# Foreign Exchange Order Flow as a Risk Factor

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**Abstract**

We propose a novel pricing factor for currency returns motivated by the market-microstructure literature. Our factor aggregates order flow data to provide a measure of buying and selling pressure related to conventional currency trading strategies. It successfully prices the cross-section of currency returns sorted on the basis of forward discount and momentum. The association between our factor 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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# I. Introduction

Motivated by the market microstructure literature, we construct a reduced-form stochastic discount factor (SDF) model that explains the returns to popular currency trading strategies. Our model is based on customer order-flow data from one of the largest dealer banks in the foreign exchange market. The risk factor that we consider takes on more positive values when order flow, aggregated across currencies, indicates that customers are buying currencies favored by carry trade and momentum signals, and selling currencies disfavored by these signals. When this factor takes on more negative values, it indicates that customers are reversing or unwinding these trades. Our model successfully prices the cross-section of currency portfolios sorted by forward discount and momentum. This reflects the positive (negative) correlation between our factor and the returns to portfolios of currencies with positive (negative) forward discounts, with the same pattern prevailing for positive (negative) momentum-based portfolios. A plausible interpretation of our findings, consistent with the market microstructure literature, is that when customers receive information that, in the aggregate, encourages them to take larger speculative positions in favor of currencies with large forward discounts and strong momentum, this causes these currencies to appreciate. When the arriving information causes them to reverse these positions, these currencies depreciate.

For those currencies with greater market share, we have access to order-flow classified according to customer type. These data indicate that the behavior of aggregate order flow is dominated by that of financial customers (hedge funds and asset managers), and that there are systematic differences in how the order flow of financial customers and nonfinancial customers (corporate and private clients) relate to currency returns. When the order flow of financial customers leans more towards taking carry trade or momentum positions, these investment strategies tend to do well. But we see the opposite pattern for nonfinancial 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 between dealers). This may reflect that there are underlying shocks that drive exchange rate dynamics, and to which financial and nonfinancial customers have different ex-ante exposure.

Our work is closely related to the empirical microstructure literature that focuses on the relationship between order flow and bilateral exchange rates.[1] Like Lyons (2001) and Evans and Lyons (2002), we show that order flow can explain a large part of exchange rate variation, as well as, by extension, currency excess returns. They argue that this is because order flow maps a significant part of customers' private information into price discovery. The evidence we find is consistent with Evans and Lyons (2006), who show that there are significant differences, across customer segments, between the estimated price-impacts of order flow. Relatedly, Menkhoff, Sarno, Schmeling, and Schrimpf (2016) show that financial customer order flow contains information that has a long-term impact on currency returns, and that financial and nonfinancial customers trade in opposite directions, thus providing evidence of risk sharing taking place in the customer market. Ranaldo and Somogyi (2021) also document heterogeneity across customer segments.

Taking inspiration from this literature, we measure buying and selling pressure in the

[1] See Sarno and Taylor (2001), Osler (2009), Evans (2011), Evans and Rime (2012), Evans and Rime (2019) for comprehensive overviews.

foreign exchange market, but do so by aggregating order flow (vis-a-vis the U.S. dollar) across currencies using standard trading signals for carry trade and momentum strategies. To illustrate, when we study the carry trade in isolation, our measure of aggregate order flow sums the value of buy orders for positive forward discount currencies and the value of sell orders for negative forward discount currencies, having normalized the measures of order flow to the scale of the market for each currency. When the value of this aggregate increases, we interpret this as customers, in general, favoring trades in the direction that carry-trade investing would predict. When the value of this factor decreases, we interpret this as customers reversing or unwinding these positions. We take a similar approach when studying momentum strategies in isolation. In this case, we aggregate the same order flow data but sign order flow based on a momentum signal. Then we combine our two measures by averaging them. This provides us a measure of the extent to which trading, in general, favors standard speculative strategies (or disfavors them). We find that this single measure of aggregated order flow is able to price the cross-section of currency portfolios sorted on the basis of forward discount and momentum.

Our findings are also related to a relatively new literature emphasizing the role of different market participants' asset holdings in determining asset prices. For example, Koijen and Yogo (2019) introduce a model in which different investors (say, institutions versus households) have different optimal portfolios because they have different beliefs. He and Krishnamurthy (2013) introduce an "intermediary" asset pricing model in which the marginal investor is a financial intermediary facing a capital constraint. When the constraint binds risk premia increase. He, Kelly, and Manela (2017) use this model to demonstrate that shocks to the equity capital ratio of intermediaries, as reflected in a novel equity-capital factor, can explain cross-sectional variation in expected returns across a number of asset classes. There is good reason to believe these findings are relevant to the foreign exchange market, which is an over-the-counter market dominated by a relatively small number of large dealers. At the same time, it isn't entirely clear which entities should be regarded as "intermediaries" in this market. As we show, order flow on the demand side of the market is dominated by asset managers and hedge funds who could also be regarded as intermediaries. We do not have a direct measure of equity capital for dealers in the foreign exchange market, nor for the large players on the demand side. However, we show that our novel order flow factor and the estimated SDF based on it are significantly associated with the weekly average of the daily version of He et al.'s factor (which is based on the equity capital ratios of large broker-dealers in financial markets in general). This is especially true in the period after 2007, which is perhaps not surprising given the substantial increase in balance sheet costs for dealers since the onset of the Global Financial Crisis. More generally, our empirical findings suggest that the order flow of financial customers is particular relevant.

A closely related empirical literature uses SDF models to explain currency returns.[2] Villanueva (2007), Burnside, Eichenbaum, and Rebelo (2011b), Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011a), and Burnside (2012) establish that traditional risk factors used to price equities do not correctly price carry trade and momentum portfolios. On the other hand, SDFs based on risk factors derived from currency-specific data have been reasonably successful in pricing portfolios of currencies. For example, Lustig, Roussanov, and Verdelhan (2011) use a "high-minus-low" carry trade portfolio to price a set of currency portfolios sorted by forward discount. Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) use a measure of global currency volatility to price these same portfolios,

[2]Burnside (2012) and Lustig and Verdelhan (2012) review the early literature.

as well as momentum portfolios. In our sample, our model appears to perform better than either of these traditional models in that it is able to price both the forward-discount-sorted and momentum-sorted portfolios, and our order-flow factor is robustly significant.

Another branch of the literature emphasizes the reversal of standard trading strategies. Galati, Heath, and McGuire (2007) find that excess returns to carry trades tend to reverse under market stress. They provide evidence from international banking data that currency flows are associated with these reversals. Brunnermeier, Nagel, and Pedersen (2008) 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 positions gradually, but liquidate their positions quickly, causing investment currencies to depreciate. In this paper, we generalize these ideas by extending them to the cross-section of currency returns, and we provide a natural empirical measure of trading pressure in the foreign exchange market. We find an association between signed order flow and currency returns that is broadly consistent with notions of trading reversals.

# II. 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. Let $F_{k,t}$ be the one period forward exchange rate between the same currencies. Define $s_{k,t} = \ln S_t$ and $f_{k,t} = \ln F_{k,t}$. Up to a log approximation, the net return to using one dollar to buy $F_{k,t}$ FCUs forward and then exchanging them for $F_{k,t}/S_{k,t+1}$ dollars in the next period's spot market is

(1) $$r_{k,t+1} = f_{k,t} - s_{k,t+1}.$$

If the forward rate unbiasedness (FRU) condition holds, up to a log approximation,

(2) $$E_t s_{k,t+1} = f_{k,t},$$

where $E_t$ is the expectations operator given information available at time $t$. In this case, of course, $E_t r_{k,t+1} = 0$.

Carry trade strategies generally involve systematically managing a portfolio in which an investor buys forward currencies for which $f_{k,t} - s_{k,t}$ is positive (or the most positive) and sells forward currencies for which $f_{k,t} - s_{k,t}$ is negative (or the most negative). Under FRU we would not expect this strategy to be profitable. However, the empirical failure of the FRU condition is well-documented.[3] In fact, it is widely understood that nominal exchange rates are well approximated, empirically, as random walks; i.e. $E_t s_{k,t+1} \approx s_{k,t}$.[4] When this is true

(3) $$E_t r_{k,t+1} = f_{k,t} - s_{k,t}.$$

This fact provides motivation for carry trade strategies because it suggests that by systematically

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

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

buying currencies at a forward discount, and selling currencies at a forward premium, the investor can expect to earn positive profits.[5]

## A. Carry Trade Portfolios

We base our empirical work on currency portfolios studied in the previous literature. Following Lustig et al. (2011), at each date $t$, we allocate the available currencies into five portfolios, sorted on the basis of the forward discount. These portfolios are labeled C1, C2, C3, C4 and C5, with C1 corresponding to the currencies with the lowest values of $f_{k,t} - s_{k,t}$, and C5 containing those currencies with the highest values of $f_{k,t} - s_{k,t}$. We can think of each portfolio as holding an equally weighted long position in its constituent currencies financed by borrowing dollars. Hence, the log return of the $i$th portfolio is

$$r_{t+1}^{\mathrm{C}i} = \sum_{k \in \mathcal{K}_{i,t}} \frac{1}{N_{i,t}} (f_{k,t} - s_{k,t+1}) = \sum_{k \in \mathcal{K}_{i,t}} \frac{1}{N_{i,t}} r_{k,t+1}, \tag{4}$$

