Foreign exchange order flow as a risk factor*

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October 29, 2018

Abstract

This paper proposes a set of novel pricing factors for currency returns that are motivated by microstructure models. In so doing, we bring two strands of the exchange rate literature, namely market-microstructure and risk-based models, closer together. Our novel factors use order flow data to provide direct measures of buying and selling pressure related to carry trading and momentum strategies. We find that they appear to be good proxies for currency crash risk. Additionally, we show that the association between our order-flow factors and currency returns differs according to the customer segment of the foreign exchange market. In particular, it appears that financial customers are risk takers in the market, while non-financial customers serve as liquidity providers.

*Preliminary and incomplete.

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1 Introduction

Two strands of the exchange rate literature offer explanations of anomalies in foreign exchange markets that are at odds with one another. One strand, which we refer to as the stochastic discount factor (SDF) approach, uses frictionless common-information environments to explain the behaviour of exchange rates. In this framework, whether the underlying model is a reduced-form model or a structural representative agent model, the returns to various currency-based investment strategies are interpreted as compensation for risk.[1] The other strand uses a market microstructure framework in which agents have heterogeneous information. In these models customer order flow is a key determinant of bilateral exchange rate changes and, therefore, currency excess returns.[2] In this paper we explore whether the empirical facts are, in fact, consistent with both the reduced-form SDF approach and the market microstructure approach. We argue that, in fact, empirical evidence that might normally be interpreted as favourable to the SDF approach is also compatible with the order-flow driven view of the world.

To give an example, a commonly studied anomaly in foreign exchange markets is the profitability of the carry trade, which is a zero-cost investment strategy in which an investor borrows short term funds in low interest rate currencies and lends equivalent amounts short term in high interest rate currencies. According to the uncovered interest-rate parity (UIP) condition, this investment strategy should have zero expected returns, both conditionally and unconditionally. However, it is well-established that carry trades have been profitable in historical data, and this is considered to be a puzzle akin to the equity premium puzzle in stock markets.[3]

According to the SDF approach, any asset that bears a positive mean excess return is risky, in the sense that the returns to the asset are systematically correlated with some measure of risk. According to this view, carry trades are profitable because holding long positions in high interest rate currencies financed by short positions in low interest rate currencies is risky. Finding measures of risk that are systematically correlated with carry trade returns has, however, not been easy. Lustig and Verdelhan (2007) argue that a consumption-based

[1] A non-exhaustive list includes Lustig and Verdelhan (2006), Lustig and Verdelhan (2007), Verdelhan (2010), Colacito and Croce (2011), Lustig and Verdelhan (2012), Lustig et al. (2014).

[2] See, among others, Evans and Lyons (2002), Cerrato et al. (2011), Evans (2011), Evans and Rime (2012), Cerrato et al. (2015), Breedon et al. (2016), and Menkhoff et al. (2016).

[3] See, for example, Fama (1984a), Engel (1996), Burnside (2012), Burnside (2014), and Engel (2016).

model can price the cross-section of currency returns as well as explain the returns to the carry trade. Burnside (2011) argues that consumption-based risk factors are, however, unrelated to currency returns and that their results are explained by the properties of weakly identified estimators. Burnside et al. (2011), Menkhoff et al. (2012a) and Burnside (2012) have argued that standard measures of risk used to price stock returns do not appear to be successful in pricing currency returns. Lustig et al. (2011) show that their carry-trade portfolio, HMLFX, is useful in pricing the cross-section of currency returns but they do not explain the carry-trade portfolio, itself, with some other underlying factor. Menkhoff et al. (2012a) price the cross-section of currency returns with a global currency volatility factor. They find that high interest rate currencies have a tendency to depreciate when volatility in currency markets increases, while low interest rate currencies provide a hedge. But their factor is only weakly linked to a particular economic theory.

In this paper we let the microstructure literature guide the construction of a model that explains carry trade returns using the SDF approach. In this literature, the emphasis is on how dispersed information is aggregated within the market and translated into price changes.[4] The simplest models are linear and relate exchange rate changes to news about fundamentals that are common knowledge and changes that are driven by net order flow in the foreign exchange market. For a particular currency, net order flow is the value of buy orders net of sell orders, faced by foreign exchange dealers. Order flow, itself, is driven by the common and dispersed information received within the customer market (i.e. the agents in the market other than dealers). The literature emphasizes the importance the market's structure, with dealers interacting directly with customers but also with each other through an inter-dealer market. This is usually captured, in models, by having sequential market stages where customers arrive first, and the inter-dealer market clears later. What the models show is that in market equilibrium, the change in the spot rate of a currency's value over some interval is related linearly to the order flow that dealers face over that interval, and this is the basis on which these models have been evaluated empirically.

We use order-flow data to construct risk factors that are designed to capture notions of currency crash risk. In particular we measure buying and selling pressure in the foreign exchange market that is relevant to particular currency investment strategies, with the emphasis being on the carry trade. Our main risk factor, which we refer to as a carry-trade

[4]See Evans (2011) for a comprehensive review.

order-flow factor, sums the value of buy orders for high interest rate currencies and the value of sell orders for low interest rate currencies, having normalized the measures of order flow to the scale of the market for each currency. When carry trade activity is strong, we expect the value of this factor to increase. When carry trade activity is weaker we expect it to have a lower value. Most importantly, if carry-trade investors dominate the market and suddenly reverse their positions, we might expect our factor to turn negative because there is net selling pressure on the high interest rate currencies. We find that this factor is strongly associated with the returns to a variety of carry trade portfolios, and is very successful in pricing the cross-section of currency returns. We find that a similar factor performs well in pricing currency momentum portfolios.

Our paper is related to two branches of the empirical literature. The microstructure literature focuses on bilateral exchange rate behaviour. Lyons et al. (2001) and Evans and Lyons (2002) show that order flow maps a significant part of customers' private information into price discovery and it can explain a large part of exchange rate variation as well as, by extension, currency excess returns. Evans and Lyons (2009) argue that order flow conveys information about future macroeconomic conditions and that this information filters into the exchange rate. They show that order-flow data have significant predictive power for future macroeconomic variables.

Another branch of the literature emphasizes currency crashes. Galati et al. (2007) find that excess returns to carry trades tend to reverse abruptly under market stress. They provide evidence from international banking data that currency flows are associated with these reversals. Brunnermeier et al. (2008) propose a novel theoretical model which links customer order flow to currency excess returns via the risk premium. They emphasize the role of risk averse market dealers who use the information in order flow to adjust the risk premium when they quote the spot rate. In their model, investors who engage in carry trades build their position gradually but liquidate their positions quickly, causing a currency crash. As market dealers predict the future unwind, they increase the risk premium associated with carry trade portfolios. Differently from Brunnermeier et al. (2008), in this paper we generalize that idea by extending it to the cross-section of currency returns and we provide a natural empirical measure of carry-trading pressure in the foreign exchange market. In related work, Brunnermeier and Pedersen (2008) propose a liquidity spiral model in which, as currencies crash, losses to carry trade positions force investors to further liquidate their positions causing liquidity to dry out quickly. Inspired by the volatility factor of Menkhoff et al. (2012a), Rafferty (2012) constructs a global currency skewness factor, by measuring intramonth daily skewness, signed by the interest differential versus the US dollar, and averaged across a basket of currencies. This factor can be thought of as a reduced-form measure of crash risk. His factor prices both carry trade and momentum portfolios. Our factor is somewhat related, but measures signed order flow rather than currency movements themselves.

Another important feature of our analysis, is that we that order flow behaves systematically differently across distinct segments on the customer side of the market. In particular, we find that aggregate order flow is related to currency returns in the same way that order flow for financial customers (hedge funds and asset managers) is. On the other hand, we tend to see an inverse relationship for the order flow of non-financial customers (private and corporate customers). When the order flow of financial customers leans more towards taking carry trade positions, carry trade portfolios tend to do well. But we see the opposite pattern for non-financial customers. This suggests that order flow conveys different information to dealers depending on its origin within the customer base. It also suggests that a certain degree of risk sharing happens within the customer base, not just between customers and dealers and within the inter-dealer market. In this respect, our paper is also related to Menkhoff et al. (2016) who, using a large data-set of customer order flow from a large foreign exchange dealer, show that order flow carries important information which can be used for predicting currency returns. They also show that financial flows contain information which have a long-term impact on currency returns and that financial and non-financial customers trade in opposite directions and therefore they provide evidence of risk sharing taking place in the customer market. Our paper, on the other hand, focuses mainly on how order flow is related to the carry trade rather than exchange rate predictability.

In Section 2 we describe the currency portfolios that we analyze in our empirical work. These include standard interest-rate sorted portfolios used in the extant literature, carry-trade portfolios, and a set of portfolios sorted on the basis of order flow. In Section 3 we introduce our order-flow related pricing factors. Section 4 contains the bulk of our empirical work, which is based on sample of weekly data from 2001 to 2012. We study the behavior of various currency portfolios in this period, as well as the performance of standard risk factors used in the prior literature. We then show cross-sectional asset pricing results for our order-flow based pricing factor. In Section 5 we explore a brief extension to momentum portfolios. Section 6 concludes.

