(Why) Does Order Flow Forecast Exchange Rates?*

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Preliminary

October 12, 2011

*__Acknowledgements:__ We thank UBS for providing the customer order flow data used in this paper. Sarno acknowledges financial support from the Economic and Social Research Council (No. RES-062-23-2340). Tsiakas acknowledges financial support from the Social Science and Humanities Research Council of Canada. **Corresponding author:** Lucio Sarno, Cass Business School, City University, 106 Bunhill Row, London EC1Y 8TZ, UK.

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Abstract

We investigate the predictive information content of order flow for exchange rate returns, using a unique data set on daily end-user transactions for nine exchange rates across four customer types from 2001 to 2011. We find that a multi-currency trading strategy based solely on customer order flow strongly outperforms the popular carry trade strategy. More importantly, the excess portfolio returns generated from conditioning on customer order flow 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; Market Microstructure; Forecasting; Asset Allocation.

JEL Classification: F31; G11.

1 Introduction

The foreign exchange (FX) is a decentralized market comprising two distinct groups of participants: dealers and end-user customers. Dealers act as financial intermediaries who facilitate trades by quoting prices at which they are willing to trade with customers. The trades between dealers and customers are not transparent, however, since prices and transaction volumes are only observed by the two transacting counterparties. Therefore, customer orders are an important source of private information to dealers as, for example, they may signal the customers' interpretation of public news and future risk premia. This private information is then revealed to the rest of the market when dealers trade with each other motivated primarily by liquidity and inventory concerns.[1] Trades between dealers account for 38.9% of FX turnover and the remainder is customer trades (Bank of International Settlements, 2010).[2]

This trading mechanism implies that customer order flow may be a predictor of future FX excess returns. Order flow is a measure of the net demand for a particular currency defined as the value of buyer-initiated orders minus the value of seller-initiated orders.[3] The argument is as follows (see, e.g., Evans and Lyons, 2005, 2006, 2007). The spot exchange rate is the rate quoted by FX dealers and hence reflects the dealers' information set. If dealers first receive the private information conveyed by customer order flow and subsequently incorporate it in their quotes, then customer order flow should be able to forecast FX excess returns. Note that the information conveyed by customer order flow can only be used by the dealer who facilitated the transaction as it is not observed by other market participants. Furthermore, customers are heterogeneous in their motivation for trading, attitude towards risk and horizon leading them to adopt different trading strategies. Therefore, different customer groups will provide dealers with different information. Through interdealer trading this information will be aggregated and mapped to a price thus establishing a transmission mechanism from customer order flow to the exchange rate.

To put it in perspective, order flow is the centerpiece of the market microstructure approach to

[1] In the interdealer market, dealers have access to two different trading channels: they can trade directly with each other or through brokers, where the latter includes FX trading platforms such as Reuters and Electronic Broking Systems. The direct interdealer trades are private since the bid and ask quotes, the amount and direction of trade are not announced to the rest of the market. The second channel is more transparent as electronic brokers announce best bid and ask prices and the direction of all trades. However, this information is only available to dealers (see, e.g., Bjonnes and Rime, 2005).

[2] For further details on the institutional structure of the FX market, see, for example, Lyons (2001), Bjonnes and Rime (2005), Evans and Lyons (2006), Sager and Taylor (2006), and Evans (2011).

[3] Earlier studies use a simpler definition of order flow as the number (not value) of buyer-initiated trades minus the number of seller-initiated trades (e.g., Evans and Lyons, 2002).

exchange rates pioneered by Evans and Lyons (2002). This line of research has emerged as an exciting alternative to traditional economic models of exchange rate determination, which despite thirty years of research have had limited success in explaining and predicting currency movements. As a result, exchange rates are thought to be largely disconnected from macroeconomic fundamentals in what is widely known as the "exchange rate disconnect" puzzle (Obstfeld and Rogoff, 2001). The market microstructure literature asserts that transactions can affect prices because they convey information. News can be impounded directly in currency prices or indirectly via order flow (Evans and Lyons, 2008).[4] Order flow can also affect the price for reasons unrelated to publicly available news (e.g., changing risk aversion, liquidity and hedging demands).

This paper investigates the predictive ability of customer order flow using a new and comprehensive order flow data set obtained from UBS, a global leader in FX trading. The data set disaggregates customer order flows into trades executed between UBS (the dealer) and four segments (customers): asset managers, hedge funds, corporates and private clients. The disaggregated nature of the data is crucial as it allows us to determine whether conditioning on the four different types of UBS customers, as opposed to using the aggregated order flow typically used in the literature, can improve the explanatory and predictive power of order flow for exchange rate returns. Overall, this is a rich data set that contains the US dollar value of daily order flows over an 11-year sample period ranging from January 2001 to May 2011 and covers nine major currencies relative to the US dollar. Therefore, it provides us with a unique opportunity to examine the predictive ability of customer order flow over a long sample and a large set of exchange rates.

Armed with these data, our paper has two main objectives. First, we assess the predictive ability of the four types of customer order flow on FX excess returns from the point of view of an investor (or dealer) implementing a multi-currency dynamic asset allocation strategy. We choose a trading strategy to assess the predictive ability of customer order flow since it is through trades that customers reveal their information. Second, we relate the excess portfolio returns generated from order flow strategies to the excess portfolio returns of other public information strategies commonly used in the literature. In other words, if customer order flow has predictive private information that

[4] Evans and Lyons (2008) provide an excellent example of the indirect channel to the price adjustment process. Consider a scheduled macro announcement on US GDP growth that is higher than the expectation of market participants. Suppose that everyone agrees that the GDP announcement represents good news for the US dollar but there are diverse opinions as to how large the appreciation should be relative to the Japanese yen. In this case, some participants may view the initial rise in the yen/dollar spot rate as too large while others as too small. Those who view the rise as too small will place orders to purchase the dollar, while those who view the rise as too large will place orders to sell. Positive order flow signals that the initial yen/dollar spot rate was below the balance of opinion among market participants and vice versa.

can consistently generate excess portfolio returns, can we replicate these returns by conditioning on publicly available (e.g., macroeconomic) information? For example, to what extent do customer orders reflect changes in interest rates, real exchange rates or monetary fundamentals? Finally, is there a component of the predictive information of customer order flows (e.g., an alpha in the trading strategies) that is completely private and hence cannot be replicated by combining public information?

In answering these questions, we adopt the carry trade as the benchmark for assessing the performance of order flow strategies. This is a popular trading strategy that borrows in low-interest rate currencies and lends in high-interest rate currencies, and has been the focus of recent academic research (e.g., Burnside, Eichenbaum, Kleshchelski and Rebelo, 2011; Lustig, Roussanov and Verdelhan, 2011; Menkhoff, Sarno, Schmeling and Schrimpf, 2011). Note that a plain version of the carry trade is based on the assumption that the spot exchange rate follows a random walk, which is the benchmark in the literature on exchange rate forecasting ever since the seminal paper of Meese and Rogoff (1983).

We find that the order flow strategies conditioning separately on each individual customer type strongly outperform the standard carry trade strategy as they deliver a superior Sharpe ratio net of transaction costs. This is especially true in the post-2007 sample. The strategy that conditions on all four customer flows together tends to perform the best in sample and out of sample. In particular, a mean-variance investor is willing to pay an out-of-sample performance fee of up to 800 basis points annually to switch from the carry trade to conditioning on customer order flow. Therefore, there is high economic value in the predictive information of customer order flow, which is magnified when using all segments of the disaggregated data.

Furthermore, 60% to 70% of the excess portfolio returns generated from conditioning on order flow can be replicated using a combination of strategies based on publicly available information. These strategies include the random walk, forward premium, purchasing power parity, monetary fundamentals, Taylor rule, cyclical external imbalances and momentum. Hence publicly available information captured by variables such as interest rates, past values of exchange rates, inflation, money supply, output, external imbalances and momentum is key in determining the net demand for currencies as observed in FX order flow. More importantly, however, once the role of public information strategies is accounted for, there is no remaining alpha for the order flow strategies. We conclude, therefore, that the information conveyed by customer order flow is a particular aggregation of public information. Customers simply interpret and use public information, each in their own way.

Finally, the way customer order flow aggregates public information is not constant over time. We find evidence of strong time variation in the relative importance of different strategies driving order flow. For example, while the carry trade is a critical driver of order flow during the pre-crisis period, after the crisis erupted in July 2007 and the carry trade collapsed, it is replaced by purchasing power parity and monetary fundamentals. This is consistent with the scapegoat theory of Bacchetta and van Wincoop (2004, 2006), which suggests that the relation between macroeconomic fundamentals and the exchange rate is highly unstable. This parameter instability is due to the different weight that on a given day traders assign to a given macroeconomic indicator as the market rationally searches for an explanation for the observed exchange rate change. A variable can be given excessive weight a one day and zero weight the next day. As a result, different observed variables become scapegoats. Bacchetta and van Wincoop (2004, 2006) term this "rational confusion" about the true source of exchange rate fluctuations. In the short run, rational confusion plays an important role in disconnecting the exchange rate from observed fundamentals, but allows them to be connected in the long run.

The remainder of the paper is organized as follows. In the next section we describe the data used in the empirical analysis, with particular emphasis on the UBS data set for FX order flows. Section 3 reviews the literature on models that link order flow, exchange rates and the macroeconomy. The set of empirical models based on public information are described in Section 4. In Section 5 we present the mean-variance framework for measuring the economic value of conditioning on order flow in the context of a dynamic asset allocation strategy. Section 6 discusses the results from estimating the empirical models conditioning on order flow and comparing their performance to the carry trade strategy. It also analyzes the relation between the excess returns generated by the information in order flow and the excess returns obtained from public information models. Section 7 summarizes the key results and concludes.

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 macroeconomic 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 data range from January 2001 to May 2011 and cover 2618 daily observations after removing holidays and weekends.