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

Lustig et al. (2011) use C1–C5 to construct two additional portfolios: the DOL portfolio and the HMLC portfolio. Their version of the DOL portfolio is an equally weighted average of the C1 through C5 portfolios. By contrast, we construct DOL as the equal weighted average of the

[5]Given that we quote exchange rates as FCUs per USD, $f_{k,t} - s_{k,t}$ measures the size of the forward discount of the foreign currency. Given our notational choice, the forward premium of the foreign currency is $s_{k,t} - f_{k,t}$.

currency excess returns for nine of the G10 currencies:[6]

(5)
$$r_{t+1}^{\mathrm{DOL}} = \frac{1}{9} \sum_{k \in \{\mathrm{G10}\}} r_{k,t+1}.$$

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 HMLC portfolio is a standard "high-minus-low" portfolio which takes a long position in the C5 portfolio and a short position in the C1 portfolio. In this sense, it can be thought of as a carry-trade portfolio that takes long positions in the currencies with the largest forward discounts, and short positions in the currencies with the smallest (or most negative) forward discounts. Its return is

(6)
$$r_{t+1}^{\mathrm{HMLC}} = r_{t+1}^{\mathrm{C5}} - r_{t+1}^{\mathrm{C1}}.$$

[Insert Table 1 approximately here]

For the 2001–12 period, we form the C1–C5, HMLC and DOL portfolios using data for a set of 20 of the most liquid currencies according to trading volume.[7] The portfolios are formed on a weekly basis, each with a holding period of one week. Descriptive statistics are summarized in

[6] The USD is left out as it is the base currency in our analysis. Details regarding the other currencies can be found in our appendix.

[7] The currencies in our data set are detailed in the appendix. We observe the exchange rates from the first week of November 2001 to the fourth week of March 2012.

Table 1, with returns being expressed in percentage points per annum. Table 1 shows the mean return, standard deviation, skewness, kurtosis, Sharpe ratio, and the first order autocorrelation coefficient of the returns. We also report two coskewness measures, described in the appendix, relative to the returns to the DOL portfolio. Portfolios with higher coskewness earn higher returns when global volatility is high. Thus, greater coskewness is often interpreted as making a portfolio more effective as a hedge against global volatility.

As Table 1 shows, the mean returns monotonically increase from portfolio C1 to portfolio C5 with the lowest return being 1.4% (on an annual basis) and the highest being 12.6%. 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 C1 to C5, but it does not rise in proportion to the expected return, so the Sharpe ratios also increase from C1 to C5. The HMLC portfolio (equivalent to C5-C1) has a large mean return (11.6%), and Sharpe ratio (0.99). The returns of all of the portfolios are negatively skewed, indicating the possibility of large negative realizations. However, for portfolio C1 the skewness coefficient is approximately zero, suggesting that it is less subject to large losses.

## B. Momentum Portfolios

As documented by Burnside et al. (2011b), 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.

Similar to our approach for the carry trade, we form five momentum portfolios (M1, M2, M3, M4 and M5) based on the average value of each currency's log return over the previous four weeks. Portfolio M1 contains the currencies with the smallest lagged returns and portfolio M5 has the currencies with the largest lagged returns. In this regard, our portfolios are similar to those studied by Burnside et al. (2011b), Menkhoff et al. (2012b), Fan, Londono, and Xiao (2022), and Zhang (2022), which are formed on the basis of the previous month's return. However, in our case, investors reshuffle their positions each week, rather than each month. We also consider a "high-minus-low" momentum portfolio that we denote as HMLM. Its return is equal to the return on the M5 portfolios minus the return on the M1 portfolio.

Table 1 provides a variety of summary statistics for these portfolios. The mean returns increase from portfolio M1 to portfolio M5 with the lowest return being 2.9% (on an annual basis) and the highest being 10.7%, although the pattern is not quite monotonic (portfolio M3 being the outlier). Consistent with the prior literature, we find that a strategy of holding the HMLM portfolio was profitable in historical data, with a large mean return (7.9%) and Sharpe ratio (0.75).

## C. Order Flow and Exchange Rates

We also form portfolios based on order flow data. 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.[8] Let $x_{k,t+1}$ 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

[8]The appendix provides further details of our data set.

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.

[Insert Table 2 approximately here]

In Table 2 we present estimates of the following equation for each currency:

$$s_{k,t+1} - s_{k,t} = a_k + x_{k,t+1} b_k + u_{k,t+1}, \tag{7}$$

where $u_{k,t+1}$ is an error term, and $k$ indexes the currencies. Given that we measure exchange rates in FCUs per USD, and $x_{k,t+1}$ measures net buy orders of the foreign currency, we expect negative estimates of $b_k$. In fact, this is what we see in Table 2, with $b_k$ being negative 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. Order flow being significant at the weekly horizon mirrors the findings of Menkhoff et al. (2016), who demonstrate the predictive power of order flow over several days. It also reflects the results of several studies using longer-than-daily sampling frequencies that are surveyed by King, Osler, and Rime (2013).

## D. Order Flow Portfolios

Order flow is not easily compared across currencies, due to heterogeneity in the volume of trade. To make such comparisons, we adjust currency $k$'s order flow at time $t+1$ using the standard deviation of the order flow of currency $k$. To do this, we recursively define the sample variance of currency $k$'s order flow as

(8) $$\hat{\sigma}^2_{k,t} = \frac{1}{t}\sum_{s=1}^{t}(x_{k,s} - \bar{x}_{k,t})^2 \quad \text{with} \quad \bar{x}_{k,t} = \frac{1}{t}\sum_{s=1}^{t} x_{k,s}.$$

Then we define adjusted order flow as

(9) $$y_{k,t+1} = \frac{x_{k,t+1}}{\hat{\sigma}_{k,t}}.$$

We have found our results to be qualitatively robust to using a rolling-window definition of the standard deviation, as well as the full-sample standard deviation.

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 at time $t-1$ 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.

[Insert Table 3 approximately here]

Table 3 shows summary statistics for these portfolios. There is a clear monotonically increasing pattern in the average returns and Sharpe ratios across the O1–O5 portfolios. Unlike the interest rate sorted portfolios, C1–C5, 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 1. The BMS portfolio earns a large positive average return, with a very large Sharpe ratio. These results confirm the notion that contemporaneous order flow is strongly positively correlated with exchange rate changes and currency returns.

Cerrato, Sarantis, and Saunders (2011) argue that order flows from different segments of the customer market reflect the different information available to each segment, as well as their different motivations for trade. It is easy to imagine, for example, that leveraged hedge funds and corporate customers participate in the market for different reasons. To investigate whether there are systematic differences in the relationship between order flow and returns across customer-type we use data on order flow that are disaggregated into four categories: Asset Manager (AM), Hedge Fund (HF), Corporate (CO), and Private Client (PC). However, these data are only available for the nine G10 currencies, so we sort the currencies into four portfolios based on the magnitude of order flow in each of the customer segments. These results are reported in Table 4. For asset managers and hedge funds—referred to here as financial customers—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 and private clients—referred to here as nonfinancial customers—the pattern is reversed, and sharply so for the latter category. The portfolios with the most buying pressure from nonfinancial customers earn negative returns, while the ones with the most selling pressure earn positive returns. Cerrato et al. (2011) show that these nonfinancial customers tend to act as liquidity providers. The evidence in Table 4 seems consistent with this view, in that currencies being bought by financial customers do better, while the opposite is true for nonfinancial customers.

[Insert Table 4 approximately here]

Next, we compare the informational content of order flow with that of forward discounts 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.[9] In both cases, the implication is that volatility has an association with the riskiness of, and return to, holding different currencies and currency portfolios. We believe that the apparent importance of volatility is strongly linked to order flow and that, in fact, order flow contains the relevant information to price the returns of carry trade and momentum portfolios.

[Insert Table 5 approximately here]

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 5 and 6. In Table 5, we first sort our currencies into three portfolios based on their forward discounts. Thereafter, within each portfolio, we sort currencies into two bins based on the magnitude of order flow.[10] The main conclusion of Table 5 is that even after conditioning on the forward discount (i.e., choosing a column in the table), buying a portfolio with the highest buying pressure (high order flow) and

[9]We measure the idiosyncratic volatility innovation of a currency following the method used by Menkhoff et al. (2012a) to construct their risk factor, DVOL. For each week, and each currency, we average the absolute daily spot rate changes to proxy for the volatility of that currency in that week. We then model the volatility time series of each currency as an AR(1) process and take the residual term from the model as a proxy for the idiosyncratic volatility innovation of that currency.