2 Currency Portfolios

Let $S_{k,t}$ be the exchange rate between the US dollar (USD) and foreign currency k, measured as foreign currency units (FCUs) per USD. Define $s_{k,t} = \ln S_t$. The logarithmic return to borrowing one US dollar (USD) in the short term money market and investing it in a short-term security denominated in foreign currency k, is

$$r_{k,t+1} = i^*_{k,t} - i_t - (s_{k,t+1} - s_{k,t}) \tag{1}$$

where i_t is the US interest rate and $i^*_{k,t}$ is the foreign interest rate. The uncovered interest parity (UIP) condition states that

$$E_t(s_{k,t+1} - s_{k,t}) = i^*_{k,t} - i_t, \tag{2}$$

or, equivalently, that

$$E_t r_{k,t+1} = 0, \tag{3}$$

where E_t is the expectations operator given information available at time t. That is, if the foreign interest rate exceeds the US interest rate, the foreign currency is expected to depreciate by the amount of the interest differential.

Let $F_{k,t}$ be the one period forward exchange rate between the same currencies, and let $f_{k,t} = \ln F_{k,t}$. Up to a log approximation, covered interest parity (CIP) implies that

$$i^*_{k,t} - i_t = f_{k,t} - s_{k,t}. \tag{4}$$

Therefore, assuming that CIP holds, the log return to being long foreign currency k and short the USD is

$$r_{k,t+1} = f_{k,t} - s_{k,t+1}. \tag{5}$$

Thus, under CIP, the UIP condition implies forward rate unbiasedness:

$$E_t s_{k,t+1} = f_{k,t} \tag{6}$$

2.1 Carry Trade Strategies

Carry trade strategies generally involve systematically managing a portfolio in which the investor borrowing funds in low interest rate currencies and invests (or lends) in high interest rate currencies. Under uncovered interest parity, however, we would not expect this strategy to be profitable because $E_t r_{k,t+1} = 0$. However, the empirical failure of UIP condition is well-documented.[5] In fact, it is widely understood that nominal exchange rates are well approximated, empirically, as random walks; i.e. $E_t s_{k,t+1} \approx s_{k,t}$.[6] When this is true

$$E_t r_{k,t+1} \approx i^*_{k,t} - i_t = f_{k,t} - s_{k,t}. \tag{7}$$

This fact provides motivation for carry trade strategies because it suggests that by systematically borrowing low interest rate currencies and lending in high interest rate currencies, the investor can expect to earn profits equal to the interest differential.

We study several carry trade strategies discussed in the previous literature. Burnside et al. (2011) introduce an equally-weighted carry trade (EWC) strategy that is also studied by Burnside et al. (2011) and Burnside (2012). This strategy uses the USD as a base currency. Each of the N_t foreign currencies in the available data is treated as follows. If the currency has a higher interest rate than the USD, the investor lends in that currency and borrows $1/N_t$ dollars. If the currency has a lower interest rate than the USD, the investor borrows that currency and lends $1/N_t$ dollars. Thus, the total bet of this strategy is normalized to one USD. The return of the EWC portfolio between t and $t+1$ is:

$$r^{\text{EWC}}_{t+1} = \sum_{k=1}^{N_t} \frac{1}{N_t} \operatorname{sign}(f_{k,t} - s_{k,t}) \cdot (f_{k,t} - s_{k,t+1}) = \sum_{k=1}^{N_t} \frac{1}{N_t} \operatorname{sign}(f_{k,t} - s_{k,t}) \cdot r_{k,t+1}. \tag{8}$$

Following Lustig et al. (2011), at each date t, we also allocate the available currencies into five portfolios, labeled P1, P2, P3, P4 and P5, with P1 corresponding to the currencies with the lowest interest rates, and P5 containing those currencies with the highest interest rates. Each portfolio holds an equally weighted long position in its constituent currencies financed by borrowing dollars. Hence, the log return of the ith portfolio is

$$r^{\text{P}i}_{t+1} = \sum_{k \in \mathcal{K}_{i,t}} \frac{1}{N_{i,t}} (f_{k,t} - s_{k,t+1}) = \sum_{k=1}^{N_t} \frac{1}{N_{i,t}} r_{k,t+1}, \tag{9}$$

[5] Hansen and Hodrick (1980), Bilson (1981), Fama (1984b) provide early tests. More recently, Engel (1996) and Burnside (2014) provide updated tests of UIP.

[6] The classic reference is Meese and Rogoff (1983).

where $\mathcal{K}_{i,t}$ is the set of currencies in the ith portfolio and $N_{i,t}$ is the number of currencies in the ith portfolio.

Lustig et al. (2011) use P1–P5 to construct two additional portfolios: the DOL portfolio and the HML portfolio. The DOL portfolio is an equally weighted average of the P1–P5 portfolios. Therefore, its return is

$$r_{t+1}^{\text{DOL}} = \frac{1}{5}\sum_{i=1}^{5} r_{t+1}^{\text{P}i}. \tag{10}$$

The HML portfolio is a typical high-minus-low portfolio which takes a long position in the P5 portfolio and a short position in the P1 portfolio. In this sense, it can be thought of as a carry trade portfolio that finances long positions in the highest interest rate currencies, financed by borrowing the lowest interest rate currencies. Its return is

$$r_{t+1}^{\text{HML}} = r_{t+1}^{\text{P5}} - r_{t+1}^{\text{P1}}. \tag{11}$$

We also follow Daniel et al. (2017) by constructing a spread-weighted carry trade portfolio (SPD) and a dollar-neutral carry trade portfolio (DNC). The SPD portfolio modifies the EWC portfolio by weighting each currency based on the size of its interest differential relative to the average absolute interest differential. The return of SPD portfolio is

$$r_{t+1}^{\text{SPD}} = \sum_{k=1}^{N_t} \frac{f_{k,t} - s_{k,t}}{\sum_{j=1}^{N_t} |f_{j,t} - s_{j,t}|} \cdot (f_{k,t} - s_{k,t+1}) \tag{12}$$

The EWC and SPD carry trade strategies are rationalized based on the perspective of a US investor who believes that each exchange rate is a random walk and that the position in each currency should be based on whether the expected return is positive or negative. The decision to buy each currency is based on the interest rate differential with the USD, and this means these portfolios are not dollar neutral. The DNC portfolio, by contrast, is constructed in a way that means there is no basis currency. Each currency is included in an equally-weighted way depending on its interest rate relative to the median interest rate among all the currencies. Thus, the return of the DNC portfolio is

$$r_{t+1}^{\text{DNC}} = \sum_{k=1}^{N_t} \frac{1}{N_t} \operatorname{sign}(f_{k,t} - s_{k,t} - \phi_t) \cdot (f_{k,t} - s_{k,t+1}), \tag{13}$$

where $\phi_t = \text{median}\{f_{k,t} - s_{kt}\}_{k=1}^{N_t}$.

For the 2001–12 period, we form the P1–P5, EWC, SPD, DNC, HML and DOL portfolios using data for a set of 20 of the most liquid currencies according to trading volume.[7] The portfolios are formed on a weekly basis, each with a holding period of one week. Descriptive statistics for the portfolio returns are summarized in Table 1. It shows the mean (median) return, standard deviation, skewness, kurtosis, Sharpe ratio and the first order autocorrelation coefficient. We also report two coskewness measures relative to the returns to the DOL portfolio.[8] Portfolios with higher coskewness earn higher returns when global volatility is high. Thus, greater coskewness is often interpreted as making a portfolio more effective as a hedge against global volatility.

As Table 1 shows, the mean returns monotonically increase from portfolio P1 to portfolio P5 with the lowest return being 1.6% (on an annual basis) and the highest being 13.9%. The return from DOL portfolio is the average of the five portfolios, 6.9%. This suggests that investors require a positive risk premium to invest in non-US short-term securities. Volatility also displays an increasing pattern moving from P1 to P5, but it does not rise in proportion to the expected return, so the Sharpe ratios also increase from P1 to P5. So high interest rate currencies still yield higher returns after a standard adjustment for risk.

All of the carry trade portfolios have positive average returns and large Sharpe ratios. The HML portfolio has the largest mean return (12.2%), but the SPD portfolio has the largest Sharpe ratio, followed by HML, DNC and EWC. The returns of all of the portfolios are negatively skewed, indicating the possibility of large negative realizations of the returns. However, for portfolio P1 the skewness coefficient is approximately zero, suggesting that it is less subject to the potential for big losses.

[7] The currencies in our data set are the EUR, JPY, GBP, CHF, AUD, NZD, CAD, SEK, NOK, MXN, BRL, ZAR, KRW, SGD, HKD, TRY, HUF, PLN, CZK, and SKK. We observe the exchange rates from the first week of November 2001 to the fourth week of March 2012. Appendix A provides further details.

[8] Following Harvey and Siddique (2000) a direct measure for coskewness is

$$\beta_{\mathrm{SKS}} = \frac{E[\varepsilon_{t+1}\varepsilon^2_{M,t+1}]}{E[\varepsilon_{t+1}]^{0.5}E[\varepsilon^2_{M,t+1}]},$$

where ε_{t+1} is the innovation of the excess return of a portfolio, and $\varepsilon_{M,t+1}$ is the innovation of the excess return of some market factor (here we use the DOL factor). The innovations are constructed using first order autoregressive models for both the portfolio return and the DOL return.

The second coskewness measure is based on the regression

$$r_{t+1} = \beta_0 + \beta_1 r^{\mathrm{DOL}}_{t+1} + \beta_{\mathrm{SKD}}(r^{\mathrm{DOL}}_{t+1})^2 + u_{t+1},$$

where r_{t+1} is the return on some portfolio and $(r^{\mathrm{DOL}}_{t+1})^2$ is a proxy for market volatility.

