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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.

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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 of 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 up 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 data is that order flow behaves systematically differently across distinct segments of 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. Sections 4 and 5 contain 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 6 we explore a brief extension to momentum portfolios. Section 7 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:

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

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

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

[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. Their version of the DOL portfolio is an equally weighted average of the P1 through P5 portfolios. By contrast, we construct DOL as the equal weighted average of the currency excess returns for nine of the G10 currencies:[7]

$$r_{t+1}^{\mathrm{DOL}} = \frac{1}{9} \sum_{k \in \{\mathrm{G10}\}} r_{k,t+1}. \tag{10}$$

This ensures that our DOL portfolio has a consistent definition across the different currency samples that we use by always measuring the tendency of the USD to depreciate or appreciate against the other G10 currencies.

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

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

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

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

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

[7] The nine currencies are EUR, JPY, GBP, CHF, AUD, NZD, CAD, SEK, NOK, with the USD being left out as it is the base currency in our analysis.

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

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

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.[8] 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 2. 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.[9] 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 2 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 13.1%. The mean return of the DOL portfolio is 5.3%. 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 SPD and HML portfolios have the largest mean returns (11.7% and 11.6%), and the

[8] 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.

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

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

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

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

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

largest Sharpe ratios (1.11 and 0.99), followed by 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.

2.2 Order Flow and Exchange Rates

We also form portfolios based on order flow data for the set of currencies in our data set. In order to do so, 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.[10] 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 $t+1$. Typically, empirical implementations of order flow models relate the change of the exchange rate to this flow, as well as to changes in observable fundamentals (such as the interest differential between the two currencies), and an error term. Our intention, here, is not to implement a specific order flow model. Instead, in our preliminary analysis, we demonstrate the apparent correlation between order flow and exchange rate changes at the weekly frequency.

In Table 1 we present estimates of the following equation:

$$s_{k,t+1} - s_{k,t} = a_k + x_{k,t} b_k + u_{k,t+1}, \tag{14}$$

where $u_{k,t+1}$ is an error term. Given that we measure exchange rates in FCUs per USD, and $x_{k,t}$ measures net buy orders of the foreign currency, we expect negative estimates of b_k. In fact, this is what we see in Table 1, with b_k being positive and statistically significant for 17 of our 20 currencies. This evidence is suggestive that order flow data may be useful in explaining exchange rate changes and the returns to currency investments.

2.3 Order Flow Portfolios

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

$$y_{k,t} = \frac{x_{k,t}}{\mathrm{std}(x_k)}. \tag{15}$$

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

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 3 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 3) behaves similarly to the DOL portfolio in Table 2. 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 into four portfolios rather than five.[11] As these are all major currencies we do not normalize order flow by its standard deviation. These results are also reported in Table 3. 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.[12]

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

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

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

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 4 and 5. In Table 4, 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.[13] The main conclusion of Table 4 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 5, 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.

3 A Carry-Trade Order-Flow Factor

The empirical results presented in Tables 3–5 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

$$\mathrm{CTOF}_{t+1} = \frac{1}{N_t} \sum_{k \in N_t} y_{k,t} \cdot \mathrm{sign}(f_{kt} - s_{kt}). \tag{16}$$

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

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

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.[14]

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.[15]

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 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.

[14]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.

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

4 The Risk Exposure of Currency Portfolios

In this section, we measure the risk exposures of the portfolios we constructed in Section 2.1. To do so we follow the standard approach in the literature, which is to perform time series regressions of the returns of these portfolios on vectors of risk factors. These risk factors include ones selected from the literature, as well as the novel order-flow based factor we introduced in Section 3. Each time series regression is of the form

$$r^e_{i,t} = \alpha_i + f_t'\beta_i + \epsilon_{i,t}, \qquad i = 1, \ldots, N, \quad t = 1, \ldots, T, \tag{17}$$

where $r^e_{i,t}$ is the excess return of portfolio i at time t, f_t is a $k \times 1$ vector of risk factors (not a vector of forward rates!), N is the number of portfolios and T is the sample size. In this part of our analysis, we consider the five interest-rate sorted currency portfolios, P1–P5, as well as the two carry trade portfolios, EWC and SPD.

4.1 Betas of Traditional Pricing Factors

We begin by considering the two risk factors similar to those proposed by Lustig et al. (2011): DOL and HML. Table 6, we start with the DOL and HML factors proposed by Lustig et al. (2011). Overall, the results are in line with what has been documented in the empirical literature. For the interest-rate sorted portfolios, P1–P5, the betas for DOL are scaled near unity, although in our sample they increase in magnitude across P1 through P4, and then decline for P5. The betas for the HML factor increase across portfolios for the HML portfolio (although they are small in magnitude for P2, P3 and P4). P1 has a negative exposure to HML, indicating that it is a hedge against carry trade risk. By contrast the beta is large and positive for P5, indicating that it is highly exposed to carry trade risk. These results are not surprising given the construction of the factors.[16] We also note that EWC and SPD are both positively and statistically significantly exposed to DOL and HML.

Table 7 shows results for factors similar to those used by Menkhoff et al. (2012a), which are DOL and a global volatility innovation factor (DVOL). The DVOL factor is constructed by measured as the change of the cross-sectional average of the intra-week volatility for each currency in our sample. In Menkhoff et al. (2012a) the same measure is used but it is computed on an intra-month basis. Again, the results are in line with what has been

[16] This follows from the fact that DOL is similar to the average of P1–P5 while HML is P5 minus P1. See Burnside (2010) for further details.

documented in the literature. The pattern in the betas for DOL are similar to what we observed for the DOL-HML model. For DVOL, the betas are positive for the low-interest-rate currency portfolios (P1 and P2) and negative, and increasingly so, for the high-interest-rate portfolios (P3, P4 and P5). This indicates that when global currency volatility rises, high interest rate currencies tend to do poorly, while low interest rate currencies, again, act as a hedge against increasing volatility. Not surprisingly, EWC and SPD are both negatively exposed to DVOL, although the beta for EWC is not statistically significant.

4.2 Betas of the Carry Trade-Order Flow Factor

Table 8 shows results obtained using our aggregate carry-trade order-flow risk factor, CTOF, in tandem with the DOL factor. The pattern in the betas for DOL are similar to what we observed for the DOL-HML and DOL-DVOL models. The results indicate 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, in the case of P1, 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.[17] As a consequence, low interest rate portfolios act as hedges against a reversal of investors' carry trade positions, while high interest rate portfolios are exposed to this risk. The carry trade portfolios, EWC and SPD, are both positively and significantly exposed to CTOF.