The order flow data come from proprietary daily transactions between four end-user segments (customer groups) and UBS. UBS is a global leader in the FX market with a market share in turnover higher than 10%.[5] Order flows 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 long-term real money investors, such as mutual funds and pension funds. Highly leveraged traders and short-term asset managers not included in the previous group are classified as hedge funds. The corporates segment includes non-financial corporations that import or export products and services around the world or have an international supply chain. Treasury units of large non-financial corporations are treated as corporates unless they pursue an aggressive (highly leveraged) investment strategy, in which case they are classified as hedge funds. The final segment, private clients, includes wealthy clients with in excess of $3 million in investible liquid assets. Private clients trade primarily for financial reasons and with their own money.

The order flow data are assembled as follows. Each transaction booked in the UBS execution system at any of its world-wide offices is tagged with a client type. At the end of each business day, global transactions are aggregated across the four segments. Order flow is measured as the difference between the dollar value of purchase and sale orders for foreign currency initiated by UBS clients. Specifically, let V_t be the dollar value of a transaction initiated by a customer at time t. The transaction is recorded with a positive (negative) sign if UBS fills a purchase (sale) order of foreign currency. 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. It follows that positive order flow indicates a net demand of foreign currency whereas negative order flow a net supply.[6]

The order flow data set used in our analysis is the most comprehensive in this literature to date and is also unique in many respects. First, in contrast to most other empirical studies that focus on interdealer data, we use customer order flow data disaggregated into the four segments

[5] Table C1 in the Appendix displays the top 10 global leaders in the FX market in terms of market share in annual turnover from 2001 to 2011 based on the Euromoney FX Survey.

[6] It is important to note 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 (i.e., customer) is buying or selling. Consider, for example, a sale of 10 units by a customer acting on a dealer's quotes. Then transaction volume is 10, but order flow is –10 (Lyons, 2001).

discussed above. Second, our data set spans more than 11 years of daily observations for nine currency pairs and it comes from a major FX market leader. Although there are recent studies that employ customer order flow data, they typically suffer 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, Evans and Lyons (2005, 2006, 2007) and Evans (2010) employ six years of data for one currency pair from Citibank. Cerrato, Sarantis and Saunders (2011) use six years of data for nine currency pairs from UBS but, in contrast to this paper, their data are weekly; they have 317 weekly observations compared to our 2618 daily observations. Froot and Ramadorai (2005) use seven years of data for eighteen currency pairs from State Street, a global custodian bank. These are flow data with primarily institutional investors, which are however aggregated, and hence cannot capture the same diversity in currency demand as with the UBS end-user segments.

Third, most 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). Finally, our order flow data are raw data with minimal filtering. For instance, data are adjusted to take into account for large merger and acquisition deals which are announced weeks or months 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-publisized and thus are anticipated in advance by market participants. Furthermore, FX reserve managers, UBS proprietary (prop) traders and small banks not participating in the interbank market are excluded from the data set. Flows from FX reserve managers are stripped out due confidentiality issues, flows from prop traders because they trade with UBS's own money, while small banks often have non-financial customers behind them.

The exchange rates are Thomson Reuters data obtained through *Datastream*. We use daily spot and spot-next forward rates for the daily analysis, and end-of-month spot and one-month forward rates for the monthly analysis. 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. Most of the empirical work uses mid-quotes, but bid and ask quotes are used to construct transaction costs as detailed in Section 5. For 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, with the following exceptions that are published quarterly: IPI for Australia, New Zealand and Switzerland; and CPI for Australia and New Zealand. For the 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).[7] We mimic as closely as possible the information set available to 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.[8] From OECD statistics, we also obtain annual data on the purchasing power parity (PPP) spot exchange rate. Finally, we use the *International Financial Statistics* (IFS) database to obtain quarterly data on external assets and liabilities, exports and imports of goods and services, and GDP.[9] Note that 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.

We convert the data by taking logs, except for interest rates and order flows. Henceforth the symbols s_t, f_t, x_t, i_t, m_t, π_t, y_t and $\overline{y}_t$ refer to the log spot exchange rate, log forward exchange rate, order flow, interest rate, log money supply, inflation rate, log real output and log output gap, respectively. We use an asterisk to denote the 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.[10]

[7] Orphanides (2001) stresses the importance of using real-time data to estimate Taylor rules for the United States. However, 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.

[8] 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).

[9] 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.

[10] Following Gourinchas and Rey (2007) 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 analysis, however, we implement the Hodrick-Prescott filter and compute the weights only using information available at the time of the forecast in order to avoid any look-ahead bias.

2.2 Preliminary Analysis

Table 1 reports UBS's market share by customer type and its rank relative to the top 10 global FX dealers from 2001 to 2011 based on the Euromoney annual survey. The table reveals that UBS has been one of the top dealers for both the overall market and particular end-user segments. Although the Euromoney survey uses different groupings than UBS, three of the groups defined by Euromoney (real money, leveraged funds and non-financial corporations) seem to align well with three of the UBS segments (asset managers, hedge funds and corporates).[11] The table indicates that 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.

Table 2 presents descriptive statistics for daily log exchange rate returns and order flows across the four customer groups for the nine currency pairs from January 2001 to May 2011. Order flow tends to be more volatile for asset managers and hedge funds and least volatile for the corporates. This fits with the view that asset managers and hedge funds are very active traders, whereas corporate clients trade mostly for import and export reasons.

Table 3 presents the contemporaneous cross-correlations between flows and returns: while asset managers and hedge funds are positively correlated with exchange rate returns, corporate and private clients are typically negatively correlated. These results are consistent with previous empirical evidence reported by Evans and Lyons (2002) and Sager and Taylor (2006) indicating that asset managers and hedge funds are informed traders (push customers) whereas corporate and private clients act as overnight liquidity providers (pull customers).

3 Predictive Regressions

This section describes two sets of predictive regressions for exchange rate returns. The first set conditions on the private information of customer order flows, whereas the second set conditions on the public information contained in a battery of macroeconomic variables. All predictive regressions have the following linear structure:

$$\Delta s_{t+1} = \alpha + \beta x_t + \varepsilon_{t+1}, \tag{1}$$

[11] 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 a 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.

where s_{t+1} is the nominal US dollar spot exchange rate for a particular currency at time $t+1$, $\Delta s_{t+1} = s_{t+1} - s_t$ is the log-exchange rate return at time $t+1$, x_t is a predictive variable, α and β are constant parameters to be estimated, and ε_{t+1} is a normal error term. The empirical models differ in the way they specify the predictive variable x_t that is used to forecast exchange rate returns.

3.1 Order Flow Models

We capture the predictive information content in the orders of four heterogeneous customer groups by estimating three types of predictive regressions for each exchange rate. The first type conditions separately on the order flow of each of the four customers: asset managers (x_t^{AM}), hedge funds (x_t^{HF}), corporates (x_t^{CO}), and private clients (x_t^{PC}). We call these the individual order flows. The second type conditions on all four customer order flows, which we call the disaggregated order flows: $x_t = \left\{x_t^{AM}, x_t^{HF}, x_t^{CO}, x_t^{PC}\right\}$. Finally, we condition on the sum of the four order flows, which we call the aggregate (or total) order flow: $x_t = x_t^{AM} + x_t^{HF} + x_t^{CO} + x_t^{PC}$. These regressions will determine whether there is predictive information in customer order flows and the extent to which different customer groups provide different information.

3.2 Public Information Models

3.2.1 Random Walk

The first specification based on public information 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; Lustig, Roussanov and Verdelhan, 2011; Menkhoff, Sarno, Schmeling and Schrimpf, 2011). The RW model is the benchmark to which we compare the predictive regressions conditioning on order flow.

3.2.2 Forward Premium

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

$$x_t = f_t - s_t, \tag{2}$$

where f_t is the one-period log-forward exchange rate. The predictive regression using FP as conditioning information captures deviations from the 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.[12]

3.2.3 Purchasing Power Parity

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

$$x_t = p_t - p_t^* - s_t, \tag{3}$$

where p_t (p_t^*) is the log of the domestic (foreign) price level. This is equivalent to a trading strategy that buys undervalued currencies and sells overvalued currencies relative to PPP. The PPP hypothesis states that national price levels should be equal when expressed in a common currency and is typically thought of as a long-run condition rather than holding at each point in time (e.g., Rogoff, 1996; and Taylor and Taylor, 2004).

3.2.4 Monetary Fundamentals

The fourth regression conditions on monetary fundamentals (MF):

$$x_t = (m_t - m_t^*) - (y_t - y_t^*) - s_t, \tag{4}$$

where m_t (m_t^*) is the log of the domestic (foreign) money supply and y_t (y_t^*) is the log of the domestic (foreign) real output. The relation between exchange rates and fundamentals defined in Equation (4) 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 in what is commonly referred to as the "exchange rate disconnect" puzzle (Obstfeld and Rogoff, 2001). On the other hand, there is growing evidence that exchange rates and monetary fundamentals are cointegrated, which requires that the exchange rate and/or the fundamentals move in a way to restore and equilibrium relation between them in the long run (e.g., Groen, 2000; Rapach and Wohar, 2002).

[12] Note that we implicitly assume that covered interest parity (CIP) holds, so that the interest rate differential is equal to the forward premium, $f_t - s_t = i_t - i_t^*$, where i_t and i_t^* are the domestic and foreign nominal interest rates, respectively. In this case, testing UIP is equivalent to testing for forward unbiasedness in exchange rates (Bilson, 1981). There is ample empirical evidence that CIP holds in practice for the data frequency examined in this paper. For recent evidence, see Akram, Rime and Sarno (2008). The only exception in our sample is the period following Lehman's bankruptcy, when the CIP violation persisted for a few months (e.g., Mancini-Griffoli and Ranaldo, 2011).

3.2.5 Taylor Rule

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

$$x_t = 1.5\,(\pi_t - \pi_t^*) + 0.1\,(\overline{y}_t - \overline{y}_t^*) + 0.1\,(s_t + p_t^* - p_t)\,, \tag{5}$$

where π_t (π_t^*) is the domestic (foreign) inflation rate, and $\overline{y}_t$ ($\overline{y}_t^*$) 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.[13] 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).

3.2.6 Cyclical External Imbalances

The sixth model employs as the predictive variable a bilateral measure of cyclical external imbalances between the US and the foreign country. 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 squares estimator as in Della Corte, Sarno and Sestieri (2011). We first 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.