2.2 Order Flow Portfolios

We also form portfolios based on order flow data for the set of currencies in our data set. We use a unique data set, from one of the top foreign exchange dealers, covering more than eleven years (2001–2012) of weekly end-user order flow for up to 20 currencies.[9]

Let $x_{k,t}$ denote the aggregate order flow (the total value of buy orders, net of sell orders) for currency k in the interval between periods t and $t+1$. Order flow is not easily compared across currencies, due to the heterogenous volume of trade in each of the currencies. Therefore, to make such comparisons we adjust the aggregated order flow for currency k at time t with the standard deviation of the order flow of currency j over the full sample. That is, we define adjusted order flow as

$$y_{k,t} = \frac{x_{k,t}}{\text{std}(x_k)}. \tag{14}$$

At each week t, we sort the 20 currencies into five portfolios according to $y_{k,t}$, which are labeled O1, O2, ..., O5 where O1 consists of the currencies with greatest selling pressure (lowest, or most negative, order flow) and O5 consists of the currencies with the greatest buying pressure (most positive order flow). These are not tradable portfolios because the measure of order flow is contemporaneous to the return. Our purpose in studying these portfolios is, in fact, to measure the degree to which order flow and the returns are associated. We also define a buy-minus-sell (BMS) portfolio, which is long portfolio O5 and short portfolio O1.

Table 2 shows summary statistics for these portfolios. There is a clear monotonically increasing pattern in the expected returns and Sharpe ratios of the O1–O5 portfolios. Unlike the interest rate sorted portfolios, P1–P5, the standard deviations of the returns do not vary much across the five portfolios. Unsurprisingly, the average of the O1–O5 portfolios (indicated by 'Avg' in Table 2) behaves similarly to the DOL portfolio in Table 1. The BMS portfolio earns a large positive average return, with a very large Sharpe ratio. These results, in a sense, confirm the notion that contemporaneous order flow is strongly positively correlated with exchange rate changes and currency returns.

We also have data on order flow that is disaggregated by the customer type: Asset Manager (AM), Hedge Fund (HF), Corporate (CO), and Private Client (PC). However, these data are only available for nine developed country currencies, so we sort the currencies

[9] Appendix A provides further details of our data set.

into four portfolios rather than five.[10] As these are all major currencies we do not normalize order flow by its standard deviation. These results are also reported in Table 2. For Asset Managers and Hedge Funds the pattern across portfolios is the same as for aggregate order flow. The portfolios with the most buying pressure earn the largest returns. For Corporate customers the pattern is partially reversed, and for Private Clients it is sharply reversed: The portfolios with the most buying pressure earn negative returns, while the ones with the most selling pressure earn positive returns.[11]

Next, we compare the informational content of order flow with that of interest differentials and volatility innovations. Menkhoff et al. (2012a) show that a global volatility proxy contains important information which can be used to price returns of carry trade portfolios. Relatedly Menkhoff et al. (2012b) show that momentum strategies are more profitable among currencies that have greater idiosyncratic volatility. In both cases, the implication is that volatility has an association with the riskiness of and return to holding different currencies and currency portfolios. We believe that the apparent importance of volatility is strongly linked to order flow and that, in fact, order flow contains the relevant information to price returns of carry trade portfolios.

To provide the reader with a first intuitive view of this, we double sort our currencies in two different ways with the results being shown in Tables 3 and 4. In Table 3, we first sort our currencies into three portfolios based on their short term interest rates. Thereafter, within each portfolio, we sort currencies into two bins based on the magnitude of order flow.[12] The main conclusion of Table 3 is that even after considering interest rates, a strategy consisting in buying a portfolio with the highest buying pressure (high order flow) and selling a portfolio with the highest selling pressure (low order flow), gives a positive and statistically significant return. In other words, taking interest rates into account does not drive out order flow as an important apparent determinant of currency returns.

In Table 4, we first sort our currencies into three portfolios based on their idiosyncratic volatility innovation, and thereafter on the magnitude of order flow. Again, even after considering idiosyncratic volatility innovations, a portfolio of the currencies with the highest buying pressure has an economically and statistically significantly higher return than the one with the greatest selling pressure.

[10] The nine currencies are EUR, JPY, GBP, CHF, AUD, NZD, CAD, SEK, NOK.

[11] Cerrato et al. (2011) show that these customer groups tend to act as liquidity providers.

[12] We build a total of just six portfolios due to the limited number of currencies in our sample.

3 A Carry Trade-Order Flow Factor

The empirical results presented in Tables 2–4 suggest that order flow contains significant information that could be relevant for pricing the returns to carry trade portfolios, and potentially the returns to other currency trading strategies. In this section, we propose a set of novel pricing factors based on order flow that are motivated by microstructure models and the prevalence of carry trading in foreign exchange markets.

Our first factor is based on the aggregate order flow measure that we described above. In particular, this factor, which we denote as CTOF, is defined as

$$\text{CTOF}_{t+1} = \frac{1}{N_t} \sum_{k \in N_t} y_{k,t} \cdot \text{sign}(f_{kt} - s_{kt}). \tag{15}$$

If investors build portfolios based on carry trade considerations, we might expect, $y_{k,t}$ to be positive for high interest rate currencies and $y_{k,t}$ to be negative for low interest rate currencies. Thus, we would expect CTOF to generally be positive. But $y_{k,t}$ should also reflect news that arrives after investors form their portfolios, because it measures order flow between periods t and $t+1$. If arriving news is favorable to carry trades, we would expect CTOF to be especially high. On the other hand, if news arrives that induces investors to cash out their carry trade positions, CTOF will fall, and possibly even turn negative. In a sense, therefore, CTOF can be interpreted as a factor that measures the degree of sentiment in favor of carry trading.[13]

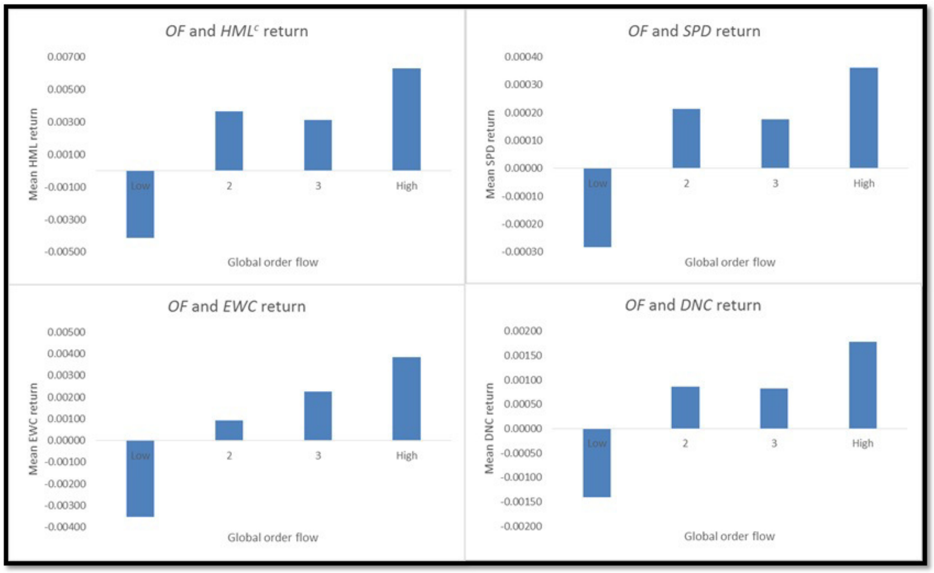
We also consider alternative carry-trade order-flow factors that use our order flow data disaggregated by customer segment: Asset Manager, Hedge Fund, Corporate, and Private Client. These are denoted as CTAM, CTHF, CTCO and CTPC. In a sense, these factors measure the degree of carry trade activity by each customer type. As we saw, above, order flow behaves differently across customer segments, so we expect the risk premium to change across customers segments as well.[14]

We now explore the relationship between our carry-trade order-flow factor and the excess returns of carry trade strategies. To do this, we divide the sample into four sub-samples that are selected according to order flow size. The first sub-sample contains the 25% of the weeks within our full sample with the lowest values of CTOF and the fourth sub-sample contains

[13] Burnside (2012) suggests that a significant part of trading activity in foreign exchange markets is triggered by carry trade investors. Breedon et al. (2016) show that there is a strong relationship between order flow data and currency forward premia.

[14] See Cerrato et al. (2015) and Menkhoff et al. (2016).

Figure 1: Aggregate Carry-Trade Order-Flow and Carry-Trade Returns



Note: This figure shows mean excess returns for the carry-trade portfolios HML, SPD, EWC and DNC depending on the quartile of the distribution of the carry-trade order-flow factor (CTOF).