A potential concern with our order-flow risk factor, CTOF, is that it might explain the interest differential component of the return, but not the change of the exchange rate. Suppose, for example, that order flow simply responds to changes in interest rates with agents taking on stronger buying (seeling) positions when a currency's interest differential widens favorably (unfavorably). If this were the case, CTOF might not represent an improvement over average absolute interest differentials as an explanatory variable. As it turns out, this is very much not the case. Instead, we find that CTOF is much more correlated with changes in the change of the exchange rate component of the return. To demonstrate this, we break

[17] 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.

the returns to each portfolio into the component due to the interest differentials between the underlying currencies and the dollar, and the component due to the change in the exchange rate:

$$r_{t+1}^{\mathrm{P}i} = r_{t+1}^{\mathrm{P}i,f-s} + r_{t+1}^{\mathrm{P}i,\Delta s} = \sum_{k\in\mathcal{K}_{i,t}} \frac{1}{N_{i,t}}(f_{k,t} - s_{k,t}) + \sum_{k\in\mathcal{K}_{i,t}} \frac{1}{N_{i,t}}(s_{k,t} - s_{k,t+1}). \tag{18}$$

In Table 9 we report the separate betas of these two components with respect to our two factors. As is clear from the table, most of the explanatory power of CTOF runs through its relationship with the exchange rate component of the return. In fact, the betas of $r_{t+1}^{\mathrm{P}i,\Delta s}$ with respect to CTOF are almost identical of those of $r_{t+1}^{\mathrm{P}i}$ with respect to CTOF.[18]

4.3 Risk Exposures Before and After the Financial Crisis

If the CIP and UIP conditions hold, then, as we saw above, the forward rate unbiasedness condition, (6), holds. For foreign currency k, this condition can be rewritten as

$$E_t s_{k,t+1} - s_{k,t} = f_{k,t} - s_{k,t}. \tag{19}$$

Consequently, UIP is often tested by running the regression

$$s_{k,t+1} - s_{k,t} = \beta_0 + \beta_1(f_{k,t} - s_{k,t}) + \epsilon_{k,t}, \tag{20}$$

and testing the null hypothesis that $(\beta_0, \beta_1) = (0, 1)$. As a vast literature has documented, estimates of β_1 often deviate significantly from 1 and are often negative, especially for the major currencies.[19] However, there may have been a structural break around the time of the Global Financial Crisis of 2008, as documented by Bussiere et al. (2018) and Burnside (2019). Burnside (2019) demonstrates this by estimating equation (19) using rolling samples of five years of monthly data. When these samples encompass or post-date the crisis period, the estimates become unstable, have a wider cross-sectional distribution and are often positive. Relatedly, Burnside (2019) documents that even after the crisis was over, the profitability of the carry trade did not return to the same levels it achieved before the crisis. Finally, Mancini-Griffoli and Ranaldo (2010) and Du et al. (2018) document that during and after

[18] In additional results (not reported here) we further decompose $r_{t+1}^{\mathrm{P}i,\Delta s}$ into two additional components. To do so we use an equation similar to (14) to split the change in the exchange rate for each constituent currency into a component "due to" order flow and a component that is unexplained. We find a closer relationship between the order flow component and CTOF than we do between the unexplained component and CTOF, although, in both cases, the pattern in the betas is similar (increasing in magntitude from P1 through P5).

[19] Burnside (2014) provides recent estimates for industrialized and emerging market currencies.

the crisis there seem to have been deviations from CIP as measured using money market interest rate data and bid-ask spreads.

Given the apparent instability of the time series behavior of exchange rates, in the Appendix we investigate whether there were changes in the nature of the risk exposures of the currency portfolios around the time of the crisis. Tables A6–A8 are analogous to Tables 6–8, but provide estimates of the factor betas over two subsamples: The period leading up to the financial crisis (ending in October 2007), and the period that encompasses and post-dates the financial crisis (November 2007 through March 2012). We find some evidence for instability in the factor betas across these subsamples. Betas are very stable for the DOL-HML model, but this is not surprising given its construction.[20] On the other hand, there is a fairly striking decrease in the magnitude and statistical significance of the exposures of the different portfolios to DVOL and an apparent increase in the importance of DOL within the DOL-DVOL model. For our order-flow based model the main difference across subsamples is an increase of the exposures of the higher interest rate currency portfolios (P3–P5) to the DOL factor, and more especially the CTOF factor.

4.4 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 exposures of our currency portfolios may differ depending on how we measure order flow (specifically, for which customers we measure it).

Table 10 shows the results using our disaggregated order flow factors that were defined in Section 3. The upper panel provides the results for financial customers (CTAM, CTHF), while lower panel provides the results for non-financial customers (CTCO and CTPC). Many of the betas are statistically significant. What stands out in the table is the switch in the pattern in the betas for P1–P5 with respect to our order-flow factors as we move from financial to non-financial customers. The regressions indicate that the betas for Asset Managers and Hedge Funds (CTAM, CTHF) increase as we move from P1 to P5, much as they do for the aggregate order-flow factor, CTOF. The betas of the EWC and SPD portfolios are

[20] See Burnside (2010) for further details.

positive, as for aggregated order flow. A traditional interpretation would be that the high interest rate portfolios are more exposed to risk, as measured by CTAM and CTHF. The reverse pattern is observed for the betas with respect to CTCO and CTPC. The fact that the results for CTAM and CTHF are similar to those for CTOF may not be surprising given that financial order flow is more variable than nonfinancial order flow, and it accounts for more of the variation in total order flow.

These results suggest a risk-sharing story consistent with the one 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, risk sharing takes place in the customer market, not just in the inter-dealer market as suggested in Evans and Lyons (2009).[21]

5 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 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

$$E(r^e m) = 0 \tag{21}$$

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:

$$m = 1 - (f - \mu)' b, \tag{22}$$

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 (21) is combined with equation (22) it becomes

$$E(r^e) = \mathrm{cov}(r^e, f) b. \tag{23}$$

Our other moment restriction is

$$E(f) = \mu. \tag{24}$$

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

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

$$\hat{b} = (C'WC)^{-1}C'W\bar{r}^e, \tag{25}$$

$$\hat{\mu} = \bar{f}, \tag{26}$$

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.[22]

Equation (23) can also be written as

$$E(r^e) = \text{cov}(r^e, f)\Sigma_f^{-1}\Sigma_f b = \beta\lambda, \tag{27}$$

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.[23] We also do not include EWC and SPD as test portfolios.

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

[23] 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.

5.1 Traditional Pricing Factors

In Table 11, we start with the DOL and HML factors proposed by Lustig et al. (2011). 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, as is the associated risk price (λ). For the DOL factor both parameters are positive, but neither is statistically significant (except $\hat{\lambda}_{\mathrm{DOL}}$, according to the Fama-MacBeth method). The cross-sectional fit of the model is excellent, and it passes the specification tests shown in Table 11. Additionally, the KP test strongly rejects the null of reduced rank.

Table 12 shows results for a model similar to the one used by Menkhoff et al. (2012a), which includes DOL and DVOL as factors. Qualitatively, 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, indicating that portfolios with greater exposure to higher volatility (i.e. lower returns when volatility increases) have higher mean returns. However, neither $\hat{b}_{\mathrm{DVOL}}$ nor $\hat{\lambda}_{\mathrm{DVOL}}$ is statistically significant at conventional significance levels, except when we use the Fama-MacBeth method. The cross-sectional fit of the model is excellent, and it passes the specification tests shown in Table 12. The KP test marginally rejects the null hypothesis of reduced rank at the 5% level. This likely reflects the imprecision in the estimates of the betas for most of the portfolios.

In sum, our estimates of the traditional models are similar to those found in the literature. despite the fact that our sample period and frequency of our data are different.

5.2 CTOF as a Risk Factor

Table 13 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 13 strongly supports CTOF as a pricing factor. The SDF parameter (b) and risk price (λ) for the CTOF factor are 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 13. Additionally, the KP test strongly rejects the null hypothesis of reduced rank at less than the 1% level.

5.3 Disaggregated Order Flow

We now investigate whether the order flow factors associated with particular customers are relatively more important in explaining the mean returns of our currency portfolios. Table 14 show the results using our disaggregated order flow factors that were defined above. The results for financial customers (CTAM, CTHF), in panels (a) and (b), while those for non-financial customers (CTCO and CTPC) are found in panels (c) and (d).

The estimated SDF coefficients and risk premia are positive and statistically significant for hedge funds (CTHF), with the results being similar for asset managers (CTAM), but at lower levels of statistical significance. The models for financial customers both pass the specification and KP rank tests.

The results for nonfinancial customers (CTCO, CTPC) are somewhat weaker in terms of statistical significance. What stands out, qualitatively, is the sign reversal of the estimated SDF coefficients and risk premia, which are both negative.