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

selling a portfolio with the highest selling pressure (low order flow), gives a positive and statistically significant return. In other words, taking forward discounts into account does not drive out order flow as an important apparent determinant of currency returns.

[Insert Table 6 approximately here]

In Table 6, 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 conditioning on the idiosyncratic volatility innovations (i.e., choosing a column in the table), 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.

# III. Order-Flow Factors

The empirical results presented in Tables 3—6 suggest that order flow contains significant information that could be relevant for pricing the returns to currency portfolios. In this section, we propose novel pricing factors based on order flow that are motivated by microstructure models and the prevalence of carry and momentum trading in foreign exchange markets.

## A. A Carry-Trade Order-Flow Factor

Our first factor is an aggregate order flow measure motivated by carry-trading considerations. This factor, which we denote as CO, is defined as

$$\mathrm{CO}_{t+1} = \frac{1}{N_t} \sum_{k \in N_t} y_{k,t+1} \cdot \mathrm{sign}(f_{kt} - s_{kt}), \tag{10}$$

where $N_t$ denotes the total number of foreign currencies in the available data. If investors build portfolios based on carry-trade considerations, we might expect $y_{k,t+1}$ to be positive for currencies for which $f_{kt} - s_{kt}$ is positive, and negative for currencies for which $f_{kt} - s_{kt}$ is negative.[11] Thus, we would expect CO to generally be positive.[12] But $y_{k,t+1}$ 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 CO to be especially high. On the other hand, if news arrives that induces investors to cash out their carry trade positions, CO will fall, and possibly even turn negative. In a sense, therefore, CO can be interpreted as a factor that measures the degree of sentiment in favor of carry trading as reflected in customer order flow.

## B. A Momentum Order-Flow Factor

Our second factor is an aggregate order flow measure motivated by momentum-trading considerations. This factor, which we denote as MO, is defined as

$$\text{MO}_{t+1} = \frac{1}{N_t} \sum_{k \in N_t} y_{k,t+1} \cdot \text{sign}(\bar{r}_{4t}), \tag{11}$$

[11] Breedon, Rime, and Vitale (2016) show that there is a strong relationship between order flow data and currency forward discounts.

[12] This intuition is based on the notion that investors form carry-trade portfolios from the perspective of a US investor, going long (short) those currencies at a forward discount vis-a-vis the USD. If, instead, investors form these portfolios from a dollar-neutral perspective, the relevant signal variable might reflect the size of the forward discount relative to the median in the sample of currencies.

where

$$\bar{r}_{kt}^{4} = r_{kt} + r_{kt-1} + r_{kt-2} + r_{kt-3}. \quad (12)$$

If investors build portfolios based on momentum considerations, we might expect $y_{k,t+1}$ to be positive for currencies for which $\bar{r}_{kt}^{4}$ is positive, and negative for currencies for which $\bar{r}_{kt}^{4}$ is negative. Thus, like CO, we would expect MO to generally be positive.[13] If arriving news is favorable to momentum trades, we would expect MO to be especially high. On the other hand, if news arrives that induces investors to cash out their momentum positions, MO will fall, and possibly even turn negative. In a sense, therefore, MO can be interpreted as a factor that measures the degree of sentiment in favor of momentum trading as reflected in customer order flow.

## C. An Overall Currency Speculation Factor

Our third factor is motivated by the following discussion. Suppose that at time $t$, currency $k$ is at a forward discount, and has positive momentum. This means that $y_{k,t+1}$ is counted positively in the construction of CO and MO, and contributes the same amount to both measures. If we then observed that $y_{k,t+1}$ was large and positive, it would suggest that, for whatever reason, customers are increasing traditional speculative positions in currency $k$, in general. If we observed that $y_{k,t+1}$ was large and negative, it would suggest that customers are reversing traditional

[13] As for carry, this intuition is based on the notion that investors form momentum portfolios from the perspective of a US investor, going long (short) those currencies which have positive (negative) momentum versus the USD.

speculative positions in currency $k$, in general. A similar interpretation is possible when the forward discount and momentum signals are both negative.

If the carry and momentum signals take on different signs, however, it is difficult to assign the same meaning to the value of $y_{k,t+1}$. Suppose, for example, that, at time $t$, currency $k$ is at a forward discount and has negative momentum. This means that $y_{k,t+1}$ is counted positively in the construction of CO, but negatively in the construction of MO. If we then observed that $y_{k,t+1}$ was large and positive, it would suggest that, for whatever reason, customers are increasing carry positions in currency $k$, but decreasing momentum positions in currency $k$, given that momentum would suggest a negative value of $y_{k,t+1}$.

For this reason, we propose a third factor, denoted CM, which is the simple average of CO and MO:

$$\mathrm{CM}_t = \frac{\mathrm{CO}_t + \mathrm{MO}_t}{2}. \tag{13}$$

Suppose that for currency $k$, $\mathrm{sign}(f_{kt} - s_{kt}) = \mathrm{sign}(\bar{r}^4_{kt})$. Then $y_{k,t+1}$ contributes equal amounts to CO, MO and CM. However, when $\mathrm{sign}(f_{kt} - s_{kt}) \neq \mathrm{sign}(\bar{r}^4_{kt})$, $y_{k,t+1}$ contributes opposite amounts to CO and MO and, therefore, nothing to CM. Therefore, CM measures signed order flow summed across all currencies for which the trading signals point in the same direction. Thus, when we observe a large positive value of CM it suggests that customers are increasing their traditional speculative currency positions, in general. When we observe a large negative value of CM it suggests that customers are decreasing their traditional speculative currency positions, in general.

# IV. The Risk Exposure of Currency Portfolios

In this section, we measure the risk exposures of the portfolios we constructed in Section II. 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 factors we introduced in Section III. Each time series regression is of the form

(14) $$r^e_{i,t} = \alpha_i + z'_t\beta_i + \epsilon_{i,t}, \qquad i = 1, \ldots, N, \quad t = 1, \ldots, T,$$

where $r^e_{i,t}$ is the excess return of portfolio $i$ at time $t$, $z_t$ is an $n \times 1$ vector of risk factors, $N$ is the number of portfolios and $T$ is the sample size. In this part of our analysis, we consider the five forward discount-sorted currency portfolios, C1–C5, and the five momentum-sorted currency portfolios, M1–M5.

[Insert Table 7 approximately here]

## A. Betas of Traditional Pricing Factors

We begin by considering two risk factors similar to those proposed by Lustig et al. (2011): DOL and HMLC. Overall, the results, shown in Table 7, are in line with what has been documented in the empirical literature. The betas for DOL are scaled near unity, although they are somewhat smaller for C1, C5, M1 and M5 than they are for the other portfolios. The betas for the HMLC factor increase across the forward-discount sorted portfolios. With a beta of $-0.26$, C1 has a negative exposure to HMLC, indicating that it is a hedge against carry trade risk. By contrast, the beta is large and positive for C5 ($0.74$), indicating that it is highly exposed to carry trade risk. These results are not surprising given the construction of the factors.[14] The momentum portfolios have positive exposure to HMLC, across the board. The betas with respect to HMLC generally decrease from M1, which has by far the largest beta, to M5.

[Insert Table 8 approximately here]

Table 8 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 measured as the cross-sectional average of the intra-week volatility innovation for each currency in our sample (see footnote 9). 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 documented in the literature. The pattern in the betas for DOL is similar to what we observed for the DOL-HMLC model. For DVOL, the betas are positive for the low-forward-discount currency portfolios (C1 and C2) and negative, and increasingly so, for the high-forward-discount portfolios (C3, C4 and C5). This indicates that when global currency volatility rises, currencies with large forward discounts tend to do poorly, while currencies with small or negative forward discounts act as a hedge against increasing volatility. The momentum portfolios have small negative exposures to DVOL, across the board, although in many cases the estimated betas are not statistically significant.

[Insert Table 9 approximately here]

[14]This follows from the fact that DOL is similar to the average of C1–C5 while HMLC is C5 minus C1. See Burnside (2010) for further details.

## B. Betas of the Order-Flow Factors

### 1. Carry

Table 9 shows results obtained using our aggregate carry-trade order-flow risk factor, CO, in tandem with the DOL factor. The pattern in the betas for DOL is similar to what we observed for the DOL-HMLC and DOL-DVOL models. The results indicate that portfolios with large forward discounts (C3, C4, and C5) have positive and statistically significant exposure to CO. The lower forward discount portfolios (C1 and C2) have negative and, in the case of C1, statistically significant exposure to CO. The betas for C3–C5 are positive and statistically significant. The betas are monotonically increasing as we move from C1 to C5. These results mean that when the order flow data suggest stronger trading pressure consistent with the carry trade, i.e. when CO increases, the high-forward-discount portfolios earn higher returns and the low-forward-discount portfolios earn lower returns. The pattern reverses if investors reverse their carry trade holdings and CO decreases. Consequently, low-forward-discount portfolios act as hedges against a reversal of investors' carry trade positions, while high-forward-discount portfolios are exposed to this risk. The momentum portfolios also have positive exposure to CO, and in many cases it is statistically significant. The pattern in the betas is generally increasing from M1 to M5, but M2 breaks the order by having the second largest estimated beta.