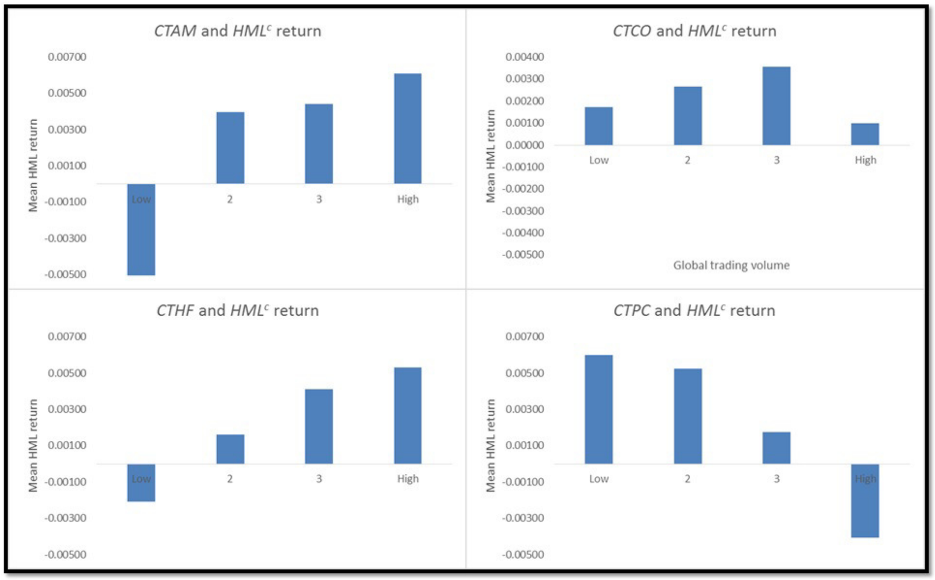
the 25% of the weeks within our full sample with the largest values of CTOF. Finally, we compute the mean return across the sub-samples after employing four different carry trade strategies (i.e. HML, SPD, EWC and DNC). Figure 1 shows the main results. High yield currencies are highly affected by the carry trade order flow and vice versa. The average excess return of the portfolios increases as we move from the left to the right. Figure 2 shows the same results across the different customer segments described above. Financial customers (i.e. asset managers and hedge funds) are the most highly affected in periods of high carry trade activity while non-financial customers (i.e. corporate customers and private clients) can even profit during these times.

These results suggest that there is a clear relationship between carry-trade order-flow and the excess returns of carry trade strategies, and that this relationship differs by the customer segment. We explore these results further in what follows.

4 Cross-Sectional Asset Pricing

In this section, we follow the standard generalized method of moments (GMM) approach to estimate linear stochastic discount factor (SDF) model, discussed in Cochrane (2005) and used by Lustig et al. (2011), Burnside et al. (2011), and Menkhoff et al. (2012a) among many

Figure 2: Disaggregated Carry-Trade Order-Flow and HML Returns



Note: This figure shows mean excess returns for the HML portfolio depending on the quartile of the distribution of the disaggregated carry-trade order-flow factors CTAM, CTHF, CTCO and CTPC.

others. Let r^e be an $N \times 1$ vector of excess returns where N is the number of test assets. If m_t is an SDF for these returns, then

$$E(r^e m) = 0 \tag{16}$$

where E is the unconditional expectations operator. As is standard in the literature, we specify the SDF as a linear function of a $k \times 1$ vector of risk factors, f:

$$m = 1 - (f - \mu)'b, \tag{17}$$

where $\mu = E(f)$ and b is a $k \times 1$ vector of parameters. Given this definition, the mean of the SDF is normalized to 1.

When equation (16) is combined with equation (17) it becomes

$$E(r^e) = \text{cov}(r^e, f)b. \tag{18}$$

Our other moment restriction is

$$E(f) = \mu. \tag{19}$$

This motivates the use of the following GMM estimators for b and μ

$$\hat{b} = (C'WC)^{-1}C'W\bar{r}^e, \tag{20}$$

$$\hat{\mu} = \bar{f}, \tag{21}$$

where $\bar{r}^e$ is the sample mean of r^e, $\bar{f}$ is the sample mean of f, C is the sample covariance matrix between r^e and f, and W is some positive definite weighting matrix. For the results reported in this paper, we use an $N \times 1$ identity matrix for W.[15]

Equation (18) can also be written as

$$E(r^e) = \text{cov}(r^e, f)\Sigma_f^{-1}\Sigma_f b = \beta\lambda, \tag{22}$$

with $\beta = \text{cov}(r^e, f)\Sigma_f^{-1}$ being an $N \times k$ matrix of factor β and $\lambda = \Sigma_f b$ being a $k \times 1$ vector of risk prices. This is the beta representation of the pricing model, which we also estimate using GMM methods described in Cochrane (2005) and the appendix to Burnside (2011).

When estimating either the SDF representation of the model or the beta representation, it is important that the matrix $\text{cov}(r^e, f)$ has full column rank (i.e. its rank should be k). When this condition fails, the model is not properly identified, both estimators have non-standard asymptotic distributions, and tests for the validity of the model also have non-standard distributions as discussed in Burnside (2016). Therefore, we perform the tests proposed by Kleibergen and Paap (2006) (KP) for testing the rank of $\text{cov}(r^e, f)$. We mainly work with models where $k = 2$. If $\text{cov}(r^e, f)$ has rank 0, it means neither risk factor is correlated with the return vector. If $\text{cov}(r^e, f)$ has rank 1, it means one risk factor is uncorrelated with the return vector or a linear combination of the two risk factors is uncorrelated with the return vector.

As test assets, we use the returns to the five portfolios sorted on the interest rate differentials described above (P1, P2, P3, P4 and P5). Since the HML and DNC portfolios are closely related to P1–P5 we do not include them as test assets.[16] We also do not include EWC and SPD as test portfolios but we report portfolio betas in our results.

4.1 Traditional Pricing Factors

We start considering the traditional risk-based factors proposed in by Lustig et al. (2011) and Menkhoff et al. (2012a). In Table 5, we start with the DOL and HML factors proposed

[15] Details of the computation of the parameter estimates and standard errors are provided in the online appendix to Burnside (2011).

[16] HML is simply P5 minus P1, while DNC would be pure linear combination of the portfolios if there were an even number of them instead of an odd number.

by Lustig et al. (2011). Overall, the results are in line with what has been documented in the empirical literature. The SDF parameter (b) for the HML factor is positive and statistically significant, while the risk prices (λ) associated with both factors are also positive and statistically significant. When we estimate the betas (β) of the test assets using time series regressions they are close to 1 for the DOL factor and increase across portfolios for HML portfolio (although they are small in magnitude for P2, P3 and P4). These results are not surprising given the construction of the factors.[17] The cross-sectional fit of the model is excellent, and it passes the specification tests shown in Table 5. Additionally, the KP test strongly rejects the null of reduced rank

Table 6 shows results for the model used by Menkhoff et al. (2012a), which includes DOL as well as their global volatility innovation factor (DVOL). Again, the results are in line with what has been documented in the literature. The SDF parameter and the risk price of DVOL are both negative and statistically significant, indicating that portfolios with greater exposure to higher volatility (i.e. lower returns when volatility increases) have higher mean returns. When we estimate the betas (β) of the test assets using time series regressions they are close to 1 for the DOL factor and decrease across portfolios for DVOL portfolio, but several of the DVOL betas are statistically insignificant, and neither EWC nor SPD has significant exposure to DVOL. The pattern in the betas reflects the fact that when global currency volatility increases, returns to low interest rate currencies increase and the returns to high interest rate currencies decrease. The cross-sectional fit of the model is excellent, and it passes the specification tests shown in Table 6. The KP test cannot reject the null of reduced rank at the 5% level, but it does so at the 10% level. This likely reflects the imprecision in the estimates of the betas for most of the portfolios.

In sum, these models seem to work well in explaining carry trade excess returns in terms of cross sectional R^2, tests of model validity, and the time series dimension.

4.2 CTOF as a Risk Factor

Table 7 shows cross sectional asset pricing results using our aggregate carry-trade order-flow risk factor, CTOF, in tandem with the DOL factor. The empirical evidence in Table 7 strongly supports CTOF as a pricing factor. The SDF parameter (b) for the CTOF factor is

[17] This follows from the fact that DOL is, effectively, the average of P1–P5 while HML is P5 minus P1. See Burnside (2010) for further details. We note that EWC and SPD are both positively and statistically significantly exposed to DOL and HML.

positive and statistically significant, while the risk prices (λ) associated with both factors are also positive and statistically significant. Thus, portfolios more positive exposure to CTOF carry larger risk premia. The cross-sectional fit of the model is excellent, and it passes the specification tests shown in Table 7. Additionally, the KP test strongly rejects the null hypothesis of reduced rank at less than the 1% level.

Time series results show that portfolios with higher interest rates (P3, P4, and P5) have positive and statistically significant exposure to CTOF. The lower interest rate portfolios (P1 and P2) have negative and statistically significant exposure to CTOF. The betas are monotonically increasing as we move from P1 to P5. These results mean that when the order flow data suggest stronger trading pressure consistent with the carry trade, i.e. when CTOF increases, the high interest rate portfolios earn higher returns and the low interest rate portfolios earn lower returns. The pattern reverses if investors reverse their carry trade holdings and CTOF decreases.[18] As a consequence, low interest rate portfolios act as hedges against a reversal of investors' carry trade positions and high interest rate portfolios are exposed to this risk.

4.3 Disaggregated Order Flow

Cerrato et al. (2011) show that order flow is highly informative but, crucially, knowing the motivation for trading is also informative. For example, the motivation of leveraged hedge funds and the information content in their order flow may be very different than that of corporate customers. They show that the order flow of financial customers is highly informative, and this suggests that the risk premia of our currency portfolios may differ depending on how we measure order flow (specifically, for which customers we measure it). For this reason, we now investigate whether the order flow factors associated with financial customers are relatively more important in explaining the mean returns of our currency portfolios.