The results seem to indicate that the positive sign of λ, when 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.

5.4 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:

$$f_t = c + r_t^{e\prime}\theta + u, \tag{28}$$

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

$$f_t^{\mathrm{FM}} = r_t^{e\prime}\hat{\theta}, \tag{29}$$

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

In Table 15, 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.

5.5 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, this indicates that 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 16, we perform simple regressions of CTOF, and our disaggregated order-flow factors, on DVOL and on a similar skewness factor.[24] 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.

6 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. These strategies involve buying a basket of currencies with previously high returns and selling a basket with previously lower returns. 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 M5 has the highest lagged returns. We also consider a momentum HML portfolio (M5 minus M1). Table 17 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 a similar approach to the one we used for the carry-trade factor:

$$\mathrm{MOOF}_{t+1} = \frac{1}{N_t} \sum_{k \in N_t} y_{k,t} \cdot \mathrm{sign}(r_{kt} + r_{kt-1} + r_{kt-2} + r_{kt-3}). \tag{30}$$

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

[24]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.

Table 18 shows the betas of the momentum portfolios with respect to our aggregate momentum order-flow risk factor, MOOF, in tandem with the DOL factor. The pattern in the betas for DOL are similar to what we observed for the earlier carry trade-based models. The results indicate that portfolios with greater momentum (M4 and M5) have positive and statistically significant exposure to MOOF. The portfolios with less momentum (M1 and M2) have negative and, in the case of M1, statistically significant exposure to MOOF. The betas are monotonically increasing as we move from M1 to M5. These results mean that when the order flow data suggest stronger trading pressure consistent with momentum trading, i.e. when MOOF increases, the positive momentum portfolios earn higher returns and the negative momentum portfolios earn lower returns. The pattern reverses if investors reverse their momentum trades and MOOF decreases. As a consequence, low momentum portfolios act as hedges against a reversal of investors' momentum positions, while high momentum portfolios are exposed to this risk.

Table 19 shows the results using disaggregated momentum order flow factors analagous to the ones we defined

for the carry trade in Section 3. The upper panel provides the results for financial customers (MOAM, MOHF), while lower panel provides the results for non-financial customers (MOCO and MOPC). Many of the betas are statistically significant, especially for the outer portfolios. As for the carry trade case, what stands out in the table is the switch in the pattern in the betas for M1–M5 with respect to our order-flow factors as we move from financial to non-financial customers. The regressions indicate that the betas for Asset Managers and Hedge Funds (MOAM, MOHF) increase as we move from M1 to M5, much as they do for the aggregate order-flow factor, MOOF. The reverse pattern is observed for the betas with respect to MOCO and MOPC.

Table 20 shows cross-sectional asset pricing results using aggregated order flow and Table 21 shows 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, for the most part, statistically significant and they carry the same signs as in Table 14.

Notably, the carry-trade order-flow factor and the momentum order-flow factor are approximately uncorrelated (their correlation coefficient is 0.012). This finding is consistent with results in the literature suggesting that carry trade and momentum returns are approximately uncorrelated and that separate pricing factors are required to price carry trade and momentum portfolios.

7 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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Table 1: Exchange Rates and Order Flow for Individual Currencies

	$a_k \times 100$	$b_k \times 100$	$\bar{R}^2$		$a_k \times 100$	$b_k \times 100$	$\bar{R}^2$
AUD	-0.149	-1.148	0.055	KRW	-0.060	-1.487	0.024
	(0.086)	(0.294)			(0.069	(0.506)	
BRL	-0.122	-1.599	0.013	MXN	0.053	-1.107	0.004
	(0.098)	(0.600)			(0.065	(0.841)	
CAD	-0.066	-0.584	0.018	NOK	-0.075	-2.450	0.040
	(0.055)	(0.200)			(0.076	(0.493)	
CHF	-0.079	-0.372	0.019	NZD	-0.167	-4.234	0.099
	(0.069)	(0.112)			(0.079	(0.576)	
CZK	-0.128	-5.329	0.019	PLN	-0.098	-4.077	0.037
	(0.083)	(1.983)			(0.098)	(1.108)	
EUR	-0.174	-0.265	0.063	SEK	-0.086	0.481	0.000
	(0.064)	(0.059)			(0.076)	(0.451)	
GBP	-0.020	-0.256	0.017	SGD	-0.071	-1.039	0.038
	(0.059)	(0.085)			(0.029)	(0.257)	
HKD	0.000	-0.038	0.006	SKK	-0.141	0.979	-0.002
	(0.003)	(0.018)			(0.072)	(2.265)	
HUF	-0.039	-5.783	0.035	TRY	0.072	-4.789	0.094
	(0.096)	(1.506)			(0.085)	(0.629)	
JPY	-0.001	-0.504	0.077	ZAR	0.005	-3.833	0.070
	(0.058)	(0.087)			(0.107)	(0.568)	

Note: The table reports estimates of equation (14),

$$s_{k,t+1} - s_{k,t} = a_k + x_{k,t} b_k + u_{k,t+1},$$

where $s_{k,t}$ is the natural log of the exchange rate between the US dollar (USD) and foreign currency k, measured as foreign currency units (FCUs) per USD, $x_{k,t}$ is the aggregate order flow (the total value of buy orders, net of sell orders) for currency k in the interval between periods t and $t+1$, and $u_{k,t+1}$ is an error term. Heteroskedasticity consistent standard errors are reported in parentheses.

Table 2: Interest-Rate Sorted and Carry-Trade Portfolios: Summary Statistics

Portfolio	P1	P2	P3	P4	P5
Mean (%)	1.60	4.92	5.89	7.15	13.14
SD	6.80	9.24	9.31	11.86	12.77
SR	0.24	0.53	0.63	0.60	1.03
Skew	-0.03	-0.80	-0.52	-0.92	-0.77
AC1	0.07*	-0.01	0.06	-0.01	-0.10***
Coskew1	0.44	-0.10	-0.04	-0.37	-0.34
Coskew2	5.49	-1.03	-0.49	-6.39	-8.94
Portfolio	**DOL**	**EWC**	**SPD**	**HML**	**DNC**
Mean (%)	5.27	4.55	11.74	11.64	2.67
SD	9.00	6.66	10.59	11.72	3.51
SR	0.59	0.68	1.11	0.99	0.76
Skew	-0.57	-1.13	-0.97	-0.78	-1.13
AC1	0.02	-0.11**	-0.09**	-0.17***	-0.17***
Coskew1	0.10	-0.34	-0.38	-0.44	-0.45
Coskew2	0.00	-4.56	-8.27	-14.59	-4.44

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 3: Order-Flow Portfolios: Summary Statistics

	O1	O2	O3	O4	O5	Avg.	BMS
A) Aggregated order flow/Full sample							
Mean (%)	-8.31	2.74	7.77	10.82	18.39	6.24	26.75
	(3.84)	(3.01)	(2.89)	(3.09)	(3.25)	(2.93)	(2.52)
SD	10.47	9.63	10.07	9.24	9.71	8.84	7.18
SR	-0.79	0.28	0.77	1.17	1.89	0.71	3.73
B) Disaggregated order flow/Major currency sample							
	Asset manager						
Mean (%)	-7.71	3.81	5.80	14.54		4.11	22.25
	(3.21)	(3.57)	(3.38)	(3.05)		(2.96)	(2.37)
SD	9.98	11.02	11.07	9.38		9.08	7.39
SR	-0.77	0.35	0.52	1.55		0.45	3.01
	Hedge fund						
Mean (%)	-8.64	3.68	5.72	15.30		4.02	23.95
	(3.23)	(3.74)	(3.33)	(3.12)		(2.94)	(2.91)
SD	9.69	11.56	10.56	9.60		9.05	8.17
SR	-0.89	0.32	0.54	1.59		0.44	2.93
	Corporate						
Mean (%)	6.52	7.25	8.66	0.85		5.82	-5.66
	(3.32)	(3.50)	(2.93)	(3.25)		(2.92)	(2.07)
SD	9.67	10.84	10.66	10.05		8.98	7.78
SR	0.67	0.67	0.81	0.09		0.65	-0.73
	Private client						
Mean (%)	24.18	7.24	1.48	-6.12		6.69	-30.30
	(2.76)	(4.05)	(3.68)	(3.01)		(2.97)	(2.40)
SD	9.66	11.04	11.21	9.62		9.06	8.03
SR	2.50	0.66	0.13	-0.64		0.74	-3.77