3.2.7 Momentum

The final specification uses the one–year rolling exchange rate return as the conditional mean of the one-period ahead exchange rate. This strategy produces a long exposure to the currencies that are trending higher, and a short exposure to the currencies that are trending lower.

[13] 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 and avoids a look-ahead bias.

4 An Economic Assessment of the Predictive Ability of Order Flow

This section describes the framework for evaluating the ability of order flow to predict exchange rate returns in the context of dynamic asset allocation strategies.

4.1 The Dynamic FX Strategy

We design an international asset allocation strategy that involves trading the US dollar vis-à-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 each period $t+1$, the foreign bonds yield a riskless return in local currency but a risky return r_{t+1} in US dollars. The expected US dollar return of investing in a foreign bond is equal to $r_{t+1|t} = i_t + \Delta s_{t+1|t}$, where $r_{t+1|t} = E_t\left[r_{t+1}\right]$ is the conditional expectation of r_{t+1} and $\Delta s_{t+1|t} = E_t\left[\Delta s_{t+1}\right]$ is the conditional expectation of Δs_{t+1}. Hence the only risk the US investor is exposed to is FX risk.

Every period the investor takes two steps. First, she uses the predictive regressions conditioning on order flow or other public information 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 using the method discussed below. This setup is designed to provide an economic assessment of the ability of order flow to predict exchange rates by informing us whether conditioning on order flow leads to a better performing allocation strategy than conditioning on the random walk or other standard public information models.

4.2 Mean-Variance Dynamic Asset Allocation with Transaction Costs

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 $t+1$, $V_{t+1|t} = E_t[(r_{t+1} - r_{t+1|t})(r_{t+1} - r_{t+1|t})']$ the $K \times K$ conditional variance-covariance matrix of r_{t+1}, τ_{t+1} the $K \times 1$ vector of proportional transaction costs, and $\tau_{t+1|t} = E_t\left[\tau_{t+1}\right]$ the conditional expectation of τ_{t+1}.

Our analysis focuses on the maximum expected return strategy, which leads to an allocation on the efficient frontier. This strategy maximizes the expected portfolio return at each period t for a given target portfolio volatility:

$$\begin{aligned} \max_{w_t} \quad r_{p,t+1|t} &= w_t' r_{t+1|t} + (1 - w_t'\iota)\, r_f - \phi_{t+1|t} \\ \text{s.t.} \quad \sigma_p^* &= \left(w_t' V_{t+1|t} w_t\right)^{1/2}, \end{aligned} \tag{6}$$

where $r_{p,t+1}$ is the portfolio return at time $t+1$, $r_{p,t+1|t} = E_t[r_{p,t+1|t}]$ is the conditional expectation of $r_{p,t+1}$, r_f is the riskless rate, σ_p^* is the target conditional volatility of the portfolio returns, and $\phi_{t+1|t}$ is the conditional expectation of the total transaction cost for the portfolio in each period defined as:

$$\phi_{t+1|t} = \sum_{i=1}^{K} \tau_{i,t+1|t} \left| w_{i,t} - w_{i,t}^{-} \right|, \tag{7}$$

where $w_{i,t}^{-} = w_{i,t-1}\,(1 + r_{i,t}) \,/\, (1 + r_{p,t})$.

The proportional transaction cost $\tau_{i,t+1|t}$ for each asset i is computed as follows. We first define the excess return of holding foreign currency for one period net of transaction costs as:

$$er_{t+1}^{net} = s_{t+1}^{b} - f_t^{a}, \tag{8}$$

where s_{t+1}^{b} is the bid-quote for the spot rate at time $t+1$, and f_t^a is the ask-quote for the forward rate at time t. This is the excess return for an investor who buys a forward contract at time t for exchanging the domestic currency into the foreign currency at time $t+1$, and then, at time $t+1$ she converts the proceeds of the forward contract into the domestic currency at the $t+1$ spot rate.

We can rewrite the above expression using mid-quotes to obtain:

$$\begin{aligned} er_{t+1}^{net} &= \left(s_{t+1} - \frac{s_{t+1}^{a} - s_{t+1}^{b}}{2}\right) - \left(f_t + \frac{f_t^{a} - f_t^{b}}{2}\right) \\ &= (s_{t+1} - f_t) - c_{t+1}, \end{aligned} \tag{9}$$

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

In the empirical implementation of the mean-variance strategy, we need to compute the time-varying weights w_t using information up to time t. These weights will determine the $t+1$ portfolio return $r_{p,t+1}$. However, the transaction cost τ_{t+1} relevant to $t+1$ returns will only be known ex post, whereas the weights (which require an estimate of τ_{t+1}) are set ex ante. We avoid this complication by estimating $\tau_{t+1|t}$ using the 3-month rolling average of the times series of τ_t using information up to time t. In short, to compute the weight w_t we use the estimate $\tau_{t+1|t}$, but to compute the net portfolio returns, which are known ex post, we use the realized τ_{t+1} value.

The inclusion of transaction costs in the optimization imply that the optimal solution for the time-varying weights w_t is not available in closed form but is obtained via numerical optimization.[14] Once the optimal weights are computed, the return on the investor's portfolio net of transaction costs is equal to:

$$r_{p,t+1} = w_t' r_{t+1} + \left(1 - w_t' \iota\right) r_f - \phi_{t+1}. \tag{10}$$

Note that we assume that $V_{t+1|t} = \overline{V}$, where $\overline{V}$ 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.[15]

4.3 Performance Measures

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

$$M\left(r_p\right) = \frac{1}{(1-\gamma)} \ln \left\{ \frac{1}{T} \sum_{t=1}^{T} \left(\frac{1 + r_{p,t}}{1 + r_f} \right)^{1-\gamma} \right\}, \tag{11}$$

where $M\left(r_p\right)$ is an estimate of the portfolio's premium return after adjusting for risk, which 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 portfolio returns and does not require the assumption of a particular utility function to rank portfolios. The parameter γ denotes the investor's degree of relative risk aversion (RRA).

We compare the performance of the exchange rate model conditioning on order flow to the benchmark RW by computing the difference :

$$\mathcal{P} = M(r_p^*) - M(r_p^b), \tag{12}$$

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

[15] See Della Corte, Sarno and Tsiakas (2009) for an empirical analysis of the effect of dynamic volatility on mean-variance strategies in FX.

where r_p^* are the portfolio returns of the order flow strategy and r_p^b of the benchmark RW. We interpret $\mathcal{P}$ as the maximum performance fee an investor will pay to switch from the RW to the order flow strategy. In other words, this performance criterion measures how much a mean-variance investor is willing to pay for conditioning on better exchange rate forecasts. We report $\mathcal{P}$ in annualized basis points (bps).

In the context of mean-variance analysis, perhaps the most commonly used performance measure 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. 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. We compute both standard and robust measures of $\mathcal{SR}$ and $\mathcal{SO}$, where the robust measures account for the serial correlation in portfolio returns as in Lo (2002). Finally, we report the maximum drawdown ($\mathcal{MDD}$), which is the maximum cumulative loss from the strategy's peak to the following trough. As large drawdowns usually lead to fund redemptions, it follows that a reasonably low $\mathcal{MDD}$ is critical to the success of any fund.

4.4 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 behaviour without knowing which model is "true" (or best) inevitably generates model uncertainty. In this section, we explore ways to combine the forecasts arising from the full set of competing predictive regressions. Although 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).

Our empirical analysis estimates N predictive regressions for a vector of K exchange rates, which provides an individual forecast $\Delta s_{j,t+1|t}$ generated by each model $j \leq N$ for the vector of one-step ahead exchange rate returns. We define the combined forecast $\Delta s_{c,t+1|t}$ for the vector of exchange rate returns as the weighted average of the N individual forecasts:

$$\Delta s_{c,t+1|t} = \sum_{j=1}^{N} \theta_{j,t} \Delta s_{jt+1|t}, \tag{13}$$

where $\{\theta_{j,t}\}_{j=1}^{N}$ 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 four types. The first type uses simple averaging schemes: mean, median, and trimmed mean. The mean combination forecast sets $\theta_{j,t} = 1/N$ in Equation (13); the median combination forecast is the median of $\left\{\Delta s_{j,t+1|t}\right\}_{j=1}^{N}$; and the trimmed mean combination forecast sets $\theta_{j,t} = 0$ for the individual forecasts with the smallest and largest values and $\theta_{j,t} = 1/(N-2)$ for the remaining individual forecasts in Equation (13). 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, it sets the weights by computing the following mean squared error (MSE) forecast combination:

$$\theta_{j,t} = \frac{MSE_{j,t}^{-1}}{\sum_{j=1}^{N} MSE_{j,t}^{-1}}, \quad MSE_{j,t} = \frac{1}{T}\sum_{t=1}^{T}\left(\Delta s_{j,t} - \Delta s_{j,t|t-1}\right)^2. \tag{14}$$

The third type follows the Welch and Goyal (2008) "kitchen sink" (KS) model that incorporates all N economic variables $\left\{x_t^j\right\}_{j=1}^{N}$ into a multiple predictive regression:

$$\Delta s_{t+1} = \alpha + \sum_{j}^{N} \beta_j x_t^j + \varepsilon_{t+1}. \tag{15}$$

The fourth and final type designs a "Fund of Funds" (FoF) strategy that equally invests in the portfolio strategy based on the N models.

5 Empirical Results

5.1 The Correlation between Exchange Rates and Order Flow

We begin our empirical analysis by calculating the simple correlation between contemporaneous currency order flows and FX returns at different horizons, as in Froot and Ramadorai (2005). Figure 1 displays for each customer type the average correlation across all exchange rates. The horizon is reported in log-scale on the horizontal axis, running from the 1-day horizon (10^0 days) to 252 days ($> 10^2$). To assess the significance of these correlations, the figure also shows the 90% confidence intervals generated by 10,000 replications under the null hypothesis that each order flow and FX return series is independent and identically distributed (i.i.d.). Consistent with the contemporaneous regression results discussed in the appendix, the correlations at the 1-day horizon are positive 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 up to a year. For HF flows, the correlations are generally positive but less significant. For CO flows, the initial 1-day correlations are negative and insignificant, but become positive for long horizons. The pattern for PC is similar to CO. Overall, this preliminary analysis provides strong evidence that the contemporaneous relation extends to relatively long horizons, thus making it empirically plausible for order flow to have predictive information for future excess FX returns. Next we turn to exploring whether the information content in order flow has predictive power for future FX excess returns in the context of dynamic asset allocation.