[Insert Table 10 approximately here]

### 2. Momentum

Table 10 shows results obtained using our momentum order-flow risk factor, MO, in tandem with the DOL factor. The pattern in the betas for DOL is similar to what we observed for the DOL-CO model. The carry portfolios (C1–C5) have small and statistically insignificant exposures to MO. For the momentum portfolios, the betas are monotonically increasing as we move from M1 to M5. These results mean that when the order flow data suggest stronger buying pressure consistent with momentum trading, i.e. when MO increases, the currency portfolios with greater momentum earn higher returns and those with less momentum earn lower returns. Consequently, portfolios with little momentum act as hedges against a reversal of investors' momentum positions, while portfolios with the most momentum are exposed to this risk.

[Insert Table 11 approximately here]

### 3. Currency Speculation

Table 11 shows results obtained using our overall currency speculation order-flow risk factor, CM, in tandem with the DOL factor. The pattern in the betas for DOL is similar to what we observed for the DOL-CO and DOL-MO models. The betas for CM increase monotonically across the carry portfolios (C1–C5) and the momentum portfolios (M1–M5). These results mean that when the order flow data suggest stronger buying pressure consistent with standard currency speculation strategies, i.e. when CM increases, the currency portfolios with greater carry or momentum earn higher returns and those with less earn lower returns. Consequently, portfolios with little carry or momentum act as hedges against a reversal of investors' speculative positions, while portfolios with the most carry or momentum are exposed to this risk.

[Insert Figure 1 approximately here]

Figure 1 summarizes the relationship between the betas that are unique to each of the five models and the average returns of the ten test portfolios. While the betas with respect to HMLC and DVOL line up reasonably with the expected returns of the carry portfolios, they capture little of the variation in expected return across the momentum portfolios. For our MO factor, the betas line up quite well with the average returns of the momentum portfolios, but not with those of the carry portfolios. However, the betas for our CO factor, and, more especially, our CM factor, line up quite well with the average returns of all of the portfolios.

An interesting feature of our DOL-CM model is that most of its cross-sectional explanatory power derives from the relationship between spot exchange rate changes and our order flow factor. We can split the return to a long position in currency $k$ into two components, its forward discount and its (negated) spot rate change; from equation (1):

$$r_{k,t+1} = f_{k,t} - s_{k,t+1} = f_{k,t} - s_{k,t} - (s_{k,t+1} - s_{k,t}). \tag{15}$$

Similarly, we can divide the return to each currency portfolio into a forward-discount component and a spot-rate-change component. We can then rerun the time series regressions in Table 11 with these separate components.

As we show in the Supplemental Material (Table 1), the results for the spot-rate-change component are quantitatively very similar to the results for the entire return. This is because DOL and CM both have considerable explanatory power for the spot-rate-change component, but relatively little explanatory power for the forward discount component. In the case of DOL, this is not surprising, as it, by construction, has a spot-rate-change component. The fact that CM is highly correlated with the spot-range-change component is also not too surprising given the results we presented in Table 2 showing that order flow is correlated with exchange rate changes at the level of individual currencies.

# V. Cross-Sectional Asset Pricing

Rather than working with the three different order-flow related models from Section IV, in this section, we estimate a linear SDF model based on the DOL and CM factors, defined in Section III.[15] Let $r^e$ be an $N \times 1$ vector of excess returns where $N$ is the number of test assets. If a variable $m_t > 0$ is an SDF for these returns, then

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

where $E$ is the unconditional expectations operator. We specify the SDF as a linear function of a $n \times 1$ vector of risk factors, $z$:

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

where $\mu = E(z)$ and $b$ is a $n \times 1$ vector of parameters. We adopt a widely used generalized method of moments [GMM, Hansen (1982)] approach to estimation, which is discussed in detail in Cochrane (2009).

We use the following moment restrictions to identify the parameters $b$ and $\mu$:

$$E(r^e) = \text{cov}(r^e, z)b \qquad E(z) = \mu \tag{18}$$

[15] In any earlier draft, we also presented results of estimating models based on DOL-HMLC and DOL-DVOL. These results are available in our Supplemental Material. Both models fit the carry portfolios relatively well, but they do not adequately explain the cross-sectional variation in the average returns of the momentum portfolios.

The first equation in (18) follows from the combination of equations (16) and (17), while the second equation is just the definition of $\mu$.

Letting $\Sigma_z = E[(z-\mu)(z-\mu)']$, the first equation in (18) can also be written as

$$E(r^e) = \left[\text{cov}(r^e, z)\Sigma_z^{-1}\right](\Sigma_z b) = \beta\lambda, \tag{19}$$

with $\beta = \text{cov}(r^e, z)\Sigma_z^{-1}$ being an $N \times n$ matrix of factor betas, and $\lambda = \Sigma_z b$ being a $n \times 1$ vector of risk prices. This is the beta representation of the pricing model, which we also estimate using GMM.[16]

As test assets, we use the returns to the ten portfolios described above (C1–C5 and M1–M5). In the tables that follow, we report parameter estimates, and standard errors. When estimating the SDF representation, we report Hansen and Jagannathan (1997)'s distance measure as a test of the model's fit. When estimating the beta representation, we report the results of a test for whether the pricing errors are zero. We also perform tests for model identification. These tests, based on Kleibergen and Paap (2006), assess whether $\text{cov}(r^e, z)$ has full column rank and are discussed in Burnside (2016).

[Insert Table 12 approximately here]

Table 12 shows cross-sectional asset pricing results for the DOL-CM model. The empirical evidence in Table 12 strongly supports CM as a pricing factor. The SDF parameter ($b$) and risk price ($\lambda$) for the CM factor are positive and statistically significant. Thus, portfolios with

[16] For both the SDF and beta representations, details of the computation of the parameter estimates and standard errors are provided in the online appendix to Burnside (2011).

more positive exposure to CM carry larger risk premia. The cross-sectional fit of the model is good, with $R^2 = 0.70$. The fit of the model is illustrated in Figure 2. Only the C5 portfolio has a large pricing error, with the model considerably under-predicting its expected return. The overall degree of fit is substantially better than for models based on DOL-HMLC and DOL-DVOL (see the Supplemental Material). Neither of those models explains the cross-sectional variation in the returns of the momentum portfolios.

[Insert Figure 2 approximately here]

The model is not rejected at conventional significance levels based on the HJ distance measure and the Fama-MacBeth pricing error test. The KP test strongly rejects the null hypothesis of reduced rank at less than the $1\%$ level.

[Insert Figure 3 approximately here]

We have explored the model's fit for a wider range of currency portfolios including alternative measures of carry trade portfolios, momentum portfolios, value portfolios based on the real-exchange rate, and liquidity-based portfolios. Details of these portfolios are provided in the Supplemental Material. For each portfolio we can compute its sample mean, as well as its model-predicted expected return computed using our model estimates. As illustrated in Figure 3, the model fits the additional portfolios quite well. The $R^2$ across all portfolios, inclusive of the ten test assets is $0.66$.

# VI. Customer Segments and Intermediary Risk

## A. Customer Segments and Disaggregated Order Flow

As discussed in Section II, we have data on order flow that are disaggregated by customer segments which reveal differences in how order-flow is contemporaneously related to currency returns across customer segments. Portfolios of currencies with more buying pressure from financial customers have higher returns than those with less buying pressure. But the reverse pattern is observed for nonfinancial customers. This suggests that different customer segments act in systematically different ways. This might reflect that they have access to different information, or have different motives for trade, possibly rooted in different *ex-ante* exposure to risk.

To explore further, we construct alternative order-flow factors corresponding to the Asset Manager, Hedge Fund, Corporate, and Private Client customer segments. These factors are conceptually the same as the CM factor, but they measure whether each customer type is trading in ways that are consistent with standard currency speculation signals. Consequently, we denote these factors as CMAM, CMHF, CMCO and CMPC. To take Asset Managers as an example, for each currency we define normalized order flow as

$$y_{k,t+1}^{\text{AM}} = \frac{x_{k,t+1}^{\text{AM}}}{\hat{\sigma}_{k,t}}, \tag{20}$$

where $x_{k,t+1}^{\text{AM}}$ is raw order flow for the Asset Manager segment, and $\hat{\sigma}_{k,t}$ is the recursively-defined standard deviation of order flow summed across all customer segments. Given this definition our normalized order-flow measures by customer segment aggregate in the same way as the raw order flow data:

$$y^{\mathrm{AM}}_{k,t+1} + y^{\mathrm{HF}}_{k,t+1} + y^{\mathrm{CO}}_{k,t+1} + y^{\mathrm{CP}}_{k,t+1} = y_{k,t+1} \tag{21}$$

Each CMxx factor is defined in the same way as the CM factor, with the segment order flow $y^{\mathrm{xx}}_{k,t+1}$ replacing aggregate order flow in the equations (10), (11), and (13).