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

	Interest rate			
Order flow	Low	Medium	High	HML
Sell	-3.74	3.19	2.31	6.05
	(2.63)	(3.34)	(4.16)	(2.91)
Buy	7.59	10.42	15.83	8.24
	(2.36)	(3.04)	(4.19)	(3.85)
BMS	11.33	7.23	13.52	
	(2.14)	(1.61)	(2.86)	

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

	Volatility Innovation			
Order flow	Low	Medium	High	HML (Vol)
Sell	6.48	0.13	-5.20	-11.68
	(2.50)	(2.97)	(4.25)	(2.98)
Buy	14.37	12.81	9.44	-4.93
	(2.11)	(2.78)	(4.69)	(3.76)
BMS	7.89	12.68	14.64	
	(1.61)	(1.44)	(2.58)	

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 6: Betas of the Carry Trade Portfolios for the DOL-HML Model

	α	β-DOL	β-HML	$\bar{R}^2$
P1	0.02	0.71	-0.26	0.79
	(0.02)	(0.02)	(0.02)	
P2	0.00	0.93	0.00	0.82
	(0.02)	(0.02)	(0.02)	
P3	0.00	0.89	0.11	0.84
	(0.02)	(0.02)	(0.02)	
P4	-0.03	1.03	0.28	0.84
	(0.03)	(0.03)	(0.04)	
P5	0.02	0.71	0.74	0.94
	(0.02)	(0.02)	(0.02)	
EWC	-0.02	0.41	0.32	0.83
	(0.02)	(0.03)	(0.02)	
SPD	0.04	0.60	0.57	0.88
	(0.03)	(0.03)	(0.02)	

Note: We present estimates of the time series regressions

$$r^e_{it} = \alpha_i + f_t'\beta_i + \epsilon_{it}, \qquad t = 1, \dots, T,$$

where r^e_{it} is the excess return of portfolio i at time t, and f_t is a vector of the two risk factors, DOL and HML. Estimates of α_i are scaled by 100. The portfolios are P1, P2, P3, P4 and P5 (the portfolios sorted by interest rate) as well as the carry trade portfolios EWC and SPD, described in the main text. Standard errors are reported in parentheses. We use weekly data, from the first week of November 2001 to the fourth week of March 2012.

Table 7: Betas of the Carry Trade Portfolios for the DOL-DVOL Model

	α	β-DOL	β-DVOL	$\bar{R}^2$	
P1	-0.03	0.60	0.19	0.62	
	(0.02)	(0.04)	(0.07)		
P2	0.00	0.94	0.11	0.83	
	(0.02)	(0.02)	(0.09)		
P3	0.02	0.94	-0.09	0.83	
	(0.02)	(0.03)	(0.08)		
P4	0.02	1.15	-0.21	0.78	CTOF
	(0.03)	(0.05)	(0.12)		
P5	0.15	1.02	-0.41	0.55	
	(0.05)	(0.08)	(0.19)		
EWC	0.03	0.55	-0.12	0.56	
	(0.03)	(0.05)	(0.09)		
SPD	0.14	0.84	-0.32	0.54	
	(0.05)	(0.07)	(0.14)		

Note: We present estimates of the time series regressions

$$r_{it}^e = \alpha_i + f_t'\beta_i + \epsilon_{it}, \qquad t = 1, \ldots, T,$$

where r_{it}^e is the excess return of portfolio i at time t, and f_t is a vector of the two risk factors, DOL and DVOL. Estimates of α_i are scaled by 100. The portfolios are P1, P2, P3, P4 and P5 (the portfolios sorted by interest rate) as well as the carry trade portfolios EWC and SPD, described in the main text. Standard errors are reported in parentheses. We use weekly data, from the first week of November 2001 to the fourth week of March 2012.

Table 8: Betas of the Carry Trade Portfolios for the DOL-CTOF Model

	α	β-DOL	β-CTOF	$\bar{R}^2$
P1	-0.05	0.62	-0.65	0.63
	(0.02)	(0.04)	(0.10)	
P2	0.00	0.94	-0.07	0.82
	(0.02)	(0.02)	(0.09)	
P3	0.04	0.91	0.57	0.84
	(0.02)	(0.03)	(0.11)	
P4	0.05	1.12	0.77	0.78
	(0.03)	(0.06)	(0.14)	
P5	0.19	0.98	1.23	0.56
	(0.05)	(0.08)	(0.21)	
EWC	0.06	0.51	0.84	0.60
	(0.03)	(0.05)	(0.12)	
SPD	0.19	0.79	1.27	0.57
	(0.05)	(0.07)	(0.19)	

Note: We present estimates of the time series regressions

$$r_{it}^e = \alpha_i + f_t'\beta_i + \epsilon_{it}, \qquad t = 1, \ldots, T,$$

where r_{it}^e is the excess return of portfolio i at time t, and f_t is a vector of the two risk factors, DOL and CTOF. Estimates of α_i are scaled by 100. The portfolios are P1, P2, P3, P4 and P5 (the portfolios sorted by interest rate) as well as the carry trade portfolios EWC and SPD, described in the main text. Standard errors are reported in parentheses. We use weekly data, from the first week of November 2001 to the fourth week of March 2012.

Table 9: Decomposing the Betas for the DOL-CTOF Model

	r^{f-s}				$r^{\Delta s}$			
	α ($\times 100$)	β-DOL ($\times 100$)	β-CTOF ($\times 100$)	$\bar{R}^2$	α ($\times 100$)	β-DOL	β-CTOF	$\bar{R}^2$
P1	-0.028	0.05	-0.43	-0.002	-0.03	0.62	-0.64	0.64
	(0.002)	(0.09)	(0.43)		(0.02)	(0.04)	(0.10)	
P2	0.001	0.07	-0.17	-0.002	-0.01	0.94	0.06	0.82
	(0.002)	(0.07)	(0.29)		(0.02)	(0.03)	(0.09)	
P3	0.025	0.05	-0.07	-0.003	0.01	0.92	0.58	0.84
	(0.003)	(0.08)	(0.35)		(0.02)	(0.03)	(0.11)	
P4	0.065	0.01	0.24	-0.003	-0.03	1.13	0.76	0.78
	(0.003)	(0.09)	(0.39)		(0.04)	(0.06)	(0.15)	
P5	0.193	0.16	2.18	0.002	-0.01	0.99	1.21	0.56
	(0.008)	(0.26)	(1.23)		(0.06)	(0.09)	(0.21)	

Note: We present estimates of the time series regressions

$$r_{it} = \alpha_i + f_t'\beta_i + \epsilon_{it}, \qquad t = 1, \ldots, T,$$

where r_{it} is, alternately, $r_t^{\mathrm{P}i,f-s}$ or $r_t^{\mathrm{P}i,\Delta s}$ the two components of the excess return of portfolio i at time t, and f_t is the vector of the two risk factors, DOL and CTOF. The portfolios are P1, P2, P3, P4 and P5 (the portfolios sorted by interest rate), described in the main text. Standard errors are reported in parentheses. We use weekly data, from the first week of November 2001 to the fourth week of March 2012.