Tables 8 and 9 show the results using our disaggregated order flow factors that were defined above. Table 8 provides the results for financial customers (CTAM, CTHF), while Table 9 provides the results for non-financial customers (CTCO and CTPC). The estimated SDF coefficients and risk premia are statistically significant with the exception of corporate

[18] If there is more positive order flow to high interest rate currencies, and more negative order flow to low interest rate currencies, our CTOF factor increases. If the reverse happens, it decreases. Thus, CTOF acts like an indicator of the pressure on currency markets consistent with investors executing carry trades.

clients (CTCO). Many of the betas are also statistically significant, and all of the models pass the KP rank tests except the one for corporate clients, which appears to have reduced rank.

What stands out in Tables 8 and 9 is the switch in the pattern in the betas for P1–P5 with respect to our order-flow factors, and the switch in the sign of the estimated risk price associated with our order-flow factors as we move from financial to non-financial customers. Time series regressions show that the betas coefficients for Asset Managers and Hedge Funds (CTAM, CTHF) increase as we move from P1 to P5 and λ is positive. The betas of the EWC and SPD portfolios are also positive. A traditional interpretation would be that the high interest rate portfolios are more exposed to risk, as measured by CTAM and CTHF. On the other hand, the reverse pattern is observed for the betas with respect to CTCO and CTPC, and the estimated λ is negative.

The results seem to indicate that the positive sign of λ in the previous section, where we used aggregate order flow, is driven by financial order flow, which may not be surprising since financial order flow is more variable and accounts for more of the variation in total order flow. The sign reversals are consistent with Menkhoff et al. (2016) who show that the order flow of financial customers generates the highest cross-sectional spread in excess returns while the order flows of corporate and private clients generate negative spreads in portfolio excess returns. Our results are consistent with the risk sharing story in Menkhoff et al. (2016) in that different group of customers (i.e. financial and non-financial) appear to trade in different directions and, therefore, that risk sharing takes place in the customer market, not just in the inter-dealer market as suggested in Evans and Lyons (2009).[19]

4.4 Factor Mimicking Portfolio

Following Breeden et al. (1989) and Menkhoff et al. (2012a), we create factor-mimicking portfolios for each of DVOL, CTOF, CTAM, CTHF, CTCO and CTCP. The factor mimicking portfolio is a zero cost strategy that mimics the corresponding factor. For each of the above factors, f_t, the following regression is performed:

$$f_t = c + r_t^{e\prime}\theta + u, \tag{23}$$

[19] Barber and Odean (2013), for the equity market, show that private investors (i.e. uninformed investors) tend to lose money from trading.

where r_t^e is the 5×1 vector containing the returns on P1, P2, P3, P4 and P5. The factor mimicking portfolio is

$$f_t^{\mathrm{FM}} = r_t^{e\prime} \hat{\theta}, \tag{24}$$

where $\hat{\theta}$ is the OLS estimate of θ.

In Table 10, we report the weights each portfolio attaches to P1–P5 as well as the mean of the estimated factor-mimicking portfolio return. We find the factor mimicking portfolio loadings for DVOL are in line with Menkhoff et al. (2012a). The loadings decrease from positive for P1 and P2 to negative for P3, P4 and P5. This is not surprising as the returns to the low interest rate portfolios tend to be high when volatility increases, and low when it decreases. The opposite pattern is observed for high interest rate currencies.

For the CTOF factor the portfolio weights are negative for P1 and P2 and positive for P3, P4 and P5. This is consistent with what we have already seen, which is that high interest rate currencies have higher returns when the order flow to them is larger. The pattern is similar for the disaggregated order-flow factors, CTAM and CTHF. The CTPC factor has, roughly-speaking, a reversed pattern in the loadings, while CTCO has no consistent pattern in the portfolio weights and almost none of them are statistically significant.

The signs of the average factor-mimicking-portfolio returns are consistent with the risk price estimates from our cross-sectional asset pricing exercise, except for the CTCO factor, which has a small positive average return (0.03%) and a negative risk price.

4.5 Economic Interpretation

In this section we argue that our carry trade factor, CTOF, can be viewed as a proxy for the realization of crash risk. When CTOF is large and positive, investors—in particular hedge funds and asset managers—are taking on larger long positions in high interest rate currencies financed by larger short positions in low interest rate currencies. They earn higher returns at these times, but the positions they are taking on involve more risk. When they reverse these positions, CTOF becomes large and negative, and our results show that high interest rate currencies tend to depreciate at these times, while low interest rate currencies appreciate. The microstructure interpretation is that the investors collective reversal of their positions in response to the arrival of new information leads to the currency crash.

While this seems like a completely reasonably interpretation of our findings one might wonder whether the behavior of CTOF can be captured by changes in volatility or changes in currency skewness. For example, Menkhoff et al. (2012a) find that carry trades tend to lose money in times of high currency volatility and Rafferty (2012) finds that carry trades tend to lose money when currency returns are more left-skewed. To see whether CTOF is capturing the same information, in Table 11, we perform simple regressions of CTOF, and our disaggregated order-flow factors, on DVOL and on a similar skewness factor.[20] The estimated coefficients have the expected signs, and in most cases are statistically significant, but the R^2 are rather small. Our conclusion is that there is more to our order-flow factors than is captured in measures of volatility and skewness.

5 Momentum

As documented by Burnside et al. (2011), Lustig et al. (2011), and Menkhoff et al. (2012b), momentum strategies in the foreign exchange market are also profitable. Simply buying a basket of currencies with previously high returns and selling a basket with previously lower returns results is highly profitable. The literature has concluded that it is difficult to rationalise the return of such strategies with traditional risk factors. In this section, we show that order flow can help to rationalise the empirically observed high returns from this trading strategy.

Similar to our approach for the carry trade, we form five momentum portfolios (M1, M2, M3, M4 and M5) based on either the return over the previous week, or the return over the previous four weeks. We assume investors open new positions each week and the holding period is one week. Portfolio M1 contains the currencies with the lowest lagged returns and portfolio P5 has the highest lag returns. We also consider a momentum HML portfolio (M5 minus M1). Table 12 provides a variety of summary statistics for these portfolios, in our full sample as well as in the pre-financial crisis period. Consistent with the prior literature, we find that, especially with the strategy based on four-week lagged returns, a momentum strategy was highly profitable in historical data.

Next we present cross-sectional asset pricing results when using the order flow as a factor to price momentum portfolios. We build a momentum-based order-flow factor, MOOF, using

[20]We use daily DOL returns to calculate the 30 days rolling sample skewness and use the end of each week data to generate the weekly series.

a similar approach to the one we used for the carry-trade factor:

$$\text{MOOF}_{t+1} = \frac{1}{N_t} \sum_{k \in N_t} y_{k,t} \cdot \text{sign}(r_{kt} + r_{kt-1} + r_{kt-2} + r_{kt-3}). \tag{25}$$

Our baseline factor is based on the sign of the of the past four weeks' returns for each currency, but we found similar results when using different lagged returns to define the factor.

Table 13 shows cross-sectional asset pricing results using aggregated order flow and Tables 14 and 15 show analogous results using momentum factors based on order-flow disaggregated by customer segment. Overall, the results are very encouraging and suggest that order flow contains important information that can also be used to price momentum portfolio returns. It is worth to point out the very different results that we obtain across the different trading segments. The estimated coefficients are all statistically significant and they carry the same sign as in Tables 8 and 9.

6 Conclusion

We have demonstrated that, at the weekly frequency, order-flow is closely associated with systematic patterns in currency returns. We have shown that if currencies are sorted on the basis of aggregated normalized order-flow, portfolios of currencies with stronger buying pressure tend to appreciate relative to currencies with weaker buying (or strong selling) pressure. At the disaggregated level, we see the same pattern when we use the order-flow of financial customers (hedge funds and asset managers). However, the pattern is reversed when we use the order-flow of non-financial customers (corporates and private customers). This suggests that a form of risk sharing takes place in the foreign exchange market, not just between dealers and non-dealers, but within the confines of the non-dealer customer base.

We have also explored the use of order-flow based risk factors in a traditional SDF approach to cross-sectional asset pricing. In particular, we built order-flow based factors that tend to increase in size if order flow reveals more buying pressure in the direction of currencies that have higher interest rates than the US dollar. We referred to these as carry-trade order-flow factors and we showed that they perform extremely well when we price a cross-section of currency returns. When aggregate order-flow or financial order flow increases towards buying more high interest rate currencies and selling low interest rate currencies, returns to the carry trade have a tendency to increase. Similarly when our order-flow factor suggests a reversal of carry trade positions, returns to the carry trade decrease. We also find that a similarly motivated set of momentum-based order-flow factors can price the cross-section of returns ordered on the basis of past currency momentum.

In sum, our results suggest that results in the extant literature, which are based on reduced-form factors such as the HML factor of Lustig et al. (2011), or the global currency volatility factor of Menkhoff et al. (2012a), may lend support to a microstructure model-based interpretation of the data.

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Data Appendix

Our data-set consists of 20 of the most liquid currencies with the largest trading volume (EUR, JPY, GBP, CHF, AUD, NZD, CAD, SEK, NOK, MXN, BRL, ZAR, KRW, SGD, HKD, TRY, HUF, PLN, CZK, SKK).

We use price quotes of spot exchange rate from the first week of November 2001 to the fourth week of March 2012. All exchange rates are quoted against US dollar, and we normalize on expressing each exchange rate as the number of foreign currency units (FCU) per US dollar (USD). The weekly and daily spot exchange rates are obtained from WM/Reuters (via Datastream).