5.2 The Predictive Information Content of Order Flow

This section discusses the empirical results from assessing the economic value of conditioning on the four types of customer order flow to predict exchange rate returns. In particular, we analyze the performance of dynamically rebalanced portfolios based on the order flow strategies relative to the random walk (RW) benchmark, which is consistent with the carry trade strategy. In this setting, the investor obtains forecasts of exchange rate returns for next period (day or month) conditioning on order flow information available at the time of the forecast; she then chooses investment weights using the maximum expected return strategy for an annual target volatility of $\sigma_p^* = 10\%$ and a coefficient of relative risk aversion $\gamma = 6$. The choice of σ_p^* and γ is reasonable and consistent with numerous previous empirical studies. We have experimented with different σ_p^* and γ values and found that qualitatively they have little effect on the asset allocation results discussed below.

The forecasting and portfolio optimization is conducted both in sample and out of sample. The in-sample prediction for exchange rate returns uses the predictive regression models described in Section 3 estimated over the full data set ranging from January 2001 to May 2011. The main focus, however, is on the out-of-sample analysis, where we first estimate the predictive regressions over the initial sample period of January 2001 to December 2003, and then reestimate recursively until the end of the full sample (May 2011). Each out-of-sample prediction is conditional on information available at the time of the forecast.

Our assessment of the economic performance of the models focuses on the realized excess returns and their descriptive statistics, the Sharpe ratio, the Sortino ratio (both calculated in the standard way and also adjusting for serial correlation in returns), the maximum drawdown and the performance fee. In assessing the profitability of the dynamic order flow strategies, the effect of transaction costs is an essential consideration. For instance, if the bid-ask spread in trading currencies is sufficiently high, the order flow strategies may be too costly to implement. Hence all asset allocation results are reported net of transaction costs. We consider an effective transaction cost that is equal to 50% of the quoted spread.[16]

It is important to recall that customer transactions are private and the details (e.g., bid and ask quotes) are known only to the dealer customers transact with. Therefore, if customer order flows have predictive information for future FX excess returns, this information is not widely available to market participants. With this in mind, our main objective is to use trading strategies as the tool for determining the nature of the predictive information conveyed by customer order flows, not as a recommended method for profitable FX trading.

We begin our discussion with the daily rebalancing results in Table 4. Our first finding is that the benchmark RW strategy has not performed particularly well, both in sample and especially out of sample. This is not surprising given that the crisis period beginning in June 2007 saw a collapse of carry trade strategies. In the context of a longer sample than the one used in this paper, the carry trade losses that characterize the 2007-2008 period would have a much smaller impact on average carry trade returns.[17] However, over our shorter 10-year sample period, the crisis reduces the in-sample Sharpe ratio of the RW to 0.13; further removing the first three years in the out-of-sample exercise leads to a negative Sharpe ratio of -0.17. It is also noteworthy that the maximum drawdown of the carry trade is very large, 37% in sample and 48% out of sample.

In the out-of-sample economic evaluation of order flow models, three main findings are noteworthy. First, the order flow models outperform the RW benchmark in all cases both in sample and out of sample. The best out-of sample performing model is PC, which has a Sharpe ratio net of transaction costs of 0.38 (compared to -0.17 for RW) and a performance fee of 841 annual basis points (bps). The HF model also performs well with $\mathcal{SR} = 0.26$ and $\mathcal{P} = 744$ bps. AM is only type of order flow that produces a negative Sharpe ratio ($\mathcal{SR} = -0.06$), which however is still better than that of RW. Second, the performance of the disaggregated predictive regression (ALL) is superior to that of the total (aggregate) order flow model (TOT). In other words, by exploiting the predictive information

[16] It is well-documented that the effective spread is generally lower than the quoted spread, since trading will take place at the best price quoted at any point in time, suggesting that the worse quotes will not attract trades (e.g., Goyal and Saretto, 2009).

[17] For an evaluation of the carry trade performance using longer samples see, for example, Burnside, Eichenbaum, Kleshchelski and Rebelo (2011), Lustig, Roussanov and Verdelhan (2001), and Menkhoff, Sarno, Schmeling and Schrimpf (2011).

of all individual customer order flows separately, we can generate substantial economic gains. Third, as expected, the in-sample results are substantially better than the out-of-sample results. This is primarily due to the removal of the first three years from the out-of-sample analysis and hence placing the heavier weight on the post-crisis returns, which tend to be negative. For example, the disaggregated model (ALL) produces $\mathcal{SR} = 1.0$ in sample but only $\mathcal{SR} = 0.23$ out of sample. In conclusion, these results show that a risk-averse investor will pay a large performance fee to switch from a random walk strategy to a strategy that conditions on order flow information as the out-of-sample performance fee ranges from 279 to 841 basis points for daily rebalancing. This is strong evidence of the predictive power of order flow information as compared to the RW benchmark.[18]

To provide a visual illustration of the daily asset allocation results, Figure 2 shows the cumulative wealth over time for the four individual order flow models relative to the RW benchmark starting with a \$1 position. The figure indicates that the cumulative wealth for each of the four order flow strategies is higher than the RW. HF and PC perform better than AM and CO. More importantly, while at the beginning the order flow models tend to comove with the RW, after the subprime crisis in 2007 the order flow models considerably outperform the RW. This suggests that much of the order flow prior to the crisis was driven by carry positions, whereas after the crisis it is not. This is not surprising as the unwinding of carry trades would have reduced the role of the carry trade in determining order flow.

The monthly results reported in Table 5 are qualitatively similar to the daily results and confirm the superior performance of strategies conditioning on order flow. Note that the Sharpe ratios tend to be higher for monthly rebalancing, which is primarily due to the lower transaction costs incurred as rebalancing takes place less often.

5.3 What Drives Customer Order Flow?

Having established the predictive ability of customer order flow, it is important to examine the extent to which this predictive information is related to other publicly available information. This effectively allow us to determine what drives order flow. In particular, we investigate whether the excess portfolio returns generated by the strategies that condition on order flow are correlated with the excess portfolio returns generated by alternative strategies commonly used in the literature.

[18] In Table C5 of the appendix we report results for the same exercise where the predictive regression is estimated using the M-estimator, which is robust to outliers. This is an important robustness check as order flow data are typically not as long as exchange rate data and we need to ensure that our results are not driven a few select outliers. The M-estimator is discussed in Appendix A. The results in Table C5 show that the performance of the order flow models improves significantly when using the robust estimator. In particular, the AM now has a positive Sharpe ratio.

The latter include the following seven public information strategies: random walk (RW), forward premium (FP), purchasing power parity (PPP), monetary fundamentals (MF), Taylor rule (TR), cyclical external imbalances (NXA) and momentum (MOM).

We assess what drives order flow by implementing the following framework. First, we estimate a set of predictive regressions for order flow and public information models that deliver a set of one-period ahead forecasts for exchange rate returns. We then use these forecasts in the mean-variance dynamic asset allocation to generate the excess portfolios net of transaction costs. Finally, we regress the excess portfolio returns of the order flow strategy for each customer type on the excess portfolio returns of seven public information strategies. This exercise is conducted in sample but we find that using out of sample returns does not affect our results.

In addition to helping us understand what drives order flow, this framework will shed light on questions such as the following: what strategies do asset managers, hedge funds, corporate clients and private clients follow? Are these strategies different among customer types? 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?

These questions are central to two lines of research. First, we can understand better the behaviour 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 on the behaviour of FX currency managers, their performance and risk exposure (e.g., Pojarlev and Levich, 2008). The main difference to our study is that this literature tends to focus on directly observed returns of (say) asset managers and hedge funds, in an attempt to replicate these returns and assess whether they provide an "alpha" due to skill or superior information. In contrast, our study conditions on trading decisions based on customer order flow, not the return of particular funds. Second, recent theoretical literature formalizes the notion that order flow conveys fundamental information about exchange rates and, hence, it aggregates dispersed economic information (e.g., Evans and Lyons, 2007, 2008; Bacchetta and van Wincoop, 2004, 2006). This implies that order flow ought to be empirically related to macroeconomic information, and it effectively summarizes it.

Table 6 shows the regression results for the excess portfolio returns of each customer flow on the seven public information strategies. For each customer type, we estimate four regressions: one where all seven public information strategies are used and three where only one of RW, FP and TR are used one at a time together with the remaining ones. This is because for the latter three models (RW, FP and TR), the key piece of predictive information is the interest rate differential, and hence the returns from these three strategies are highly correlated.[19] 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).

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. The main results can be summarized as follows: (i) cyclical external imbalances (NXA) is the strategy that consistently has the highest impact on the order flow strategies in terms of the size of its coefficient; (ii) the exposure to interest rate differentials captured by the coefficients of RW, FP and TR is individually high and even higher when taken together; (iii) all strategies enter with a positive sign 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 may be driven by contrarian strategies that buy depreciating currencies and sell appreciating currencies. In contrast, other customers' flows tend to load positively on momentum; (iv) almost all public information strategies enter significantly in the regressions; (v) the $\overline{R}^2$ is high ranging from about 60% to 75%, suggesting that the public information strategies capture well the net demand for currency manifested in the order flows; and, more importantly, (vii) there is no evidence of positive "alpha" in the order flow strategies, indicating that there is no additional positive excess return generated by the order flow strategies, over and above what can be generated by combining the public information strategies.

These results imply that trading strategies exploiting the predictive information of customer order flow deliver excess portfolio returns that are highly correlated to macroeconomic information. The absence of a significant positive alpha further suggests that there is no private information component in customer order flows that is unrelated to macroeconomic news. In other words, all private information in customer order flows that can be explained is due to a particular combination of public information. This is a new and important result in this literature that further justifies the use of order flow as the conduit through which macroeconomic information is transmitted to exchange rates.