Table 10: Betas of the Carry Trade Portfolios for Disaggregated Order-Flow Factors

	Asset Managers				Hedge Funds			
	α	β-DOL	β-CTAM	$\bar{R}^2$	α	β-DOL	β-CTHF	$\bar{R}^2$
P1	-0.04	0.61	-1.04	0.64	-0.05	0.59	-1.30	0.65
	(0.02)	(0.04)	(0.20)		(0.02)	(0.04)	(0.18)	
P2	0.00	0.94	-0.29	0.83	0.00	0.93	0.21	0.83
	(0.02)	(0.02)	(0.19)		(0.02)	(0.03)	(0.18)	
P3	0.03	0.93	0.61	0.83	0.03	0.94	0.58	0.83
	(0.02)	(0.03)	(0.16)		(0.02)	(0.03)	(0.19)	
P4	0.03	1.14	1.10	0.78	0.03	1.16	0.90	0.78
	(0.03)	(0.05)	(0.32)		(0.03)	(0.06)	(0.26)	
P5	0.16	1.02	1.17	0.55	0.17	1.05	1.54	0.55
	(0.05)	(0.08)	(0.39)		(0.05)	(0.08)	(0.45)	
EWC	0.05	0.53	1.25	0.60	0.06	0.56	1.45	0.61
	(0.03)	(0.05)	(0.26)		(0.03)	(0.05)	(0.20)	
SPD	0.16	0.83	1.50	0.55	0.17	0.86	1.76	0.55
	(0.05)	(0.07)	(0.35)		(0.05)	(0.07)	(0.33)	

	Corporate				Private Clients			
	α	β-DOL	β-CTCO	$\bar{R}^2$	α	β-DOL	β-CTPC	$\bar{R}^2$
P1	-0.02	0.59	0.60	0.61	-0.03	0.59	2.74	0.66
	(0.02)	(0.04)	(0.44)		(0.02)	(0.03)	(0.34)	
P2	0.00	0.93	0.42	0.83	0.00	0.93	0.17	0.82
	(0.02)	(0.03)	(0.34)		(0.02)	(0.03)	(0.32)	
P3	0.01	0.94	-0.84	0.83	0.02	0.94	-1.14	0.83
	(0.02)	(0.03)	(0.36)		(0.02)	(0.03)	(0.30)	
P4	0.01	1.16	-1.00	0.77	0.02	1.16	-2.34	0.78
	(0.03)	(0.06)	(0.57)		(0.03)	(0.05)	(0.58)	
P5	0.14	1.05	-0.83	0.54	0.15	1.05	-3.31	0.56
	(0.06)	(0.08)	(0.83)		(0.05)	(0.08)	(0.94)	
EWC	0.02	0.56	-1.41	0.57	0.04	0.56	-4.00	0.67
	(0.03)	(0.05)	(0.53)		(0.02)	(0.04)	(0.48)	
SPD	0.13	0.86	-1.34	0.53	0.15	0.86	-4.55	0.58
	(0.05)	(0.07)	(0.68)		(0.05)	(0.06)	(0.76)	

Note: We present estimates of the time series regressions

$$r_{it}^e = \alpha_i + f_t'\beta_i + \epsilon_{it}, \qquad t = 1, \dots, T,$$

where r_{it}^e is the excess return of portfolio i at time t, and f_t is a vector of the two risk factors, DOL and a disaggregated carry-trade order-flow factor (as indicated). Estimates of α_i are scaled by 100. The portfolios are P1, P2, P3, P4 and P5 (the portfolios sorted by interest rate) as well as the carry trade portfolios EWC and SPD, described in the main text. Standard errors are reported in parentheses. Data are weekly.

Table 11: Estimates of the DOL-HML Model

GMM Estimates				
	DOL	HML	R^2	HJ
b	2.87	7.74	0.94	1.10
	(5.04)	(3.68)		[0.78]
λ	0.10	0.22		
	(0.08)	(0.10)		
Fama-MacBeth Estimates				
	DOL	HML	R^2	χ^2
λ	0.10	0.22	0.94	2.70
	(0.05)	(0.07)		[0.61]
KP Rank Tests				
	Stat.	d.f.	p-value	
Rank(0)	234.3	10	[0.00]	
Rank(1)	153.0	4	[0.00]	

Note: We present estimates of the SDF and beta representations of the DOL-HML model, as well as 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). Estimates of λ are scaled by 100. The second panel shows estimates of λ obtained using the Fama-MacBeth method with no intercept. A χ^2 measure of fit is also reported. The third panel reports KP rank tests. In all panels, standard errors are reported in parentheses, and p-values in square brackets. The Shanken correction is used for the Fama-MacBeth standard errors. We use weekly data, from the first week of November 2001 to the fourth week of March 2012.

Table 12: Estimates of the Volatility (DOL-DVOL) Model

GMM Estimates				
	DOL	DVOL	R^2	HJ
b	0.97	-1.03	0.85	1.10
	(6.00)	(0.95)		[0.78]
λ	0.11	-25.7		
	(0.12)	(23.7)		
Fama-MacBeth Estimates				
	DOL	DVOL	R^2	χ^2
λ	0.11	-25.7	0.85	6.43
	(0.06)	(11.2)		[0.17]
KP Rank Tests				
	Stat.	d.f.	p-value	
Rank(0)	381.0	10	[0.00]	
Rank(1)	9.4	4	[0.05]	

Note: We present SDF and beta representation estimates for the DOL-DVOL model, as well as 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). Estimates of λ are scaled by 100. The second panel shows estimates of λ obtained using the Fama-MacBeth method with no intercept. A χ^2 measure of fit is also reported. The third panel reports KP rank tests. In all panels, standard errors are reported in parentheses, and p-values in square brackets. The Shanken correction is used for the Fama-MacBeth standard errors. We use weekly data, from the first week of November 2001 to the fourth week of March 2012.

Table 13: Estimates of the Carry-Trade Order-Flow (DOL-CTOF) Model

GMM Estimates				
	DOL	CTOF	R^2	HJ
b	-0.49	1.44	0.79	5.07
	(5.11)	(0.66)		[0.17]
λ	0.10	8.46		
	(0.07)	(3.71)		
Fama-MacBeth Estimates				
	DOL	CTOF	R^2	χ^2
λ	0.10	8.46	0.79	7.18
	(0.06)	(3.45)		[0.13]
KP Rank Tests				
	Stat.	d.f.	p-value	
Rank(0)	288.7	10	[0.00]	
Rank(1)	43.9	4	[0.00]	

Note: We present SDF and beta representation estimates for the DOL-CTOF model, as well as 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). Estimates of λ are scaled by 100. The second panel shows estimates of λ obtained using the Fama-MacBeth method with no intercept. A χ^2 measure of fit is also reported. The third panel reports KP rank tests. In all panels, standard errors are reported in parentheses, and p-values in square brackets. The Shanken correction is used for the Fama-MacBeth standard errors. We use weekly data, from the first week of November 2001 to the fourth week of March 2012.