We use a unique dataset, from one of the world's largest foreign exchange dealers, that contains weekly customer order flows for the same 20 currencies from November 2001 to March 2012. We have order flow data aggregated across four types of clients (9 countries, EUR, JPY, GBP, CHF, AUD, NZD, CAD, SEK, NOK): asset manager (AM), corporate clients (CO), hedge funds (HF) and private clients (PC). Asset managers and hedge funds are recognized as financial customers. Corporate and private clients are recognized as non-financial customers.

We believe that the order flows collected from this dealer are representative of the end-user currency demand in the foreign exchange market given that it has significant market share. The order flows measure the US dollar value of buyer-initiated minus seller initiated trades of a currency. A positive net order flow indicate net buying of foreign currency.

Table 1: Interest-Rate Sorted and Carry-Trade Portfolios: Summary Statistics

Portfolio	P1	P2	P3	P4	P5
Mean (%)	1.56	5.44	6.25	7.85	13.88
SD	6.23	8.49	8.17	9.87	10.77
SR	0.25	0.64	0.77	0.80	1.29
Skew	-0.04	-0.41	-0.40	-0.47	-0.45
AC1	0.07*	-0.01	0.02	0.01	-0.07*
Coskew1	0.21	-0.01	0.03	-0.09	-0.06
Coskew2	5.94	-0.27	0.74	-2.24	-2.15
Portfolio	DOL	EWC	SPD	HML	DNC
Mean (%)	6.89	4.79	12.35	12.16	2.94
SD	7.76	5.49	8.96	9.86	2.78
SR	0.89	0.87	1.38	1.23	1.06
Skew	-0.49	-0.61	-0.52	-0.41	-0.36
AC1	0.01	-0.05	-0.04	-0.12***	-0.11***
Coskew1	0.54	-0.17	-0.30	-0.15	-0.14
Coskew2	0.00	-3.76	-3.46	-9.03	-2.29

Note: The table reports the descriptive statistics for currency portfolios P1–P5, which are sorted on the basis of short term interest rates. We also report statistics for the DOL, EWC, SPD, HML and DNC portfolios. It reports the annualized mean return (%), standard deviation (SD), Sharpe ratio (SR), and skewness (Skew) for each portfolio. We also report the first order autocorrelation coefficient (AC1) and its significance (***1%, **5%, *10%). We also report two measures of coskewness between the individual portfolios and the DOL portfolio. Coskew1 and Coskew2 corresponded, respectively, to β_{SKS} and β_{SKS} as described in the main text.

Table 2: Order-Flow Portfolios: Summary Statistics

	O1	O2	O3	O4	O5	Avg.	BMS
A) Aggregated order flow/Full sample							
Mean (%)	-6.51	3.59	7.76	10.87	18.65	6.83	25.21
	(3.08)	(2.67)	(2.64)	(2.74)	(2.65)	(2.49)	(2.29)
SD	9.01	8.56	8.59	8.28	8.66	8.87	6.36
SR	-0.72	0.42	0.90	1.31	2.15	0.77	3.97
B) Disaggregated order flow/Major currency sample							
	Asset manager						
Mean (%)	-5.56	4.78	6.25	14.09		4.89	19.66
	(2.56)	(3.24)	(3.07)	(2.70)		(2.58)	(2.00)
SD	8.61	9.99	9.91	8.40		8.20	6.16
SR	-0.65	0.48	0.63	1.68		0.60	3.19
	Hedge fund						
Mean (%)	-7.62	4.38	6.84	15.34		4.73	22.96
	(2.98)	(3.10)	(2.82)	(2.70)		(2.57)	(2.30)
SD	8.96	10.11	9.48	8.52		8.19	6.79
SR	-0.85	0.43	0.72	1.80		0.58	3.38
	Corporate						
Mean (%)	7.19	7.94	8.59	1.93		6.41	-5.26
	(2.93)	(2.90)	(2.77)	(2.75)		(2.56)	(1.84)
SD	8.68	9.64	9.91	8.69		8.16	6.34
SR	0.83	0.82	0.87	0.22		0.79	-0.83
	Private client						
Mean (%)	23.64	8.76	2.20	-5.34		7.32	-28.98
	(2.59)	(3.36)	(3.01)	(2.75)		(2.57)	(2.15)
SD	8.66	9.80	9.67	8.81		8.16	6.92
SR	2.73	0.89	0.23	-0.61		0.90	-4.19

Note: For each of the portfolios O1–O5, which are sorted by contemporaneous order flow, this table reports the annualized mean excess return (with heteroskedasticity consistent standard errors reported in parentheses), standard deviation (SD) and Sharpe ratio (SR) for currencies sorted on contemporaneous order flow. Column 'Avg.' shows the average across all portfolios. Column 'BMS' (buy minus sell) reports the return of holding O5 long and O1 short. The first panel reports statistics for portfolios based on normalized aggregated order flow for the full sample of 20 currencies. The lower panels report statistics portfolios based on disaggregated order flow for a smaller sample of nine major currencies, where the disaggregation is by customer type.

Table 3: Double Sorts on Interest Rate and Order Flow: Mean Returns (%)

	Interest rate			
Order flow	Low	Medium	High	HML
Sell	-2.61	3.50	4.09	6.70
	(2.22)	(2.91)	(3.47)	(2.67)
Buy	6.67	10.78	16.41	9.73
	(2.23)	(2.63)	(3.45)	(2.99)
BMS	9.28	7.28	12.32	
	(1.56)	(1.43)	(2.63)	

Note: This table reports the annualized mean returns (with heteroskedasticity consistent standard errors in parentheses) for six double-sorted portfolios based on interest rate and the value of aggregated order flow.

Table 4: Double Sorts on Volatility Innovation and Order Flow: Mean Returns (%)

	Volatility Innovation			
Order flow	Low	Medium	High	HML (Vol)
Sell	6.44	0.73	-3.70	-10.14
	(2.46)	(2.48)	(3.51)	(2.35)
Buy	14.19	12.76	10.98	-3.21
	(2.10)	(2.50)	(3.51)	(2.69)
BMS	7.75	12.03	14.68	
	(1.56)	(1.33)	(2.21)	

Note: This table reports the annualized mean returns (with heteroskedasticity consistent standard errors in parentheses) for six double sorted portfolios based on volatility innovations and the value of aggregated order flow.

Table 5: Estimates of the DOL-HML Model

	DOL	HML	R^2	HJ
GMM				
b	4.16	10.02	0.97	1.06
	(4.58)	(3.58)		[0.79]
λ ($\times$100)	0.17	0.31		
	(0.06)	(0.08)		
FMB			χ^2	
λ ($\times$100)	0.17	0.31	1.47	
	(0.06)	(0.08)	[0.83]	
Betas	α ($\times$100)	β-DOL	β-HML	$\bar{R}^2$
P1	0.02	0.76	-0.37	0.84
	(0.02)	(0.02)	(0.01)	
P2	0.03	0.98	-0.19	0.81
	(0.03)	(0.04)	(0.03)	
P3	0.03	0.90	-0.10	0.82
	(0.02)	(0.034)	(0.03)	
P4	0.03	1.04	-0.02	0.83
	(0.03)	(0.04)	(0.03)	
P5	0.08	0.72	0.44	0.86
	(0.03)	(0.04)	(0.06)	
EWC	-0.02	0.47	0.24	0.83
	(0.02)	(0.04)	(0.02)	
SPD	0.04	0.72	0.44	0.90
	(0.02)	(0.03)	(0.02)	
	Stat.	d.f.	p-value	
Rank(0)	521	10	[0.00]	
Rank(1)	73	4	[0.00]	

Note: We present SDF and beta representation estimates for the DOL-HML model, as well as portfolio time series regressions and KP reduced-rank tests. The test assets are P1–P5, the five portfolios sorted on interest rate. The first panel shows the estimates of the SDF coefficients, b, from first stage GMM, corresponding risk prices, λ, the cross-sectional R^2 and Hansen-Jagannathan distance (HJ). The second panel show estimates of the beta representation using the Fama-MacBeth approach (FMB), including a χ^2 measure of fit. No intercept is included in the FMB approach. The third panel shows time series regression results for the five test portfolios as well as the EWC and SPD carry trade portfolios described in the main text. We report regression intercept α, factor betas and time-series R^2. The fourth panel reports the KP rank tests. In all panels, standard errors are reported in parentheses, with p-values for tests in square brackets. We use weekly data, from the first week of 2001M11 to the fourth week of 2012M3 for a sample size of 543.

Table 6: Estimates of the Volatility (DOL-DVOL) Model

	DOL	DVOL	R^2	HJ
GMM				
b	-0.04	-1.62	0.90	2.42
	(7.63)	(0.79)		[0.49]
λ ($\times$100)	0.17	-40.49		
	(0.11)	(19.45)		
FMB			χ^2	
λ ($\times$100)	0.17	-40.49	4.94	
	(0.06)	(14.20)	[0.29]	
Betas	α ($\times$100)	β-DOL	β-DVOL ($\times$100)	$\bar{R}^2$
P1	-0.03	0.51	0.17	0.50
	(0.03)	(0.05)	(0.08)	
P2	0.00	0.85	0.15	0.77
	(0.03)	(0.06)	(0.11)	
P3	0.01	0.84	0.03	0.81
	(0.02)	(0.05)	(0.08)	
P4	0.02	1.02	-0.02	0.84
	(0.03)	(0.05)	(0.11)	
P5	0.14	1.02	-0.15	0.71
	(0.04)	(0.05)	(0.11)	
EWC	0.01	0.63	-0.05	0.71
	(0.02)	(0.04)	(0.06)	
SPD	0.01	1.02	-0.19	0.73
	(0.04)	(0.05)	(0.08)	
	Stat.	d.f.	p-value	
Rank(0)	212	10	[0.00]	
Rank(1)	9	4	[0.07]	

Note: We present SDF and beta representation estimates for the DOL-DVOL model, as well as portfolio time series regressions and KP reduced-rank tests. See the note to Table 5 for details.