While the regressions are estimated over the full sample with constant parameters, it is likely that these parameters are changing over time. It is a well-documented practice in currency markets that FX participants change over time the weight they assign to different fundamentals (strategies). This is consistent with the scapegoat theory of Bacchetta and van Wincoop (2004, 2006), where

[19] This also means that in the larger regression that involves all seven strategies, the exposure to interest rates is perhaps better judged as the sum of the coefficients on the returns from these three strategies: RW, FP and TR.

every day the market may focus its attention on a different macroeconomic variable (the scapegoat). This happens when traders assign a different weight to a macroeconomic indicator every day as the market rationally searches for an explanation for the observed exchange rate change.[20]

We investigate this possibility in more detail by estimating the large regression with the seven strategies using a rolling window of one year. Figures 3 to 7 report for each customer type the rolling estimates of the coefficients associated with each of the seven strategies and the $\overline{R}^2$. As expected, the figures display clear evidence of time-variation in the parameters. They also show that all customer types reduced their exposure to carry (interest rate differentials) in the second part of the sample period, and especially after 2007. The role of cyclical external imbalances is very high in the first two years but then drastically diminishes. In the last few years, there is an increased role for purchasing power parity and fundamentals. Finally, the alpha remains insignificant throughout the sample.

Our final exercise involves using exchange rate forecast combinations by optimally combining the excess portfolio returns of the seven public information strategies. In this case, instead of regressing the excess portfolio returns of order flow strategies on the seven strategies, we regress it on the excess returns of the one forecast combination strategy. In other words, we reduce estimation of seven betas to one. This allows us to explore whether it is possible to combine period-by-period all public information in one strategy, and whether the combined public information strategy is correlated with the order flow strategy. 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 all seven portfolio strategies. The results, reported in Table 7, suggest that, with the exception of the KS approach, all other combinations work well. The $\overline{R}^2$ in most cases revolves between 50% and 70%; the beta estimates range between 0.7 and 1.2 and are significant. Once again, there is no evidence of significant positive alpha in the excess returns of the order flow strategy.

Overall, these results indicate that publicly available information captured by variables such as interest rates, past values of exchange rates, inflation, money supply, output, external imbalances and momentum is key in determining the net demand for currencies as observed in FX order flow. This information can account for over 70% of the excess portfolio returns generated by models conditioning on customer order flow information. In other words, this information is "price relevant" in generating

[20] This practice is documented, for example, in the survey evidence of Cheung and Chinn (2001) that is based on questionnaires sent to US FX traders.

currency orders and informing customers' trading decisions. We also find evidence of strong time variation in the relative importance of different strategies driving order flows over the full sample, which is particularly noticeable in samples pre- and post-crisis. Overall, we interpret this evidence as suggesting that the information content in order flow is not only economically important but also derives from aggregating disperse public information about economic fundamentals that are relevant to exchange rates.

6 Conclusions

Trades between customers and FX dealers generate a measure of order flow that conveys the customers' private information. Dealers can then act on this information and reveal it to the rest of the FX market through interdealer trading. This mechanism implies that customer order flow may be able to predict future exchange rate returns. In this paper, we examine whether this is the case. We use a unique data set on daily order flow representing the transactions of customers and UBS, a top FX dealer globally. The data set ranges from 2001 to 2011, covers nine currency pairs and, more importantly, is disaggregated across four different end-user segments of the FX market: asset managers, hedge funds, corporate clients, and private clients.

The empirical analysis first assesses the predictive ability of the four types of customer order flow on FX excess returns in the context of dynamic asset allocation strategies. We then relate the excess portfolio returns generated from order flow strategies to the excess portfolio returns of other strategies based on public macroeconomic information such as interest rates, real exchange rates or monetary fundamentals.

We find that the dynamic trading strategy based on the four types of customer order flow strongly outperforms the popular carry trade in sample and out of sample. More importantly, the excess portfolio returns generated from conditioning on order flow 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. Finally, the way customer order flow aggregates public information is not constant over time as there is strong time variation in the relative importance of different macroeconomic indicators driving order flow.

Table 1: The FX Market Share of UBS

The table displays UBS's overall market share and its market share by customer type. The rank is with respect to the top 10 global leaders in the FX market from 2001 to 2011 based on the Euromoney annual survey. The market share by customer type (available from 2003) are presented for *real money, leveraged funds* and *non-financial corporations*.

	Overall Market		Real Money		Leveraged Funds		Non-financial Corporations	
	share (%)	rank	share (%)	rank	share (%)	rank	share (%)	rank
2001	3.55	7	3.11	8	–	–	–	–
2002	10.96	2	10.77	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	9.02	2	8.21	4	3.98	9

Table 2. Descriptive Statistics

The table reports descriptive statistics for log exchange rate returns and foreign currency order flows at the 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 are 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. Cross-Correlations

The table reports the cross-correlations among the daily 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 4. The Predictive Ability of Daily 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 is the 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 total (aggregate) customer order flows. ALL is a strategy that conditions on all four (disaggregated) 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 costs. The strategy invests in a domestic bond and nine foreign bonds and is rebalanced daily. For each strategy, we report the annualized mean (r_p), annualized volatility (σ_p), skewness (*Skew*), excess kurtosis (*Kurt*), annualized Sharpe ratio (*SR*), annualized Sortino ratio (*SO*), maximum drawdown (*MDD*), and annualized 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 to outliers as in Kim and White (2004). For *SR* and *SO*, we report both standard and robust measures to 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 5. The Predictive Ability of Monthly 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 is the 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 total (aggregate) customer order flows. ALL is a strategy that conditions on all four (disaggregated) 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 costs. The strategy invests in a domestic bond and nine foreign bonds and is rebalanced daily. For each strategy, we report the annualized mean (r_p), annualized volatility (σ_p), skewness (*Skew*), excess kurtosis (*Kurt*), annualized Sharpe ratio (*SR*), annualized Sortino ratio (*SO*), maximum drawdown (*MDD*), and annualized 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 to outliers as in Kim and White (2004). For *SR* and *SO*, we report both standard and robust measures to 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 6. Daily Order Flows and Macroeconomic Information

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 times 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_{MF}	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 7. Daily Order Flows and Combined Forecasting 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 *Asset Managers* (*AM*), *corporates* (*CO*), *hedge funds* (*HF*), and *private clients* (*PC*). $r^i_{p,t}$ 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). 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 times 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)

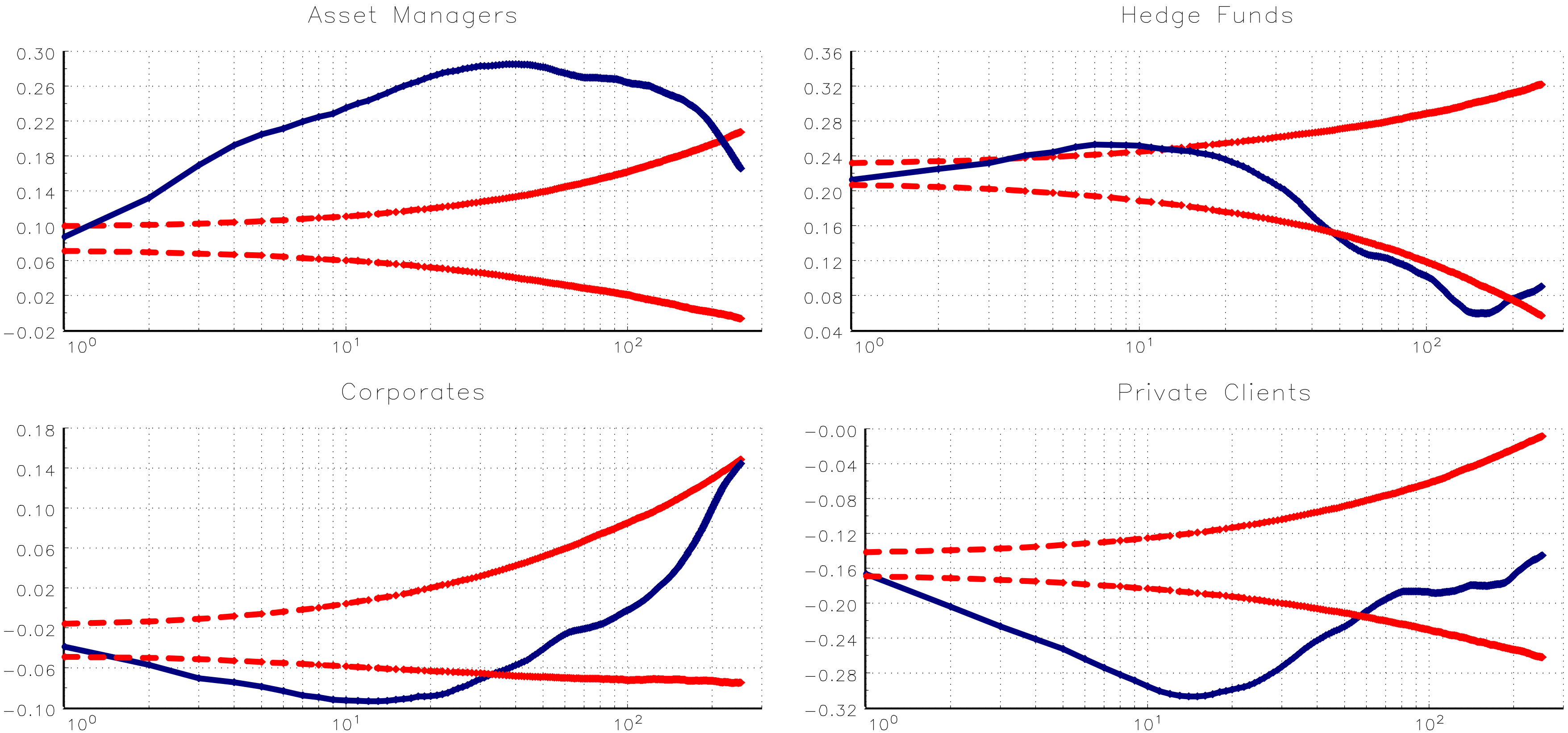

Figure 1. Contemporaneous Correlation of Currency Flows and Returns

This figure shows the correlation coefficient between the contemporaneous customer order flows and exchange rate returns for different horizons. The correlation is the average across nine US dollar nominal exchange rates. The horizon is measured in days and shown in log-scale. 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 generating by 10,000 replications. Order flows are shown for 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.