[Insert Table 13 approximately here]

Table 13 shows the correlation matrix between the disaggregated CMxx factors and the CM factor, redefined using only the nine major currencies. It shows that the signed order flow of financial customers, as measured by CMAM and CMHF, is quite highly correlated with overall signed order flow, as measured by CM. However, CMAM and CMHF are not highly correlated with each other. The order flow of nonfinancial customers, as measured by CMCO and CMPC, has much lower correlation with CM. Furthermore, both CMCO and CMPC are negatively correlated with CMAM and CMHF.[17]

These findings 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 emphasized in the early literature on order flow in currency markets.[18] That

[17]In an earlier draft, we showed a similar pattern for customer-segment order-flow measures defined separately with respect to carry and momentum.

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

said, overall order flow is dominated by that of financial customers. For example, if we consider our CMxx factors, the financial order flow variables CMAM and CMHF, summed, account for 101% of the variation in CM (when it is redefined using only the nine major currencies). In contrast CMCO and CMPC, summed, account for only 21% of CM's variation, with the residual $-22\%$ being explained by the negative covariance between financial and nonfinancial order flow.

[Insert Figure 4 approximately here]

Further evidence of systematic differences in behavior across customer segments is found in Figure 4. There we plot the betas of the disaggregated overall order-flow factors (i.e. the CMxx factors). In each case, a two factor model, with DOL as the other factor, is estimated. It is notable that the pattern in the betas for financial customers much more closely matches the pattern we observed for the CM factor. For both carry and momentum portfolios, the pattern in the betas is generally increasing as we move from low return to high return portfolios. When we move to corporate customers, the pattern is reversed for the momentum portfolios. Both patterns are reversed for private clients.

## B. Intermediary Risk

He and Krishnamurthy (2013) argue that in some markets the marginal investor is a financial intermediary who faces an equity capital constraint. He et al. (2017) show that shocks to the equity-capital ratios of primary dealers have significant explanatory power for expected returns in a wide variety of asset classes. As we argued in the introduction, there is good reason to believe these findings are relevant to the foreign exchange market, which is an over-the-counter market dominated by a relatively small number of large players. Customer order flow, aggregated across these market-makers, is constrained by their existing inventories and their ability to adjust their balance sheets. In good times, when dealer equity-capital ratios are high, market participants' speculative positions can more readily be accommodated by dealers. In bad times, dealers are more leveraged and it becomes more costly to accommodate such positions. In this situation, we expect prices to adjust to make traditional speculative positions less attractive.

[Insert Table 14 approximately here]

Unfortunately, we do not have measures of aggregate order flow for the entire foreign exchange market. We also do not have data on the equity capital constraints facing the market makers in this market alone. That said, we do have some evidence in favor of the importance of market intermediaries for pricing currencies. The data we used to establish the relevance of order flow is weekly. So we have weekly observations on our order-flow based risk factor and on our estimated SDF. To align with these data we calculate the weekly average of the daily intermediary capital risk factor in He et al. (2017), which we denote here as $H$. Table 14 reports the results of regressions in which we we use $H$ as the right-hand-side variable and alternatively use the risk factor CM, or our estimated SDF, $\hat{m}$, which is a linear combination of DOL and CM, as the left-hand side variable.

When we do this over the full sample, the estimated coefficients have the expected signs (positive for CM and negative for our SDF), and are statistically significant. When times are good, as measured by $H$ being more positive, aggregate order flow (as measured by CM) favors traditional speculative positions, and our measure of overall risk, $\hat{m}$, is lower.

Not surprisingly, given that constraints facing intermediaries increased from 2008 onward, the results are even stronger when we restrict ourselves to the 2008-12 time period. The coefficients are larger and display a greater degree of statistical significance.[19] Together, these results suggest that intermediary risk is relevant in the foreign exchange market.

We conducted similar regressions using our disaggregated risk factors, CMxx. Notably, the results are strongest for the sum of the financial subgroup factors (CMAM+CMHF), which seems to drive the correlation between CM and $H$. This is perhaps not surprising given that financial customer order flow drives most of the variation in aggregate order flow. Also, interestingly, we note the negative correlation between the nonfinancial subgroup factors (CMCO+CMPC) and $H$, although it is statistically insignificant. Once again, this suggests that nonfinancial customers provide a degree of risk sharing in foreign exchange market.

# VII. Conclusion

We have shown that order-flow is closely associated with systematic patterns in currency returns. 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 used order-flow based risk factors in a traditional SDF approach to

[19] We note that this does not mean that 2008, itself, drives the result. In fact, if we use only the 2009-12 period in our analysis, the results become even stronger.

cross-sectional asset pricing. Our model is successful in pricing the cross-section of interest-rate and momentum-sorted currency portfolios in our data set, and also fits currency portfolios that we did not use as test assets. In this respect, the model appears more successful than other notable reduced-form models from the literature.

We also find preliminary evidence linking our estimated SDF to measures of the intermediary equity capital factor from He et al. (2017). This suggests that future research could explore the particular relevance of the equity-capital ratio of foreign exchange dealers for currency pricing.

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TABLE 1

**Forward Discount and Momentum-Sorted Portfolios: Summary Statistics**

The table reports the descriptive statistics for portfolios C1 to C5, which are sorted on the basis of the forward discount, and portfolios M1 to M5, which are sorted on the basis of momentum (measured by previous 4-week returns). It reports statistics for the "high-minus-low" portfolios HMLC (C5–C1) and HMLM (M5–M1). It reports the annualized mean return (%) (with heteroskedasticity-consistent standard errors reported in parentheses), standard deviation (SD), Sharpe ratio (SR), skewness (Skew), and first-order autocorrelation coefficient (AC1) for each return, as well as the significance of the latter (***0.01%, **1%, *5%). We also report two measures of coskewness between the individual portfolios and the DOL portfolio. Coskew1 and Coskew2 correspond, respectively, to $\beta_{SKS}$ and $\beta_{SKD}$ as described in the appendix.

| Portfolio | C1 | C2 | C3 | C4 | C5 | HMLC |
|---|---|---|---|---|---|---|
| Mean(%) | 1.36 | 4.48 | 5.45 | 6.44 | 12.58 | 11.64 |
| | (2.16) | (3.01) | (3.19) | (3.83) | (4.04) | (3.54) |
| SD | 6.80 | 9.28 | 9.34 | 11.95 | 12.85 | 11.72 |
| SR | 0.20 | 0.48 | 0.58 | 0.54 | 0.98 | 0.99 |
| Skew | -0.07 | -0.88 | -0.61 | -1.08 | -0.96 | -0.78 |
| AC1 | 0.07 | -0.01 | 0.06 | -0.01 | -0.10* | -0.17*** |
| Coskew1 | 0.42 | -0.14 | -0.09 | -0.43 | -0.38 | -0.44 |
| Coskew2 | 5.33 | -1.50 | -1.09 | -7.42 | -9.98 | -14.59 |
| **Portfolio** | **M1** | **M2** | **M3** | **M4** | **M5** | **HMLM** |
| Mean(%) | 2.88 | 6.34 | 4.95 | 7.33 | 10.74 | 7.86 |
| | (3.28) | (3.26) | (3.41) | (3.22) | (3.18) | (2.83) |
| SD | 10.97 | 10.19 | 9.65 | 9.37 | 10.00 | 10.54 |
| SR | 0.26 | 0.62 | 0.51 | 0.78 | 1.07 | 0.75 |
| Skew | -0.79 | -0.60 | -0.77 | -0.66 | -0.51 | 0.22 |
| AC1 | -0.08 | -0.03 | 0.05 | 0.03 | 0.02 | -0.16*** |
| Coskew1 | -0.34 | -0.20 | -0.14 | -0.20 | 0.09 | 0.28 |
| Coskew2 | -7.03 | -2.99 | -1.72 | -2.62 | 1.85 | 8.87 |

TABLE 2

**Exchange Rates and Order Flow for Individual Currencies**

The table reports estimates of equation (7),

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

where $s_{k,t}$ is the natural log of the exchange rate between the USD and foreign currency $k$, measured as foreign currency units (FCUs) per USD, $x_{k,t+1}$ 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.

| | $a_k \times 100$ | $b_k \times 100$ | $\bar{R}^2$ | | $a_k \times 100$ | $b_k \times 100$ | $\bar{R}^2$ |
|---|---|---|---|---|---|---|---|
| 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) | |

TABLE 3

**Order-Flow Portfolios: Summary Statistics**

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. This table reports statistics for portfolios based on normalized aggregated order flow for the full sample of 20 currencies.

| | O1 | O2 | O3 | O4 | O5 | Avg. | BMS |
|---|---|---|---|---|---|---|---|
| Mean (%) | -7.45 | 1.25 | 9.33 | 10.15 | 19.47 | 5.15 | 27.37 |
| | (4.13) | (3.16) | (2.96) | (3.12) | (3.68) | (3.52) | (2.66) |
| SD | 10.94 | 9.73 | 9.51 | 9.16 | 10.30 | 9.34 | 7.31 |
| SR | -0.68 | 0.13 | 0.98 | 1.11 | 1.89 | 0.55 | 3.74 |