Table 7: Estimates of the Carry-Trade Order-Flow (DOL-CTOF) Model

	DOL	CTOF	R^2	HJ
GMM				
b	-0.22	1.75	0.83	5.43
	(6.19)	(0.74)		[0.14]
λ ($\times$100)	0.16	10.31		
	(0.06)	(3.95)		
FMB			χ^2	
λ ($\times$100)	0.16	10.31	6.25	
	(0.06)	(0.04)	[0.18]	
Betas	α ($\times$100)	β-DOL	β-CTOF ($\times$100)	$\bar{R}^2$
P1	-0.06	0.54	-0.69	0.53
	(0.03)	(0.05)	(0.12)	
P2	-0.01	0.86	-0.31	0.77
	(0.03)	(0.07)	(0.10)	
P3	0.03	0.82	0.22	0.81
	(0.02)	(0.05)	(0.09)	
P4	0.04	1.00	0.31	0.84
	(0.03)	(0.05)	(0.10)	
P5	0.16	0.99	0.61	0.71
	(0.04)	(0.05)	(0.15)	
EWC	0.03	0.60	0.56	0.73
	(0.02)	(0.05)	(0.11)	
SPD	0.13	0.98	0.77	0.74
	(0.04)	(0.05)	(0.15)	
	Stat.	d.f.	p-value	
Rank(0)	275	10	[0.00]	
Rank(1)	34	4	[0.00]	

Note: We present SDF and beta representation estimates for the DOL-CTOF model, as well as portfolio time series regressions and KP reduced-rank tests. See the note to Table 5 for details.

Table 8: Estimates of the Disaggregated Order-Flow Model for Financial Customers

	Asset Managers				Hedge Funds			
	DOL	CTAM	R^2	HJ	DOL	CTHF	R^2	HJ
GMM								
b	5.93	2.41	0.73	6.88	9.87	2.97	0.83	4.93
	(4.82)	(1.20)		[0.08]	(4.19)	(1.25)		[0.18]
λ ($\times$100)	0.17	6.49			0.16	5.91		
	(0.06)	(3.06)			(0.06)	(2.46)		
FMB			χ^2				χ^2	
λ ($\times$100)	0.17	6.49	7.39		0.16	5.91	6.38	
	(0.06)	(2.56)	[0.12]		(0.06)	(0.02)	[0.17]	
Betas	α ($\times$100)	β-DOL	β-CTAM ($\times$100)	$\bar{R}^2$	α ($\times$100)	β-DOL	β-CTHF ($\times$100)	$\bar{R}^2$
P1	-0.05	0.52	-1.04	0.53	-0.05	0.50	-1.31	0.54
	(0.03)	(0.05)	(0.21)		(0.03)	(0.05)	(0.20)	
P2	-0.01	0.86	-0.61	0.77	0.00	0.84	-0.19	0.77
	(0.03)	(0.06)	(0.18)		(0.03)	(0.06)	(0.22)	
P3	0.02	0.83	0.06	0.81	0.02	0.83	0.21	0.81
	(0.02)	(0.05)	(0.15)		(0.02)	(0.05)	(0.16)	
P4	0.03	1.02	0.33	0.84	0.03	1.02	0.28	0.84
	(0.03)	(0.05)	(0.17)		(0.03)	(0.05)	(0.19)	
P5	0.14	1.02	0.30	0.70	0.15	1.02	0.89	0.71
	(0.04)	(0.05)	(0.27)		(0.04)	(0.05)	(0.27)	
EWC	0.02	0.61	1.01	0.74	0.03	0.63	1.22	0.75
	(0.02)	(0.04)	(0.21)		(0.02)	(0.04)	(0.18)	
SPD	0.11	1.01	1.07	0.75	0.12	1.03	1.38	0.75
	(0.04)	(0.05)	(0.26)		(0.04)	(0.05)	(0.24)	
	Stat.	d.f.	p-value		Stat.	d.f.	p-value	
Rank(0)	250	10	0.00		235	10	[0.00]	
Rank(1)	19	4	0.00		49	4	[0.00]	

Note: We present SDF and beta representation estimates for the carry-trade order flow model using disaggregated order flow for financial customers, as well as portfolio time series regressions and KP reduced-rank tests. CTAM is the order flow factor for Asset Managers. CTHF is the order flow factor for Hedge Funds. See the note to Table 5 for details.

Table 9: Estimates of the Disaggregated Order-Flow Model for Non-financial Customers

	Corporate				Private Clients			
	DOL	CTCO	R^2	HJ	DOL	CTPC	R^2	HJ
GMM								
b	19.19	-18.35	0.74	3.48	10.88	-4.41	0.81	5.73
	(7.70)	(12.07)		[0.32]	(4.52)	(2.09)		[0.13]
λ ($\times 100$)	0.19	-7.05			0.17	-2.70		
	(0.08)	(4.68)			(0.07)	(1.27)		
FMB			χ^2				χ^2	
λ ($\times 100$)	0.19	-7.05	7.31		0.17	-2.70	6.6002	
	(0.06)	(2.83)	[0.12]		(0.06)	(1.05)	[0.16]	
Betas	α ($\times 100$)	β-DOL ($\times 100$)	β-CTCO	$\bar{R}^2$	α ($\times 100$)	β-DOL	β-CTPC ($\times 100$)	$\bar{R}^2$
P1	-0.03	0.49	0.80	0.50	-0.04	0.50	2.95	0.56
	(0.03)	(0.05)	(0.45)		(0.03)	(0.04)	(0.38)	
P2	0.01	0.84	0.89	0.77	0.00	0.84	1.02	0.77
	(0.03)	(0.06)	(0.41)		(0.03)	(0.06)	(0.38)	
P3	0.01	0.83	-0.18	0.81	0.02	0.83	0.09	0.81
	(0.02)	(0.05)	(0.35)		(0.02)	(0.05)	(0.27)	
P4	0.02	1.02	0.11	0.84	0.02	1.02	-0.50	0.84
	(0.03)	(0.05)	(0.40)		(0.03)	(0.05)	(0.27)	
P5	0.14	1.03	-0.16	0.70	0.14	1.02	-1.29	0.71
	(0.04)	(0.05)	(0.51)		(0.04)	(0.05)	(0.50)	
EWC	0.00	0.64	-1.28	0.72	0.01	0.63	-3.51	0.80
	(0.02)	(0.04)	(0.43)		(0.02)	(0.03)	(0.40)	
SPD	0.09	1.04	-1.20	0.74	0.10	1.0258	-3.78	0.78
	(0.04)	(0.05)	(0.05)		(0.03)	(0.04)	(0.56)	
	Stat.	d.f.	p-value		Stat.	d.f.	p-value	
Rank(0)	192	10	0.00		215	10	[0.00]	
Rank(1)	6	4	0.19		21	4	[0.00]	

Note: We present SDF and beta representation estimates for the carry-trade order flow model using disaggregated order flow for non-financial customers, as well as portfolio time series regressions and KP reduced-rank tests. CTCO is the order flow factor for Corporate customers. CTPC is the order flow factor for Private Clients. See the note to Table 5 for details.

Table 10: Factor-Mimicking Portfolios

	Factor-Mimicking Portfolio Weights					Mean Return
	P1	P2	P3	P4	P5	(%)
DVOL	5.08	5.00	-3.64	-4.69	-5.16**	-1.84
CTOF	-7.98***	-2.47***	6.71***	3.83***	2.55***	1.57
CTAM	-5.62***	-1.97	3.30***	3.53***	0.11	0.58
CTHF	-7.01***	0.80	2.40**	0.49	0.63	0.40
CTCO	0.61	0.80*	-0.77	0.03	0.05	0.03
CTPC	4.34	0.03	-1.10**	-1.06**	-0.20	-0.21

Note: This table reports factor-mimicking portfolios based on the five interest-rate sorted portfolios, P1–P5, for each of the pricing factors DVOL, CTOF, CTAM, CTHF, CTCO, and CTPC. The portfolio weights are the estimated coefficients, $\hat{\theta}$, from an OLS regression of each factor on the vector of five portfolio returns, $\mathbf{r}$. The asterisks indicate the significance level of each coefficient based on heteroskedasticity-consistent standard errors (*** for 1%, ** for 5%, * for 10%). The average return is the mean of $\mathbf{r}'\hat{\theta}$ for each factor-mimicking portfolio expressed in annualized percent.