Table 14: Estimates of the Disaggregated Order-Flow Model

	(a) Asset Managers				(b) Hedge Funds			
GMM Estimates								
	DOL	CTAM	R^2	HJ	DOL	CTHF	R^2	HJ
b	3.88	1.92	0.66	6.77	7.74	2.60	0.75	5.90
	(4.66)	(1.20)		[0.08]	(3.89)	(1.16)		[0.12]
λ	0.12	5.12			0.11	5.10		
	(0.07)	(3.09)			(0.06)	(2.30)		
Fama-MacBeth Estimates								
	DOL	CTAM	R^2	χ^2	DOL	CTHF	R^2	χ^2
λ	0.12	5.12	0.66	8.64	0.11	5.10	0.75	7.71
	(0.06)	(2.43)		[0.07]	(0.06)	(2.26)		[0.10]
KP Rank Tests								
	Stat.	d.f.	p-value		Stat.	d.f.	p-value	
Rank(0)	254.03	10	[0.00]		244.04	10	[0.00]	
Rank(1)	36.71	4	[0.00]		45.11	4	[0.00]	

	(c) Corporate				(d) Private clients			
GMM Estimates								
	DOL	CTCO	R^2	HJ	DOL	CTPC	R^2	HJ
b	13.31	-12.34	0.55	5.65	7.91	-3.72	0.74	4.06
	(6.43)	(9.61)		[0.13]	(5.05)	(2.27)		[0.25]
λ	0.12	-4.72			0.11	-2.23		
	(0.07)	(3.72)			(0.08)	(1.37)		
Fama-MacBeth Estimates								
	DOL	CTCO	R^2	χ^2	DOL	CTPC	R^2	χ^2
λ	0.12	-4.72	0.55	9.14	0.11	-2.23	0.74	7.84
	(0.06)	(3.30)		[0.06]	(0.06)	(1.01)		[0.10]
KP Rank Tests								
	Stat.	d.f.	p-value		Stat.	d.f.	p-value	
Rank(0)	253.6	10	[0.00]		260.4	10	[0.00]	
Rank(1)	7.12	4	[0.13]		24.6	4	[0.00]	

Note: We present SDF and beta representation estimates for the carry-trade order flow model using disaggregated order flow for different customer groups, as well as KP reduced-rank tests. CTAM is the order flow factor for Asset Managers. CTHF is the order flow factor for Hedge Funds. CTCO is the order flow factor for Corporate customers. CTPC is the order flow factor for Private Clients. See the note to Table 13 for other details.

Table 15: Factor-Mimicking Portfolios

	Factor-Mimicking Portfolio Weights					Mean Return
	P1	P2	P3	P4	P5	(%)
DVOL	5.89	5.16	-4.29	-4.15	-4.51	-79.0
CTOF	-7.06***	-1.56	6.70***	2.11	1.74*	58.4
CTAM	-5.55***	-1.68*	3.57***	3.07***	-0.30	21.8
CTHF	-6.43***	0.94	1.69	0.49	0.52	14.7
CTCO	0.71*	0.79**	-0.63	-0.25	0.13	1.3
CTPC	3.88***	0.31	-0.99**	-1.04**	-0.24	-8.6

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

	DVOL			SKEWNESS		
	Intercept ($\times$100)	β	$\bar{R}^2$	Intercept ($\times$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 17: 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 18: Betas of the Momentum Portfolios for the DOL-MOOF Model

	α	β-DOL	β-MOOF	$\bar{R}^2$
M1	-0.03	0.95	-0.70	0.64
	(0.04)	(0.06)	(0.17)	
M2	0.02	1.00	-0.17	0.78
	(0.03)	(0.05)	(0.12)	
M3	0.00	0.96	0.01	0.81
	(0.03)	(0.03)	(0.11)	
M4	0.04	0.91	0.30	0.76
	(0.03)	(0.02)	(0.11)	
M5	0.11	0.83	0.72	0.56
	(0.04)	(0.05)	(0.17)	

Note: We present estimates of the time series regressions

$$r_{it}^e = \alpha_i + f_t' \beta_i + \epsilon_{it}, \qquad t = 1, \ldots, T,$$

where r_{it}^e is the excess return of portfolio i at time t, and f_t is a vector of the two risk factors, DOL and MOOF. Estimates of α_i are scaled by 100. The portfolios are M1, M2, M3, M4 and M5 (the portfolios sorted by momentum), described in the main text. Standard errors are reported in parentheses. We use weekly data, from the first week of November 2001 to the fourth week of March 2012.

Table 19: Betas of the Momentum Portfolios for Disaggregated Order-Flow Factors

	Asset Managers				Hedge Funds			
	α	β-DOL	β-MOAM	$\bar{R}^2$	α	β-DOL	β-MOHF	$\bar{R}^2$
M1	-0.02	0.95	-0.98	0.63	-0.06	0.96	-1.56	0.65
	(0.04)	(0.06)	(0.34)		(0.04)	(0.06)	(0.35)	
M2	0.02	1.00	-0.27	0.78	0.01	1.00	-0.51	0.78
	(0.03)	(0.05)	(0.22)		(0.03)	(0.05)	(0.26)	
M3	-0.01	0.97	0.20	0.81	0.00	0.96	0.21	0.81
	(0.03)	(0.03)	(0.18)		(0.03)	(0.03)	(0.14)	
M4	0.05	0.90	0.08	0.75	0.06	0.90	0.84	0.76
	(0.03)	(0.02)	(0.17)		(0.03)	(0.02)	(0.17)	
M5	0.11	0.83	0.60	0.55	0.13	0.82	0.94	0.56
	(0.04)	(0.05)	(0.25)		(0.04)	(0.05)	(0.29)	
	Corporate				Private Clients			
	α	β-DOL	β-MOCO	$\bar{R}^2$	α	β-DOL	β-MOPC	$\bar{R}^2$
M1	-0.04	0.96	1.87	0.63	-0.06	0.96	3.38	0.66
	(0.04)	(0.07)	(0.62)		(0.04)	(0.06)	(0.57)	
M2	0.02	1.00	0.56	0.78	0.01	1.00	1.00	0.79
	(0.03)	(0.05)	(0.45)		(0.03)	(0.05)	(0.42)	
M3	-0.01	0.96	-0.62	0.81	-0.01	0.96	0.22	0.81
	(0.03)	(0.03)	(0.41)		(0.03)	(0.03)	(0.34)	
M4	0.04	0.90	-1.05	0.76	0.06	0.90	-1.41	0.76
	(0.03)	(0.02)	(0.38)		(0.03)	(0.02)	(0.41)	
M5	0.12	0.82	-0.71	0.55	0.13	0.82	-2.12	0.56
	(0.04)	(0.05)	(0.54)		(0.04)	(0.05)	(0.54)	

Note: We present estimates of the time series regressions

$$r_{it}^e = \alpha_i + f_t'\beta_i + \epsilon_{it}, \qquad t = 1, \ldots, T,$$

where r_{it}^e is the excess return of portfolio i at time t, and f_t is a vector of the two risk factors, DOL and a disaggregated momentum order-flow factor (as indicated). Estimates of α_i are scaled by 100. The portfolios are M1, M2, M3, M4 and M5 (the portfolios sorted by momentum), described in the main text. Standard errors are reported in parentheses. Data are weekly.