TABLE 4

**Disaggregated Order-Flow Portfolios: Summary Statistics**

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. This table reports statistics for portfolios based on disaggregated order flow for a sample of nine major currencies, where the disaggregation is by customer type.

| | O1 | O2 | O3 | O4 | O5 | Avg. | BMS |
|---|---|---|---|---|---|---|---|
| Asset manager | | | | | | | |
| Mean (%) | -7.36 | 0.74 | 6.42 | 16.36 | | 4.04 | 23.72 |
| | (3.82) | (3.61) | (3.09) | (3.19) | | (3.01) | (2.62) |
| SD | 11.25 | 10.79 | 10.18 | 9.72 | | 9.11 | 8.61 |
| SR | -0.65 | 0.07 | 0.63 | 1.68 | | 0.44 | 2.75 |
| Hedge fund | | | | | | | |
| Mean (%) | -10.34 | 2.12 | 6.71 | 17.24 | | 3.93 | 27.57 |
| | (3.59) | (3.86) | (3.12) | (3.24) | | (3.00) | (3.23) |
| SD | 10.63 | 11.26 | 9.53 | 9.97 | | 9.06 | 8.96 |
| SR | -0.97 | 0.19 | 0.70 | 1.73 | | 0.43 | 3.08 |
| Corporate | | | | | | | |
| Mean (%) | 8.55 | 8.51 | 4.80 | 1.66 | | 5.88 | -6.89 |
| | (3.72) | (3.19) | (3.40) | (3.15) | | (3.00) | (2.42) |
| SD | 10.40 | 10.35 | 10.40 | 10.26 | | 9.01 | 7.25 |
| SR | 0.82 | 0.82 | 0.46 | 0.16 | | 0.65 | -0.95 |
| Private Client | | | | | | | |
| Mean (%) | 22.39 | 11.84 | -0.42 | -6.31 | | 6.88 | -28.70 |
| | (3.25) | (3.82) | (3.79) | (2.96) | | (3.04) | (2.62) |
| SD | 10.38 | 10.53 | 10.34 | 10.06 | | 9.05 | 8.14 |
| SR | 2.16 | 1.13 | -0.04 | -0.63 | | 0.76 | -3.52 |

TABLE 5

**Double Sorts on Forward Discount and Order Flow: Mean Returns (%)**

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

| | Forward discount | | | |
|---|---|---|---|---|
| Order flow | Low | Medium | High | HML |
| Sell | -3.58 | 1.76 | 3.27 | 6.85 |
| | (2.77) | (3.48) | (4.28) | (3.05) |
| Buy | 7.79 | 10.38 | 17.75 | 9.96 |
| | (2.40) | (3.10) | (4.21) | (3.90) |
| BMS | 11.37 | 8.62 | 14.48 | |
| | (2.09) | (1.85) | (2.72) | |

TABLE 6

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

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.

| | Volatility Innovation | | | |
|---|---|---|---|---|
| Order flow | Low | Medium | High | HML |
| Sell | 7.70 | 2.09 | -2.26 | -9.96 |
| | (2.55) | (3.25) | (4.50) | (2.99) |
| Buy | 14.92 | 10.46 | 5.84 | -9.08 |
| | (2.20) | (2.76) | (4.72) | (3.94) |
| BMS | 7.21 | 8.37 | 8.09 | |
| | (1.62) | (1.76) | (2.97) | |

TABLE 7

**Betas of the Currency Portfolios for the DOL-HMLC Model**

We present estimates of the time series regressions

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

where $r_{it}^e$ is the excess return of portfolio $i$ at time $t$, and $z_t$ is a vector of the two risk factors, DOL and HMLC. Estimates of $\alpha_i$ are scaled by $100$. The portfolios are C1—C5 and M1—M5, described in the main text. . Standard errors are reported in parentheses. We use weekly data, from the last week of November 2001 to the fourth week of March 2012.

| | $\alpha$ | $\beta$-DOL | $\beta$-HMLC | $\bar{R}^2$ | | $\alpha$ | $\beta$-DOL | $\beta$-HMLC | $\bar{R}^2$ |
|---|---|---|---|---|---|---|---|---|---|
| C1 | 0.01 | 0.71 | -0.26 | 0.79 | M1 | -0.10 | 0.82 | 0.32 | 0.73 |
| | (0.02) | (0.02) | (0.02) | | | (0.03) | (0.04) | (0.05) | |
| C2 | -0.01 | 0.94 | 0.00 | 0.82 | M2 | -0.01 | 0.92 | 0.17 | 0.82 |
| | (0.02) | (0.02) | (0.02) | | | (0.03) | (0.02) | (0.04) | |
| C3 | -0.01 | 0.89 | 0.11 | 0.84 | M3 | -0.03 | 0.90 | 0.13 | 0.83 |
| | (0.02) | (0.02) | (0.02) | | | (0.03) | (0.03) | (0.02) | |
| C4 | -0.05 | 1.04 | 0.29 | 0.84 | M4 | 0.03 | 0.86 | 0.10 | 0.77 |
| | (0.03) | (0.03) | (0.04) | | | (0.03) | (0.03) | (0.03) | |
| C5 | 0.00 | 0.71 | 0.74 | 0.94 | M5 | 0.10 | 0.77 | 0.11 | 0.56 |
| | (0.02) | (0.02) | (0.02) | | | (0.04) | (0.04) | (0.06) | |

TABLE 8

**Betas of the Currency Portfolios for the DOL-DVOL Model**

We present estimates of the time series regressions

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

where $r_{it}^e$ is the excess return of portfolio $i$ at time $t$, and $z_t$ is a vector of the two risk factors, DOL and DVOL. Estimates of $\alpha_i$ and $\beta$-DVOL are scaled by 100. The portfolios are C1—C5 and M1—M5, described in the main text. Standard errors are reported in parentheses. We use weekly data, from the last week of November 2001 to the fourth week of March 2012.

| | $\alpha$ | $\beta$-DOL | $\beta$-DVOL | $\bar{R}^2$ | | $\alpha$ | $\beta$-DOL | $\beta$-DVOL | $\bar{R}^2$ |
|---|---|---|---|---|---|---|---|---|---|
| C1 | -0.04 | 0.60 | 0.19 | 0.62 | M1 | -0.04 | 0.95 | -0.13 | 0.63 |
| | (0.02) | (0.04) | (0.07) | | | (0.04) | (0.07) | (0.13) | |
| C2 | -0.01 | 0.94 | 0.10 | 0.83 | M2 | 0.02 | 1.00 | -0.04 | 0.78 |
| | (0.02) | (0.02) | (0.09) | | | (0.03) | (0.05) | (0.11) | |
| C3 | 0.01 | 0.94 | -0.10 | 0.83 | M3 | 0.00 | 0.96 | -0.12 | 0.81 |
| | (0.02) | (0.03) | (0.08) | | | (0.03) | (0.03) | (0.06) | |
| C4 | 0.01 | 1.15 | -0.25 | 0.78 | M4 | 0.05 | 0.90 | -0.10 | 0.76 |
| | (0.03) | (0.06) | (0.13) | | | (0.03) | (0.02) | (0.06) | |
| C5 | 0.14 | 1.02 | -0.45 | 0.55 | M5 | 0.12 | 0.81 | -0.15 | 0.55 |
| | (0.05) | (0.08) | (0.20) | | | (0.04) | (0.05) | (0.09) | |

TABLE 9

**Betas of the Currency Portfolios for the DOL-CO Model**

We present estimates of the time series regressions

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

where $r_{it}^e$ is the excess return of portfolio $i$ at time $t$, and $z_t$ is a vector of the two risk factors, DOL and CO. Estimates of $\alpha_i$ are scaled by $100$. The portfolios are C1—C5 and M1—M5, described in the main text. Standard errors are reported in parentheses. We use weekly data, from the third week of January 2002 to the fourth week of March 2012.

| | $\alpha$ | $\beta$-DOL | $\beta$-CO | $\bar{R}^2$ | | $\alpha$ | $\beta$-DOL | $\beta$-CO | $\bar{R}^2$ |
|---|---|---|---|---|---|---|---|---|---|
| C1 | -0.05 | 0.61 | -0.31 | 0.63 | M1 | -0.04 | 0.97 | 0.01 | 0.63 |
| | (0.02) | (0.04) | (0.06) | | | (0.04) | (0.07) | (0.11) | |
| C2 | -0.01 | 0.94 | -0.05 | 0.83 | M2 | 0.03 | 0.99 | 0.20 | 0.79 |
| | (0.02) | (0.03) | (0.04) | | | (0.03) | (0.05) | (0.07) | |
| C3 | 0.02 | 0.93 | 0.21 | 0.83 | M3 | 0.00 | 0.96 | 0.12 | 0.81 |
| | (0.02) | (0.03) | (0.07) | | | (0.03) | (0.03) | (0.07) | |
| C4 | 0.02 | 1.14 | 0.34 | 0.78 | M4 | 0.06 | 0.89 | 0.19 | 0.76 |
| | (0.04) | (0.06) | (0.08) | | | (0.03) | (0.03) | (0.08) | |
| C5 | 0.17 | 1.02 | 0.54 | 0.56 | M5 | 0.14 | 0.80 | 0.28 | 0.55 |
| | (0.05) | (0.09) | (0.13) | | | (0.04) | (0.05) | (0.10) | |