Table 11: Projections of DVOL and SKEWNESS on the Carry-Trade Order-Flow Factors

	DVOL			SKEWNESS		
	Intercept (×100)	β	$\bar{R}^2$	Intercept (×100)	β	$\bar{R}^2$
CTOF	-3.28	-8.63***	0.0296	-3.04	4.93**	0.0058
	(1.04)	(2.14)		(1.02)	(2.20)	
CTAM	-1.14	-4.62***	0.0185	-1.17	-0.43	-0.0017
	(0.71)	(1.48)		(0.72)	(1.61)	
CTHF	-1.67	1.27	0.0002	-1.52	3.08**	0.0071
	(0.66)	(1.79)		(0.67)	(1.39)	
CTCO	-0.79	-1.11**	0.0060	-0.79	0.08	-0.0018
	(0.39)	(0.49)		(0.38)	(0.73)	
CTPC	0.16	0.41	-0.0012	0.17	0.41	-0.0014
	(0.33)	(0.70)		(0.33)	(0.80)	

Note: This table reports OLS estimates (intercept and slope coefficient, β) of regressions of DVOL and a similar SKEWNESS measure on our carry-trade order -flow factors. Heteroskedasticity-robust standard errors are in parentheses. Significance levels are indicated by ***1%, **5% and *10%.

Table 12: Momentum Portfolios: Summary Statistics

	M1	M2	M3	M4	M5	HML (Mom)
A) Full Sample						
Momentum defined over one lagged week						
Mean (%)	6.69	6.20	6.83	6.32	6.96	0.27
	(3.00)	(2.49)	(2.65)	(2.75)	(3.36)	(2.95)
SD	9.38	8.40	8.74	8.69	9.22	9.09
SR	0.71	0.74	0.78	0.73	0.75	0.03
Skew	-0.43	-0.52	-0.42	-0.43	-0.51	-0.08
Momentum defined over four lagged weeks						
Mean (%)	3.86	5.40	6.61	8.57	10.61	6.75
	(2.83)	(2.98)	(2.72)	(2.75)	(3.03)	(2.51)
SD	8.90	8.96	8.61	8.70	9.19	8.77
SR	0.44	0.60	0.77	0.99	1.16	0.77
Skew	-0.44	-0.40	-0.36	-0.41	-0.60	-0.13
B) Pre-financial crisis						
Momentum defined over one lagged week						
Mean (%)	5.96	8.20	10.30	7.99	14.53	8.57
	(3.05)	(2.88)	(3.27)	(3.00)	(3.67)	(3.49)
SD	7.77	7.39	7.79	7.26	7.81	7.76
SR	0.77	1.11	1.32	1.10	1.86	1.11
Skew	-0.44	-0.37	-0.48	-0.41	-0.41	-0.07
Momentum defined over four lagged weeks						
Mean (%)	4.14	9.09	9.55	9.04	17.24	13.10
	(2.90)	(3.19)	(3.24)	(3.30)	(3.35)	(2.85)
SD	7.15	7.36	7.61	7.83	8.40	7.63
SR	0.58	1.23	1.25	1.15	2.05	1.72
Skew	-0.24	-0.18	-0.17	-0.52	-0.71	-0.29

Note: The table reports the descriptive statistics for currency portfolios M1–M5, which are sorted on the basis of lagged currency returns over either one of four weeks.. It reports the annualized mean return (%) (with heteroskedasticity consistent standard errors reported in parentheses), standard deviation (SD), Sharpe ratio (SR), and skewness (Skew) for each portfolio. The holding period of the portfolios is one week in both cases. We report results for both our full sample (panel A) and the pre-financial crisis sample (panel B).

Table 13: Estimates of the Momentum Order-Flow (DOL-MOOF) Model

	DOL	MOOF	R^2	HJ
GMM				
b	3.24	2.14	0.83	1.03
	(1.27)	(0.89)		[0.80]
λ ($\times$100)	0.51	13.48		
	(0.23)	(5.62)		
FMB			χ^2	
λ ($\times$100)	0.51	13.48	1.40	
	(0.19)	(0.05)	[0.84]	
Betas	α ($\times$100)	β-DOL	β-MOOF ($\times$100)	$\bar{R}^2$
M1	-0.19	1.12	-1.99	0.75
	(0.12)	(0.03)	(0.56)	
M2	-0.07	1.01	0.02	0.84
	(0.08)	(0.02)	(0.34)	
M3	-0.01	0.98	0.13	0.84
	(0.08)	(0.02)	(0.28)	
M4	0.17	0.95	1.08	0.78
	(0.10)	(0.02)	(0.34)	
M5	0.28	0.67	1.92	0.64
	(0.09)	(0.032)	(0.39)	
	Stat.	d.f.	p-value	
Rank(0)	382	10	[0.00]	
Rank(1)	25	4	[0.00]	

Note: We present SDF and beta representation estimates for the DOL-MOOF model, as well as portfolio time series regressions and KP reduced-rank tests. The test assets are M1–M5, the five portfolios sorted on four weeks of lagged currency returns. Other details are provided in the note to Table 5.

Table 14: Estimates of the Disaggregated Momentum Order-Flow Model for Financial Customers

	Asset Managers				Hedge Funds			
	DOL	MOAM	R^2	HJ	DOL	MOHF	R^2	HJ
GMM								
b	3.68	3.18	0.25	4.82	2.85	2.78	0.73	1.80
	(1.20)	(1.42)		[0.19]	(1.20)	(1.19)		[0.62]
λ ($\times$100)	0.51	8.35			0.53	5.87		
	(0.20)	(3.79)			(0.22)	(2.51)		
FMB			χ^2				χ^2	
λ ($\times$100)	0.51	8.35	6.13		0.53	5.87	2.16	
	(0.19)	(3.39)	[0.19]		(0.19)	(2.12)	[0.71]	
Betas	α ($\times$100)	β-DOL	β-MOAM ($\times$100)	$\bar{R}^2$	α ($\times$100)	β-DOL	β-MOHF ($\times$100)	$\bar{R}^2$
M1	-0.15	1.12	-3.20	0.75	-0.28	1.13	-5.00	0.76
	(0.12)	(0.03)	(1.02)		(0.12)	(0.03)	(0.82)	
M2	-0.08	1.01	0.79	0.84	-0.08	1.01	-1.07	0.84
	(0.09)	(0.02)	(0.49)		(0.08)	(0.0194)	(0.56)	
M3	-0.02	0.98	0.87	0.84	0.00	0.98	0.90	0.84
	(0.08)	(0.02)	(0.46)		(0.08)	(0.02)	(0.48)	
M4	0.17	0.95	1.11	0.78	0.22	0.95	2.80	0.78
	(0.10)	(0.03)	(0.71)		(0.10)	(0.02)	(0.57)	
M5	0.26	0.67	2.04	0.63	0.34	0.67	3.26	0.64
	(0.09)	(0.03)	(0.59)		(0.09)	(0.33)	(0.61)	
	Stat.	d.f.	p-value		Stat.	d.f.	p-value	
Rank(0)	371	10	[0.00]		385	10	[0.00]	
Rank(1)	15	4	[0.01]		36	4	[0.00]	

Note: We present SDF and beta representation estimates for the momentum order flow model using disaggregated order flow for financial customers, as well as portfolio time series regressions and KP reduced-rank tests. MOAM is the momentum order-flow factor for Asset Managers. MOHF is the momentum order-flow factor for Hedge Funds. See the note to Table 5 for other details.

Table 15: Estimates of the Disaggregated Momentum Order-Flow Model for Non-Financial Customers

	Asset Managers				Hedge Funds			
	DOL	MOCO	R^2	HJ	DOL	MOPC	R^2	HJ
GMM								
b	2.29	-12.03	0.36	3.13	2.99	-3.63	0.65	2.32
	(1.47)	(6.32)		[0.37]	(1.17)	(1.51)		[0.51]
λ ($\times$100)	0.52	-5.17			0.53	-2.50		
	(0.25)	(2.70)			(0.21)	(1.04)		
FMB			χ^2				χ^2	
λ ($\times$100)	0.52	-5.17	4.91					
	(0.19)	(2.06)	[0.30]					
Betas	α ($\times$100)	β-DOL	β-MOCO ($\times$100)	$\bar{R}^2$	α ($\times$100)	β-DOL	β-MOPC ($\times$100)	$\bar{R}^2$
M1	-0.20	1.13	5.22	0.74	-0.28	1.13	11.70	0.77
	(0.12)	(0.03)	(2.06)		(0.12)	(0.03)	(1.38)	
M2	-0.06	1.01	0.46	0.84	-0.08	1.01	1.89	0.84
	(0.08)	(0.02)	(1.14)		(0.08)	(0.02)	(0.86)	
M3	-0.01	0.98	-1.25	0.84	0.00	0.98	-1.16	0.84
	(0.08)	(0.02)	(1.09)		(0.08)	(0.02)	(0.93)	
M4	0.17	0.95	-3.92	0.78	0.23	0.95	-7.60	0.80
	(0.10)	(0.03)	(1.35)		(0.10)	(0.02)	(1.01)	
M5	0.29	0.67	-2.21	0.63	0.34	0.67	-6.38	0.65
	(0.09)	(0.04)	(1.57)		(0.09)	(0.03)	(1.25)	
	Stat.	d.f.	p-value		Stat.	d.f.	p-value	
Rank(0)	382	10	[0.00]		391	10	[0.00]	
Rank(1)	10	4	[0.03]		54	4	[0.00]	

Note: We present SDF and beta representation estimates for the momentum order flow model using disaggregated order flow for non-financial customers, as well as portfolio time series regressions and KP reduced-rank tests. MOCO is the momentum order-flow factor for Corporate customers. MOPC is the momentum order-flow factor for Private Clients. See the note to Table 5 for other details.