Table 20: Estimates of the Momentum Order-Flow (DOL-MOOF) Model

GMM Estimates				
	DOL	MOOF	R^2	HJ
b	10.63	1.81	0.87	2.08
	(4.37)	(0.78)		[0.56]
λ	0.13	11.29		
	(0.07)	(4.91)		
Fama-MacBeth Estimates				
	DOL	MOOF	R^2	χ^2
λ	0.13	11.29	0.87	1.95
	(0.06)	(4.82)		[0.74]
KP Rank Tests				
	Stat.	d.f.	p-value	
Rank(0)	134.3	10	[0.00]	
Rank(1)	18.7	4	[0.00]	

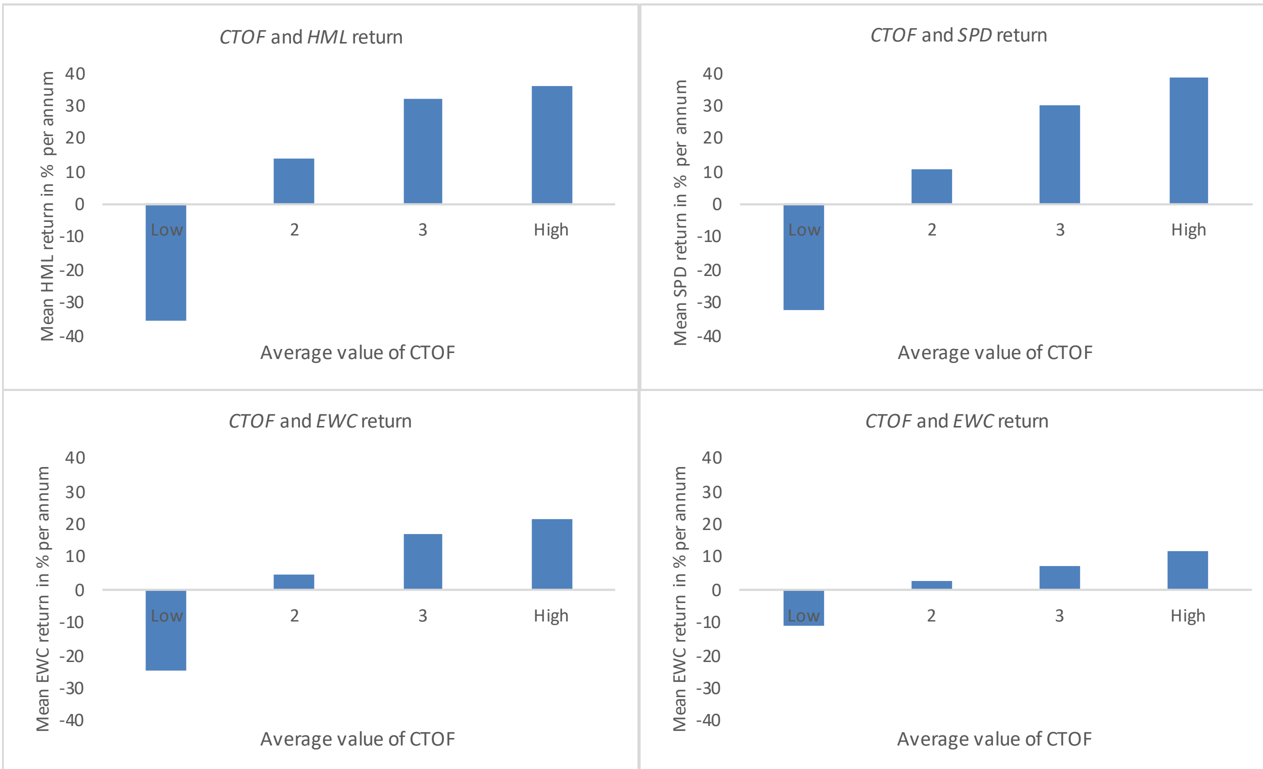
Note: We present SDF and beta representation estimates for the DOL-MOOF model, as well as KP reduced-rank tests. The test assets are M1–M5, the five portfolios sorted on four weeks of lagged currency returns. See the note to Table 13 for other details.

Table 21: Estimates of the Disaggregated Momentum Order-Flow Model

	(a) Asset Managers				(b) Hedge Funds			
GMM Estimates								
	DOL	CTAM	R^2	HJ	DOL	CTHF	R^2	HJ
b	13.26	3.42	0.61	5.09	8.47	2.42	0.60	4.22
	(5.18)	(1.55)		[0.17]	(4.24)	(1.21)		[0.24]
λ	0.14	8.90			0.13	5.11		
	(0.06)	(4.10)			(0.07)	(2.54)		
Fama-MacBeth Estimates								
	DOL	CTAM	R^2	χ^2	DOL	CTHF	R^2	χ^2
λ	0.14	8.90	0.61	5.77	0.13	5.11	0.60	4.79
	(0.06)	(4.36)		[0.22]	(0.06)	(2.32)		[0.31]
KP Rank Tests								
	Stat.	d.f.	p-value		Stat.	d.f.	p-value	
Rank(0)	206.3	100	[0.00]		123.8	10	[0.00]	
Rank(1)	8.70	4	[0.07]		21.5	4	[0.00]	
	(c) Corporate				**(d) Private clients**			
GMM Estimates								
	DOL	CTCO	R^2	HJ	DOL	CTPC	R^2	HJ
b	7.36	-8.55	0.32	5.94	9.01	-3.88	0.76	3.03
	(4.63)	(4.83)		[0.11]	(4.19)	(1.75)		[0.39]
λ	0.13	-3.67			0.14	-2.68		
	(0.07)	(2.07)			(0.07)	(1.21)		
Fama-MacBeth Estimates								
	DOL	CTCO	R^2	χ^2	DOL	CTPC	R^2	χ^2
λ	0.13	-3.67	0.32	7.33	0.14	-2.68	0.76	2.91
	(0.06)	(2.07)		[0.12]	(0.06)	(1.12)		[0.57]
KP Rank Tests								
	Stat.	d.f.	p-value		Stat.	d.f.	p-value	
Rank(0)	127.8	10	[0.00]		154.6	10	[0.00]	
Rank(1)	15.8	4	[0.00]		39.7	4	[0.00]	

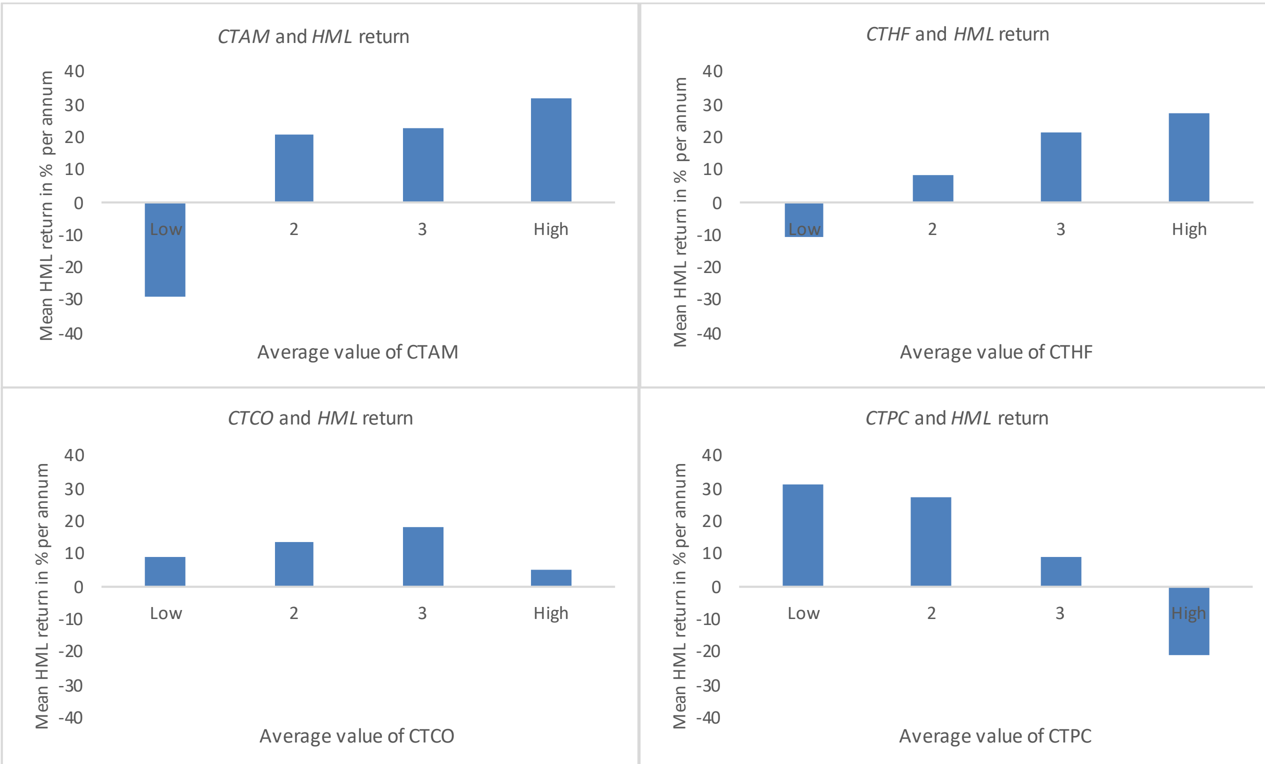
Note: We present SDF and beta representation estimates for the momentum order flow model using disaggregated order flow for different customer groups, as well as KP reduced-rank tests. MOAM is the momentum order flow factor for Asset Managers. MOHF is the momentum order flow factor for Hedge Funds. MOCO is the momentum order flow factor for Corporate customers. MOPC is the momentum order flow factor for Private Clients. See the note to Table 13 for other details.