TABLE 10

**Betas of the Currency Portfolios for the DOL-MO Model**

We present estimates of the time series regressions

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

where $r_{it}^{e}$ is the excess return of portfolio $i$ at time $t$, and $z_t$ is a vector of the two risk factors, DOL and MO. Estimates of $\alpha_i$ are scaled by $100$. The portfolios are C1, C2, C3, C4 and C5 (the portfolios sorted by interest rate) as well as M1, M2, M3, M4, and M5 (the portfolios sorted by momentum of past four week returns). Standard errors are reported in parentheses. We use weekly data, from the third week of January 2002 to the fourth week of March 2012.

| | $\alpha$ | $\beta$-DOL | $\beta$-MO | $\bar{R}^2$ | | $\alpha$ | $\beta$-DOL | $\beta$-MO | $\bar{R}^2$ |
|---|---|---|---|---|---|---|---|---|---|
| C1 | -0.03 | 0.59 | 0.05 | 0.61 | M1 | -0.03 | 0.96 | -0.32 | 0.64 |
| | (0.02) | (0.04) | (0.07) | | | (0.04) | (0.06) | (0.12) | |
| C2 | -0.01 | 0.94 | 0.12 | 0.83 | M2 | 0.02 | 1.00 | -0.05 | 0.78 |
| | (0.02) | (0.03) | (0.05) | | | (0.03) | (0.05) | (0.06) | |
| C3 | 0.00 | 0.95 | 0.00 | 0.83 | M3 | -0.01 | 0.97 | 0.07 | 0.81 |
| | (0.02) | (0.03) | (0.05) | | | (0.03) | (0.03) | (0.06) | |
| C4 | 0.00 | 1.17 | -0.05 | 0.77 | M4 | 0.04 | 0.90 | 0.14 | 0.76 |
| | (0.04) | (0.06) | (0.08) | | | (0.03) | (0.02) | (0.10) | |
| C5 | 0.14 | 1.06 | -0.12 | 0.55 | M5 | 0.12 | 0.82 | 0.32 | 0.56 |
| | (0.05) | (0.08) | (0.14) | | | (0.04) | (0.05) | (0.11) | |

TABLE 11

**Betas of the Currency Portfolios for the DOL-CM Model**

We present estimates of the time series regressions

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

where $r_{it}^e$ is the excess return of portfolio $i$ at time $t$, and $z_t$ is a vector of the two risk factors, DOL and CM. Estimates of $\alpha_i$ 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 third week of January 2002 to the fourth week of March 2012.

| | $\alpha$ | $\beta$-DOL | $\beta$-CM | $\bar{R}^2$ | | $\alpha$ | $\beta$-DOL | $\beta$-CM | $\bar{R}^2$ |
|---|---|---|---|---|---|---|---|---|---|
| C1 | -0.03 | 0.60 | -0.25 | 0.62 | M1 | -0.05 | 0.98 | -0.36 | 0.63 |
| | (0.02) | (0.04) | (0.10) | | | (0.04) | (0.07) | (0.15) | |
| C2 | -0.01 | 0.94 | 0.09 | 0.83 | M2 | 0.02 | 1.00 | 0.13 | 0.78 |
| | (0.02) | (0.03) | (0.07) | | | (0.03) | (0.05) | (0.09) | |
| C3 | 0.01 | 0.94 | 0.21 | 0.83 | M3 | 0.00 | 0.96 | 0.19 | 0.81 |
| | (0.02) | (0.03) | (0.08) | | | (0.03) | (0.03) | (0.09) | |
| C4 | 0.01 | 1.16 | 0.28 | 0.77 | M4 | 0.05 | 0.89 | 0.34 | 0.76 |
| | (0.04) | (0.07) | (0.12) | | | (0.03) | (0.02) | (0.10) | |
| C5 | 0.15 | 1.04 | 0.39 | 0.55 | M5 | 0.14 | 0.80 | 0.63 | 0.56 |
| | (0.06) | (0.09) | (0.20) | | | (0.04) | (0.05) | (0.16) | |

TABLE 12

**Estimates of the DOL-CM Model**

We present SDF and beta representation estimates for the DOL-CM model, as well as KP reduced-rank tests. The test assets are C1 to C5, the five portfolios sorted on interest rate, and M1 to M5, the five portfolios sorted on momentum. Panel a shows the estimates of the SDF coefficients, $b$, from first stage GMM, corresponding risk prices, $\lambda$, the cross-sectional $R^2$ and Hansen-Jagannathan distance (HJ). Estimates of $\lambda$ are scaled by 100. Panel b shows estimates of $\lambda$ obtained using the Fama-MacBeth method with no intercept. A $\chi^2$ measure of fit is also reported. Panel c 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 third week of January 2002 to the fourth week of March 2012.

| | a. GMM Estimates | | | | b. Fama-MacBeth Estimates | | | |
|---|---|---|---|---|---|---|---|---|
| | DOL | CM | $R^2$ | HJ | DOL | CM | $R^2$ | $\chi^2$ |
| $b$ | -0.54 | 2.17 | 0.70 | 11.30 | | | | |
| | (4.51) | (0.71) | | [0.19] | | | | |
| $\lambda$ | 0.10 | 17.60 | | | 0.10 | 17.60 | 0.70 | 9.87 |
| | (0.06) | (5.69) | | | (0.06) | (5.54) | | [0.27] |

c. KP Rank Tests

| | Stat. | d.f. | p-value |
|---|---|---|---|
| Rank(0) | 238.70 | 20 | [0.00] |
| Rank(1) | 40.63 | 9 | [0.00] |

TABLE 13

**Correlation Matrix of Order Flow Factors Disaggregated by Customer Segment**

The table reports the correlation matrices for groups of factors defined in Sections III and VI.

| | Aggregate Factor | Disaggregated Factors | | | |
|---|---|---|---|---|---|
| | CM | CMAM | CMHF | CMCO | CMPC |
| CMAM | 0.70 | 1 | | | |
| CMHF | 0.61 | 0.10 | 1 | | |
| CMCO | 0.22 | -0.06 | -0.11 | 1 | |
| CMPC | 0.10 | -0.11 | -0.29 | 0.14 | 1 |

TABLE 14

**Order-Flow Factors and Shocks to the Equity-Capital Ratio of Intermediaries**

The table reports estimates of time series regressions

$$y_t = \alpha + H_t\beta + \epsilon_t, \qquad t = 1, \ldots, T,$$

where $y_t$ is the dependent variable indicated in the table and $H_t$ is the weekly average of He et al.'s (2017) intermediary equity-capital risk factor. "SDF" indicates the fitted values of the SDF from our DOL-CM model. The full sample runs from the third week of January 2002 to the fourth week of March 2012. The 2008-12 sample runs from the first week of 2008 to the same end date. Standard errors are in parentheses.

| | Full Sample | | | 2008-12 | | |
|---|---|---|---|---|---|---|
| Dependent Variable | $\alpha$ | $\beta$ | $R^2$ | $\alpha$ | $\beta$ | $R^2$ |
| Aggregate Measures of Risk | | | | | | |
| SDF | 1.00 | -1.09 | 0.007 | 1.02 | -1.51 | 0.030 |
| | (0.03) | (0.57) | | (0.03) | (0.58) | |
| CM | -0.014 | 0.532 | 0.008 | -0.023 | 0.727 | 0.033 |
| | (0.012) | (0.263) | | (0.018) | (0.266) | |
| Disaggregated Risk Factors (CMxx) | | | | | | |
| Financial (AF+HF) | -0.028 | 0.622 | 0.007 | -0.049 | 0.875 | 0.030 |
| | (0.015) | (0.326) | | (0.022) | (0.335) | |
| Nonfinancial (CO+PC) | -0.002 | -0.091 | 0.001 | -0.011 | -0.076 | 0.002 |
| | (0.007) | (0.148) | | (0.008) | (0.114) | |

FIGURE 1

**Betas of Risk Factors and Average Returns**

This figure shows the betas of our ten currency portfolios C1–C5 (black dots) and M1–M5 (rings), calculated with respect to the HMLC, DVOL, CO, MO and CM factors (when each factor is combined with DOL in a two factor model), plotted against the mean annualized excess returns of the portfolios.