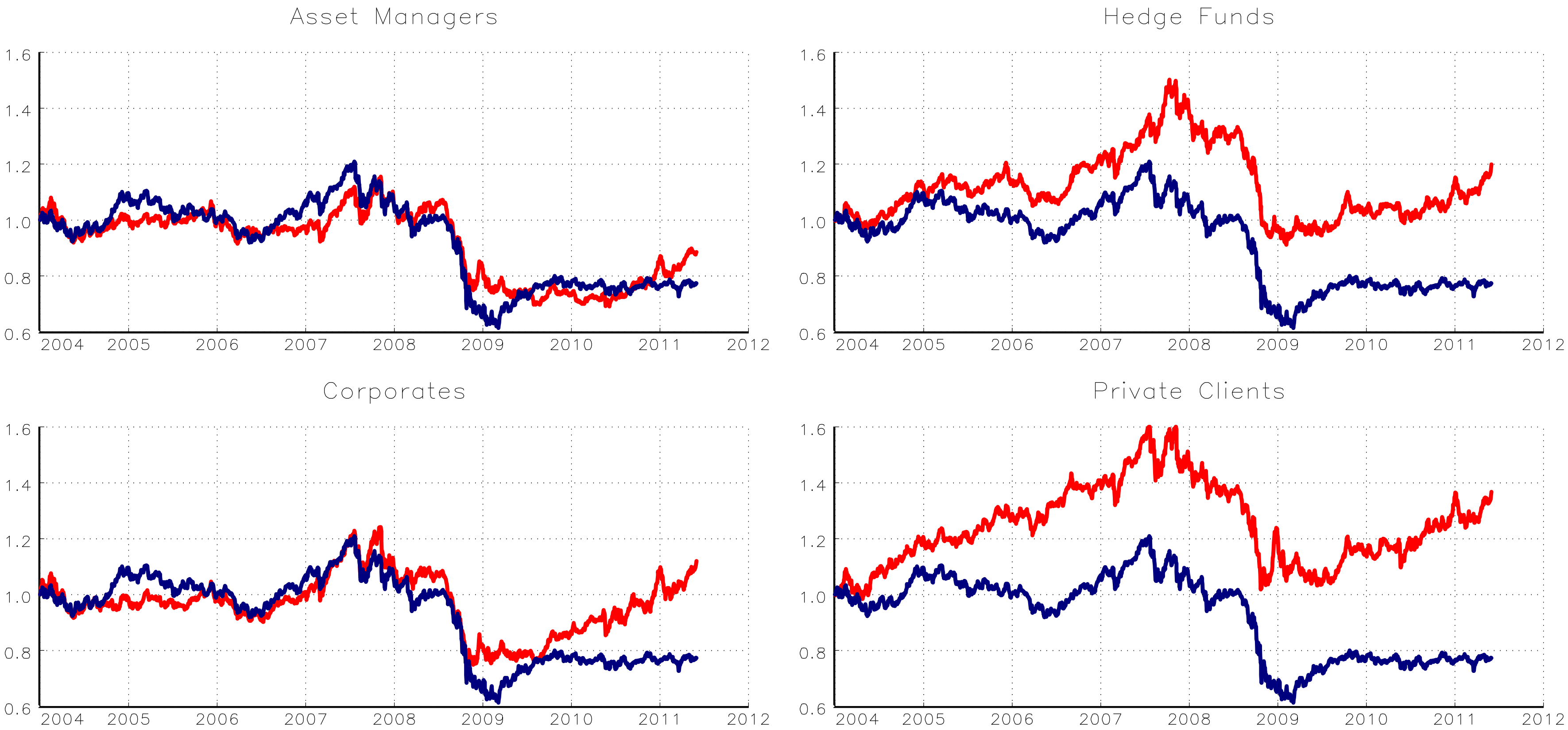

Figure 2. Daily Cumulative Wealth of Currency Flow Strategies

This figure displays the cumulative wealth of out-of-sample currency strategies investing in the G-10 developed countries with daily rebalancing. The blue line represents the benchmark strategy based on the naïve random walk model. The red line indicates a strategy conditioning on order flow for one of 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.

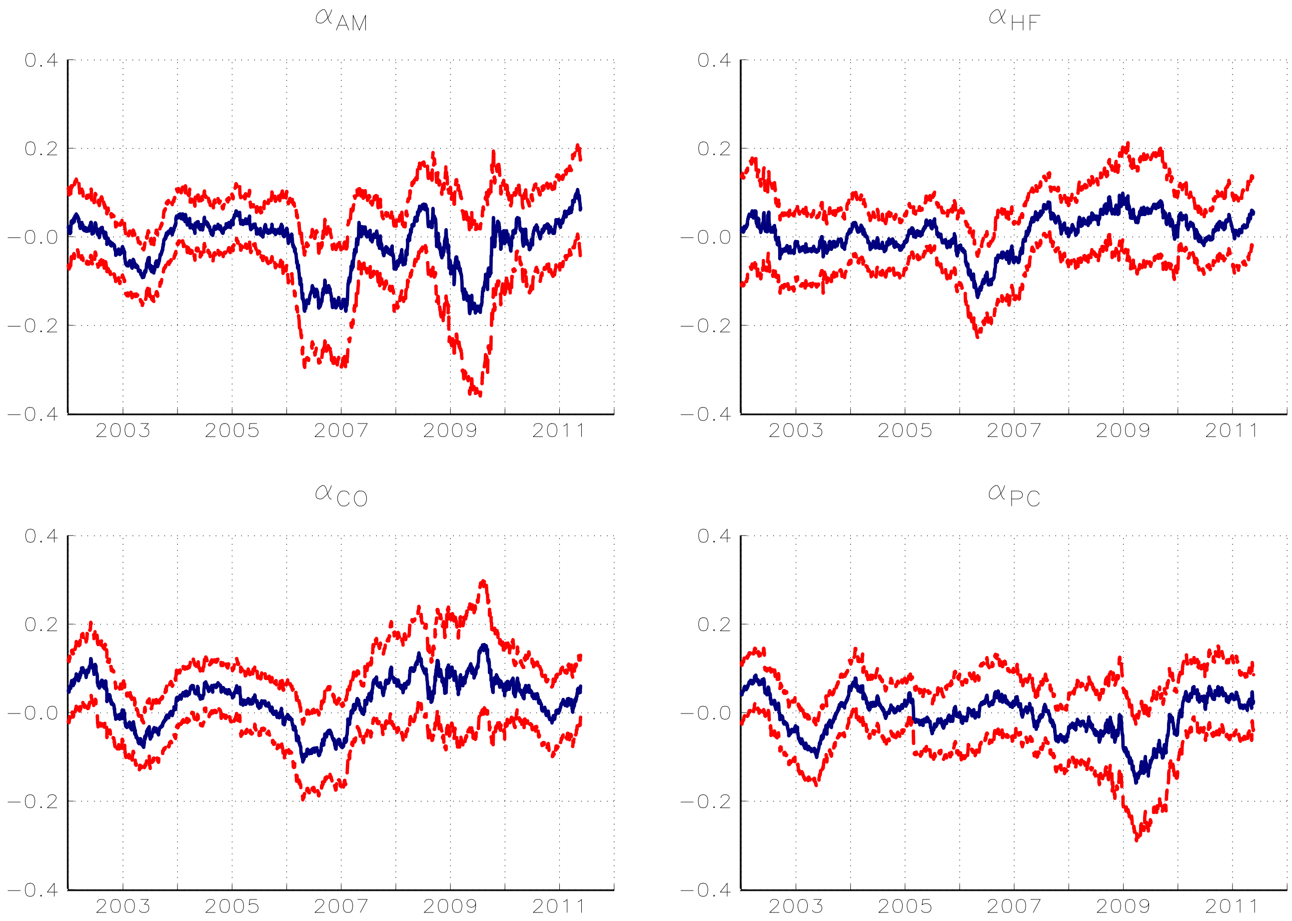

Figure 3. Rolling Estimates: the Alphas

The figure displays the one-year rolling estimate of α (solid line) and its 95% confidence interval (dashed lines) for 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). 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. 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.