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



Note: This figure shows mean annualized 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).

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



Note: This figure shows mean annualized 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.

Appendix

Data

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 A6: Exposures of the Carry Trade Portfolios to the DOL and HML Factors

Subsample	2001M11–2007M10				2007M11–2012M3			
	α	β-DOL	β-HML	$\bar{R}^2$	α	β-DOL	β-HML	$\bar{R}^2$
P1	-0.01	0.72	-0.23	0.83	0.03	0.71	-0.28	0.76
	(0.03)	(0.03)	(0.02)		(0.03)	(0.04)	(0.03)	
P2	0.03	0.96	0.01	0.86	-0.05	0.91	0.00	0.80
	(0.03)	(0.03)	(0.02)		(0.04)	(0.04)	(0.03)	
P3	0.06	0.76	0.05	0.81	-0.04	0.99	0.10	0.88
	(0.02)	(0.02)	(0.02)		(0.04)	(0.03)	(0.03)	
P4	-0.01	0.95	0.15	0.80	0.01	1.05	0.35	0.87
	(0.03)	(0.03)	(0.03)		(0.06)	(0.05)	(0.06)	
P5	-0.01	0.73	0.77	0.92	0.03	0.71	0.72	0.95
	(0.03)	(0.03)	(0.02)		(0.03)	(0.04)	(0.03)	
EWC	0.00	0.27	0.27	0.63	-0.02	0.52	0.30	0.92
	(0.02)	(0.05)	(0.03)		(0.02)	(0.03)	(0.02)	
SPD	0.08	0.44	0.56	0.72	0.01	0.74	0.52	0.96
	(0.04)	(0.04)	(0.04)		(0.03)	(0.03)	(0.03)	

Note: We present estimates of the time series regressions

$$r^e_{it} = \alpha_i + f'_t\beta_i + \epsilon_{it}, \qquad t = 1, \ldots, T,$$

where r^e_{it} is the excess return of portfolio i at time t, and f_t is a vector of the two risk factors, DOL and HML. Estimates of α_i are scaled by 100. The portfolios are P1, P2, P3, P4 and P5 (the portfolios sorted by interest rate) as well as the carry trade portfolios EWC and SPD, described in the main text. Standard errors are reported in parentheses. Data are weekly.

Table A7: Exposures of the Carry Trade Portfolios to the DOL and DVOL Factors

Subsample	2001M11–2007M10				2007M11–2012M3			
	α	β-DOL	β-DVOL	$\bar{R}^2$	α	β-DOL	β-DVOL	$\bar{R}^2$
P1	-0.06	0.72	0.38	0.74	0.01	0.52	0.09	0.53
	(0.03)	(0.05)	(0.11)		(0.04)	(0.05)	(0.07)	
P2	0.03	0.96	-0.01	0.86	-0.07	0.92	0.18	0.81
	(0.03)	(0.03)	(0.08)		(0.04)	(0.04)	(0.12)	
P3	0.08	0.76	0.01	0.80	-0.02	1.06	-0.09	0.87
	(0.02)	(0.03)	(0.07)		(0.04)	(0.04)	(0.09)	
P4	0.03	0.96	-0.12	0.78	0.05	1.28	-0.25	0.80
	(0.03)	(0.03)	(0.12)		(0.06)	(0.07)	(0.14)	
P5	0.20	0.76	-0.69	0.42	0.08	1.21	-0.25	0.65
	(0.07)	(0.06)	(0.22)		(0.07)	(0.10)	(0.22)	
EWC	0.08	0.28	-0.22	0.30	0.00	0.74	-0.05	0.75
	(0.03)	(0.06)	(0.07)		(0.03)	(0.05)	(0.07)	
SPD	0.24	0.47	-0.47	0.27	0.05	1.10	-0.19	0.74
	(0.06)	(0.06)	(0.14)		(0.05)	(0.07)	(0.13)	

Note: We present estimates of the time series regressions

$$r^e_{it} = \alpha_i + f_t'\beta_i + \epsilon_{it}, \qquad t = 1, \ldots, T,$$

where r^e_{it} is the excess return of portfolio i at time t, and f_t is a vector of the two risk factors, DOL and DVOL. Estimates of α_i are scaled by 100. The portfolios are P1, P2, P3, P4 and P5 (the portfolios sorted by interest rate) as well as the carry trade portfolios EWC and SPD, described in the main text. Standard errors are reported in parentheses. Data are weekly.

Table A8: Exposures of the Carry Trade Portfolios to the DOL and CTOF Factors

Subsample	2001M11–2007M10				2007M11–2012M3			
	α	β-DOL	β-CTOF	$\bar{R}^2$	α	β-DOL	β-CTOF	$\bar{R}^2$
P1	-0.10	0.71	-0.62	0.73	0.00	0.55	-0.54	0.56
	(0.03)	(0.05)	(0.21)		(0.04)	(0.05)	(0.12)	
P2	0.03	0.96	-0.07	0.86	-0.05	0.91	-0.04	0.80
	(0.02)	(0.03)	(0.15)		(0.04)	(0.04)	(0.11)	
P3	0.09	0.76	0.23	0.80	-0.01	1.03	0.50	0.87
	(0.02)	(0.02)	(0.14)		(0.04)	(0.04)	(0.15)	
P4	0.05	0.96	0.33	0.78	0.06	1.24	0.74	0.80
	(0.03)	(0.03)	(0.14)		(0.06)	(0.08)	(0.20)	
P5	0.26	0.78	0.49	0.39	0.11	1.13	1.24	0.67
	(0.06)	(0.07)	(0.35)		(0.08)	(0.12)	(0.28)	
EWC	0.11	0.29	0.53	0.30	0.02	0.69	0.67	0.78
	(0.03)	(0.06)	(0.20)		(0.03)	(0.05)	(0.12)	
SPD	0.29	0.48	0.67	0.26	0.08	1.03	1.10	0.76
	(0.06)	(0.06)	(0.29)		(0.05)	(0.08)	(0.22)	

Note: We present estimates of the time series regressions

$$r_{it}^e = \alpha_i + f_t'\beta_i + \epsilon_{it}, \qquad t = 1, \ldots, T,$$

where r_{it}^e is the excess return of portfolio i at time t, and f_t is a vector of the two risk factors, DOL and CTOF. Estimates of α_i are scaled by 100. The portfolios are P1, P2, P3, P4 and P5 (the portfolios sorted by interest rate) as well as the carry trade portfolios EWC and SPD, described in the main text. Standard errors are reported in parentheses. Data are weekly.