.69	Bank of America	3.86	Bank of America	5.29	JPMorgan	4.19
7	JPMorgan	5.29	HSBC	3.66	HSBC	4.36	HSBC	4.10
8	Goldman Sachs	4.39	JPMorgan	3.36	Goldman Sachs	4.14	Lehman Brothers	3.58
9	ABN Amro	4.19	Dresdner Kleinwort W.	2.54	JPMorgan	3.33	Goldman Sachs	3.47
10	Morgan Stanley	3.92	Goldman Sachs	2.50	Morgan Stanley	2.86	Morgan Stanley	2.56

	FX Market in 2009	share (%)	FX Market in 2010	share (%)	FX Market in 2011	share (%)
1	Deutsche Bank	20.96	Deutsche Bank	18.06	Deutsche Bank	15.84
2	**UBS**	14.58	**UBS**	11.30	Barclays Capital	10.75
3	Barclays Capital	10.45	Barclays Capital	11.08	**UBS**	10.59
4	RBS	8.19	Citi	7.69	Citi	8.88
5	Citigroup	7.32	RBS	6.50	JPMorgan	6.43
6	JPMorgan	5.43	JPMorgan	6.35	HSBC	6.26
7	HSBC	4.09	HSBC	4.55	RBS	6.20
8	Goldman Sachs	3.35	Credit Suisse	4.44	Credit Suisse	4.80
9	Credit Suisse	3.05	Goldman Sachs	4.28	Goldman Sachs	4.13
10	BNP Paribas	2.26	Morgan Stanley	2.91	Morgan Stanley	3.64