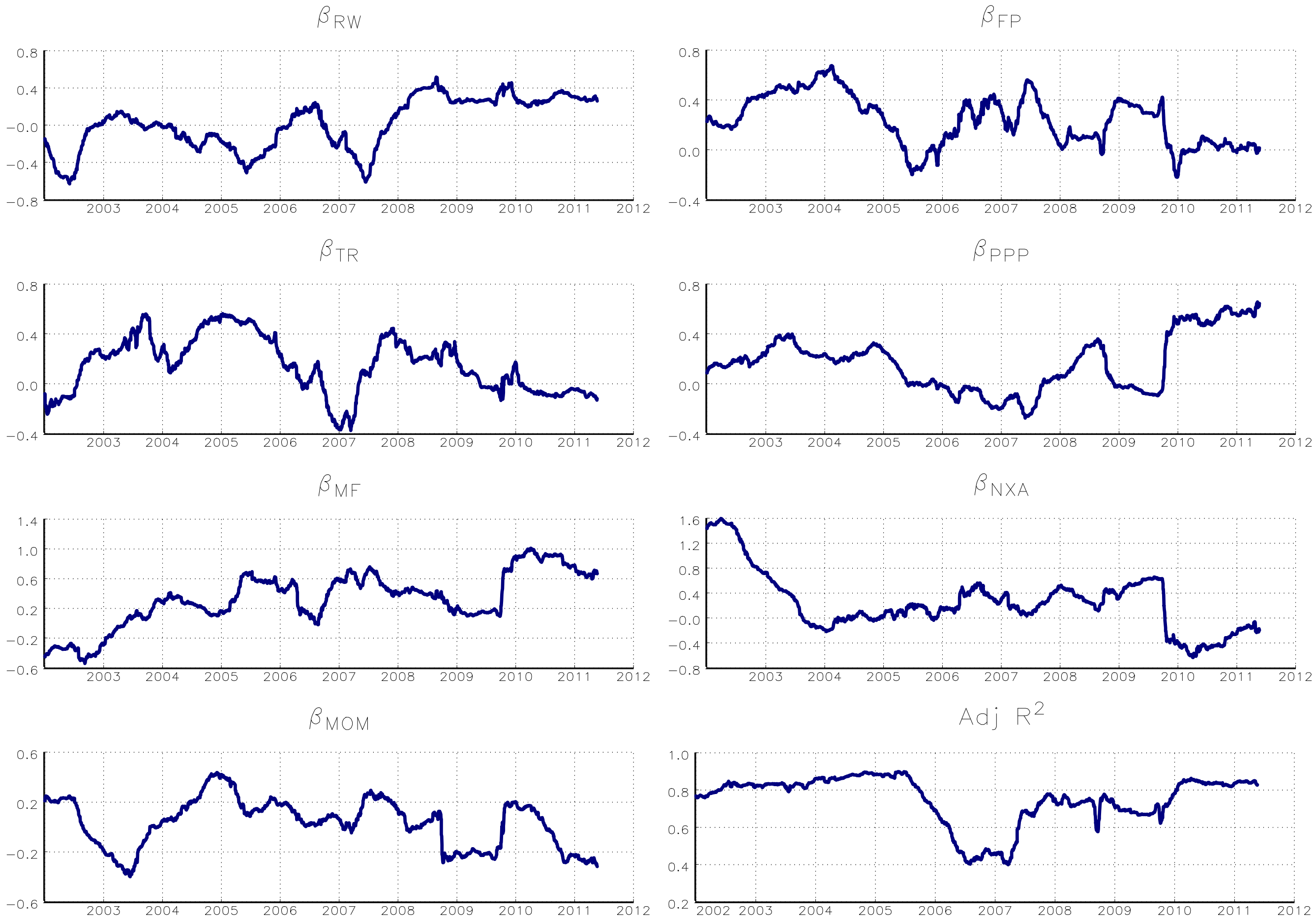

Figure 4. Rolling Estimates: Asset Managers

The figure displays the one-year rolling estimates of β_i for the regression $(r^{AM}_{p,t} - r_f) = \alpha + \sum_i \beta_i (r^i_{p,t} - r_f) + \varepsilon_t$ 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. 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. 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.

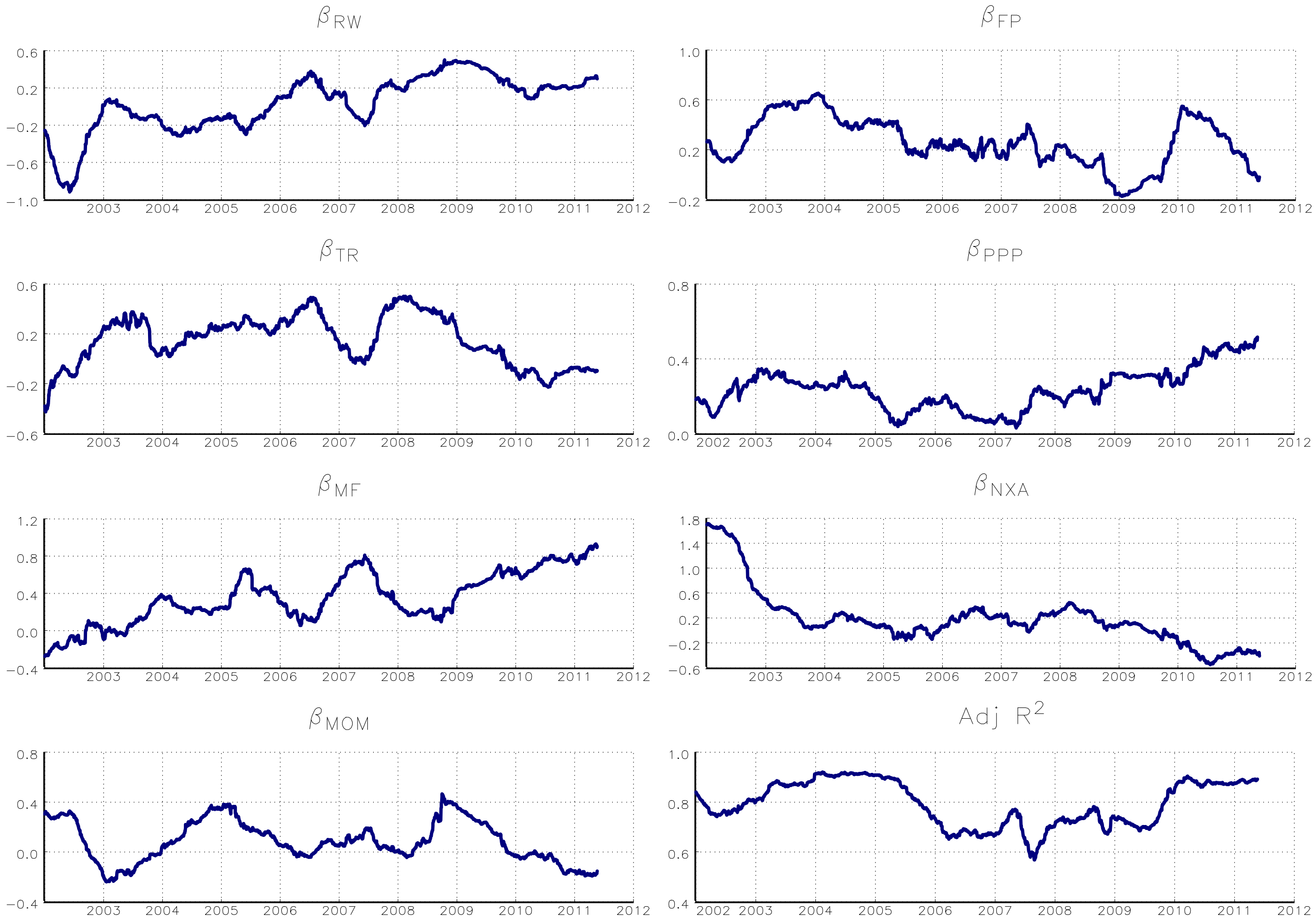

Figure 5. Rolling Estimates: Hedge Funds

The figure displays the one-year rolling estimates of β_i for the regression $(r^{HF}_{p,t} - r_f) = \alpha + \sum_i \beta_i (r^i_{p,t} - r_f) + \varepsilon_t$ 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 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. 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.

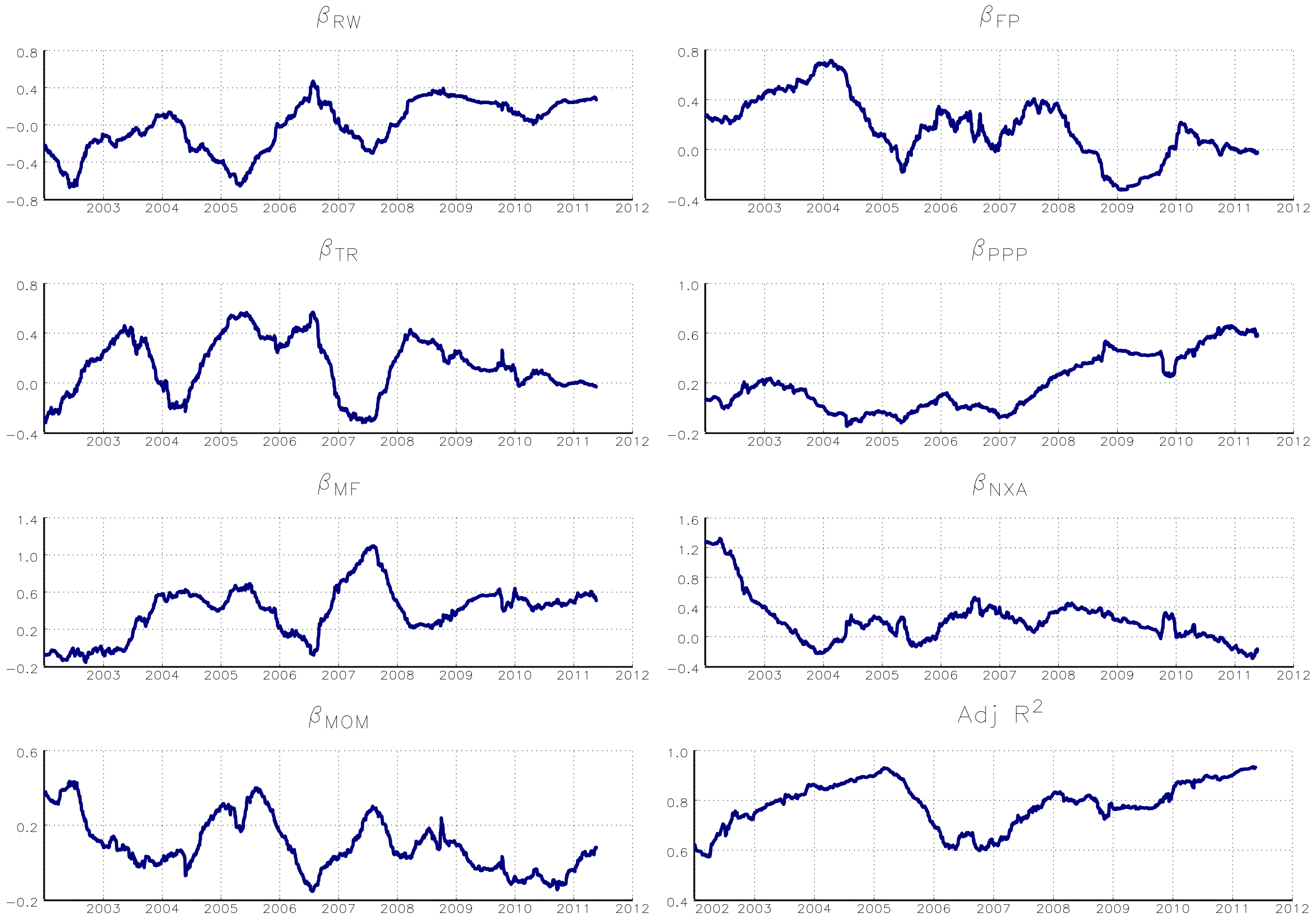

Figure 6. Rolling Estimates: Corporates

The figure displays the one-year rolling estimates of β_i for the regression $(r_{p,t}^{CO} - r_f) = \alpha + \sum_i \beta_i (r_{p,t}^{i} - r_f) + \varepsilon_t$ 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. 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.

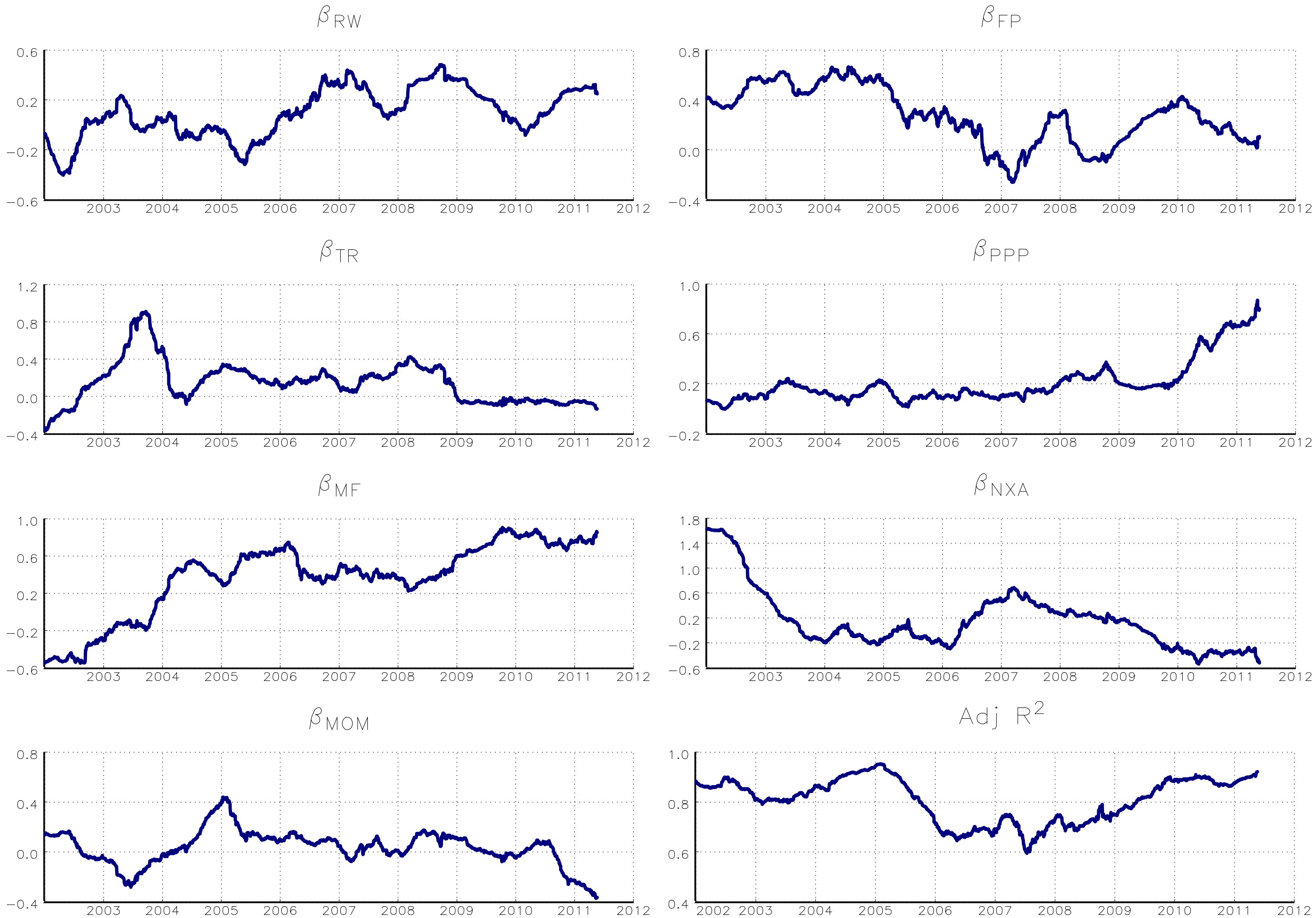

Figure 7. Rolling Estimates: Private Clients

The figure displays the one-year rolling estimates of β_i for the regression $(r_{p,t}^{PC} - r_f) = \alpha + \sum_i \beta_i (r_{p,t}^i - r_f) + \varepsilon_t$ 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. 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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Appendix A: 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. Instead, robust regression 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).

Appendix B: Contemporaneous Regressions between Exchange Rates and Order Flow

We investigate the relation between exchange rates and order flow by estimating contemporaneous regressions using ordinary least squares (OLS). For each exchange rate, we estimate three types of regressions: (i) the excess FX return on each of the four types of order flow separately (individual regressions); (ii) the excess FX return on the four types of order flow together in one regression (disaggregated regressions); and (iii) the excess FX return on the single total order flow (aggregate regressions). The results are presented in Table C3 for daily data and Table C4 for monthly data.[21]

For the daily results of individual regressions in Table C3, the order flow coefficients are always positive for asset managers (AM) and hedge funds (HF), but tend to be negative for corporate clients (CO) and private clients (PC). The positive sign for AM and HF implies that net buying pressure of these customers for foreign currency is contemporaneously related to positive FX excess returns. In other words, increased demand leads to positive return. Similarly, the negative sign for CO and PC implies that net selling pressure of these customers for foreign currency is contemporaneously related to negative FX excess returns. At first glance, the negative sign of some coefficients appears counterintuitive. Evans and Lyons (2006, 2007) find similar results when using customer order flows from Citibank for the euro-US dollar exchange rate. They argue that it is difficult to disentangle liquidity-motivated order flow from informative order flow. Hence one interpretation is simply that CO and PC may act as liquidity providers. They also show that individual coefficients have no structural interpretation in terms of measuring the price impact of different customer orders, they simply map variations in customer order flows into an estimate of the information flow being used by dealers across the market.[22] Note that the positive sign of the AM and HF betas is highly statistically significant for all exchange rates (but one), whereas the negative sign of the CO and PC betas is significant only for about half of the exchange rates. The $\overline{R}^2$ revolves around 1% but can be as high as 12% in the case of PC for GBP.

The results improve significantly when we move to the disaggregated regressions. Whereas the

[21] Note that Evans and Lyons (2002) and all their subsequent papers use FX returns rather than FX excess returns on the left hand side of these regressions. We report results for FX excess returns as this is the relevant quantity to predict in determining the weights for allocating wealth across international bonds. Note that the results remain qualitatively identical when using as the dependent variable either FX returns or FX excess returns (results available upon request).

[22] Evans and Lyons (2006, 2007) build a model where realized FX returns reflect the revision in dealer's quotes driven by new information concerning fundamentals. This information arrives in the form of public news, macro announcements and inter-dealer order flow, but not the customer order flows of individual dealers.

sign and significance of the betas is similar to the individual regressions, the $\overline{R}^2$ is much higher ranging from about 3% to 20%. In other words, using the distinct information from all four order flow types can substantially improve the explanatory power of order flow. We find further evidence of this in the aggregate order flow regression, where the betas are positive and significant but the $\overline{R}^2$ is much lower than the disaggregated regression, revolving around 1%-2%.

Turning to Table C4, we find that the results for monthly data are qualitatively identical to those for daily data. The one important difference is that the monthly $\overline{R}^2$ is much higher than the daily $\overline{R}^2$. For the disaggregated order flow, for example, the average $\overline{R}^2$ is about 16% and can be as high as 30%. The monthly results confirm that the disaggregated order flow has superior explanatory power than the total order flow.

In conclusion, this analysis provides strong evidence of a contemporaneous relation between FX excess returns and customer flows, leading to two main conclusions. First, there is a positive relation between AM and HF flows with FX excess returns and a negative relation for CO and PC flows. Second, the inclusion of all four types of order flow separately in the contemporaneous regressions provides the highest explanatory power.

Appendix C: Further Tables

Table C1: Top 10 Leaders in FX Market Share

The table displays the overall market share in annual turnover 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	JP Morgan Chase	6.79	JP Morgan	5.78
5	Chase Manhattan Bank	4.69	JP Morgan 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	JP Morgan	4.19
7	JP Morgan	5.29	HSBC	3.66	HSBC	4.36	HSBC	4.10
8	Goldman Sachs	4.39	JP Morgan	3.36	Goldman Sachs	4.14	Lehman Brothers	3.58
9	ABN Amro	4.19	Dresdner Kleinwort W.	2.54	JP Morgan	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	JP Morgan	6.43		
6	JP Morgan	5.43	JP Morgan	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		

Table C2. Descriptive Statistics Across Calendar Years

The table reports the means and the standard deviations of daily 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 C2. 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 C3: 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 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*. Total order flow is the sum of the four customer order flows. *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 C3: Daily Excess Returns and Contemporaneous Order Flows *(continued)*

	Disaggregated 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 C4: 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 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*. Total order flow is the sum of the four customer order flows. *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 C4: Monthly Excess Returns and Contemporaneous Order Flows *(continued)*

	Disaggregated 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 C5. 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 parameter estimates are computed using the M-estimator (see Appendix A). The benchmark strategy is the 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 total (aggregate) customer order flows. ALL is a strategy that conditions on all four (disaggregated) 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 costs. The strategy invests in a domestic bond and nine foreign bonds and is rebalanced daily. For each strategy, we report the annualized mean (r_p), annualized volatility (σ_p), skewness (*Skew*), excess kurtosis (*Kurt*), annualized Sharpe ratio (*SR*), annualized Sortino ratio (*SO*), maximum drawdown (*MDD*), and annualized 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 to outliers as in Kim and White (2004). For *SR* and *SO*, we report both standard and robust measures to 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	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