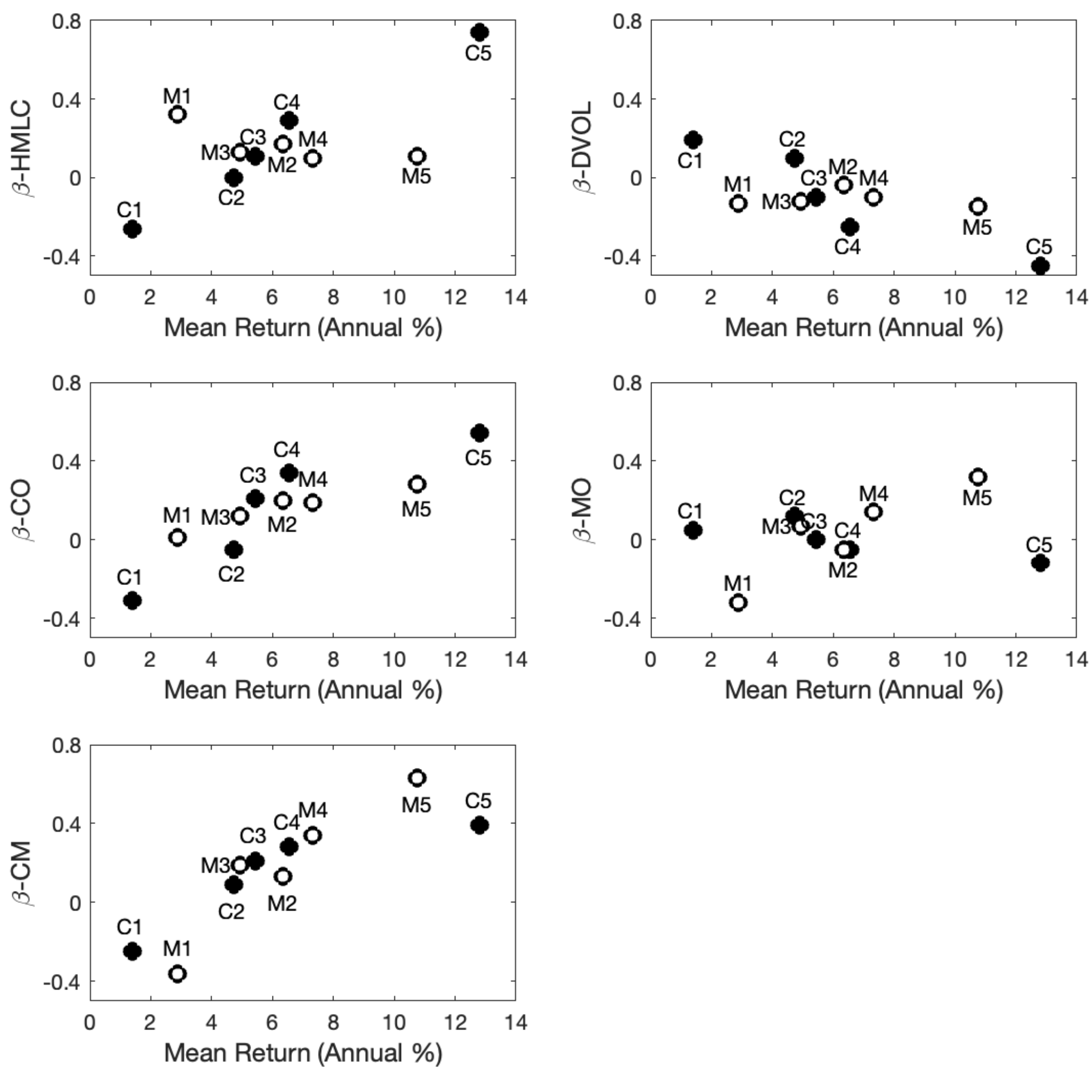


FIGURE 2

**Cross-Sectional Fit of the DOL-CM Model**

This figure illustrates the cross-sectional fit of the DOL-CM model (see Table 12). The model-predicted expected return is plotted against the mean annualized excess return of each of our ten currency portfolios: C1–C5 (black dots) and M1–M5 (rings).

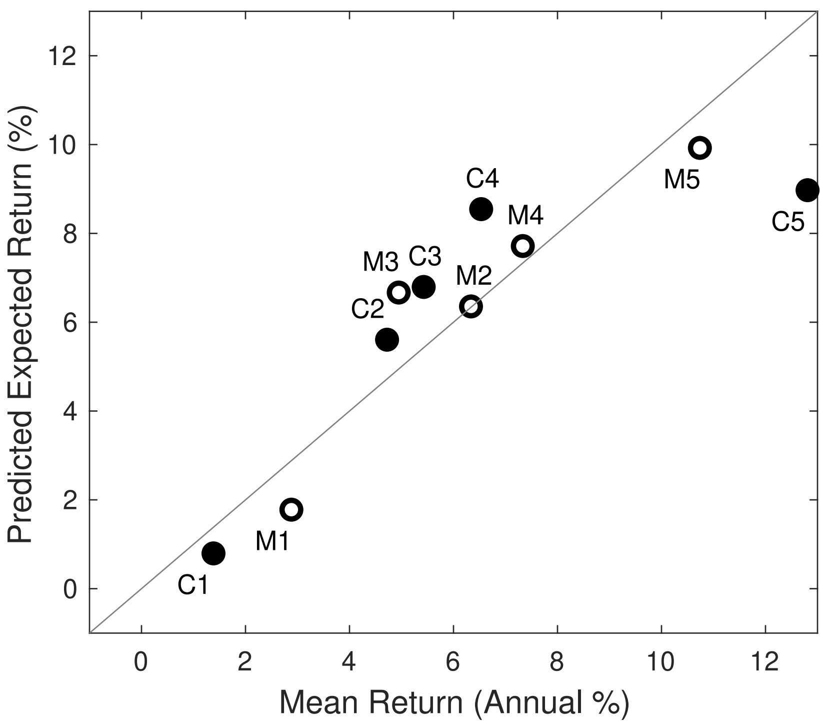


FIGURE 3

**Cross-Sectional Fit of the DOL-CM Model for a Broad Set of Currency Portfolios**

This figure illustrates the cross-sectional fit of the DOL-CM model for a broad set of currency portfolios described in the Supplementary Material. The model-predicted expected return is plotted against the mean annualized excess return of each portfolio. Carry type portfolios are indicated by black dots; momentum type portfolios by black rings, value portfolios by plus signs, Big Mac based value portfolios by squares, and a liquidity portfolio as a gray dot.

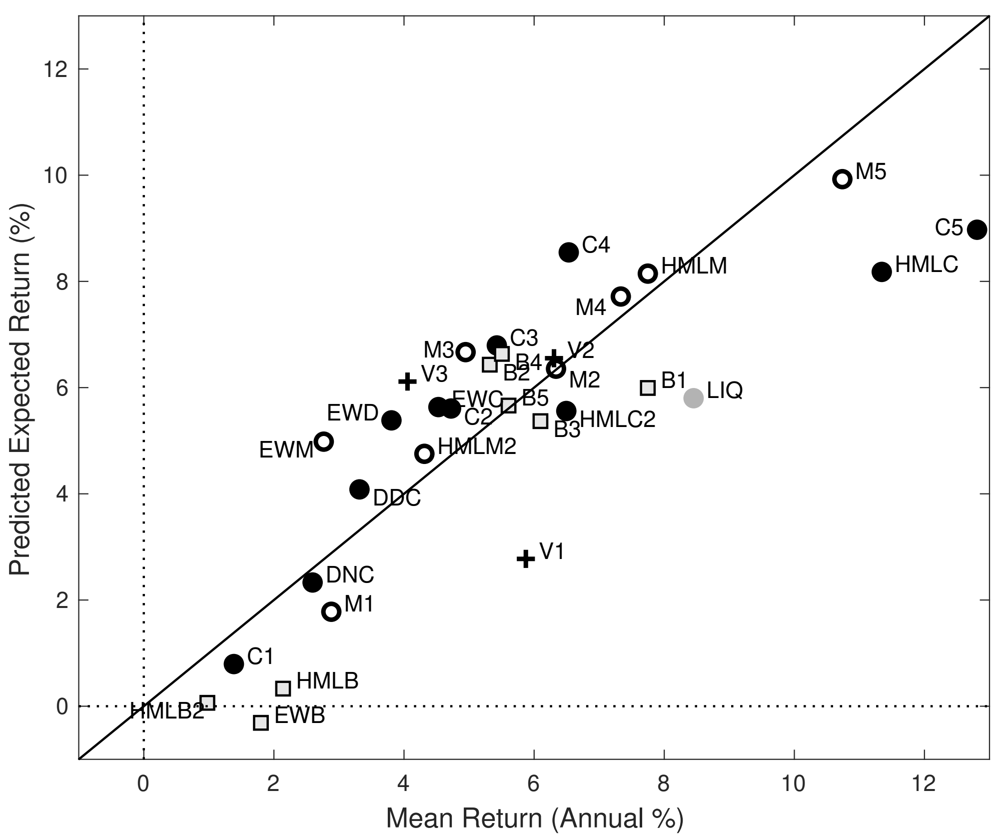
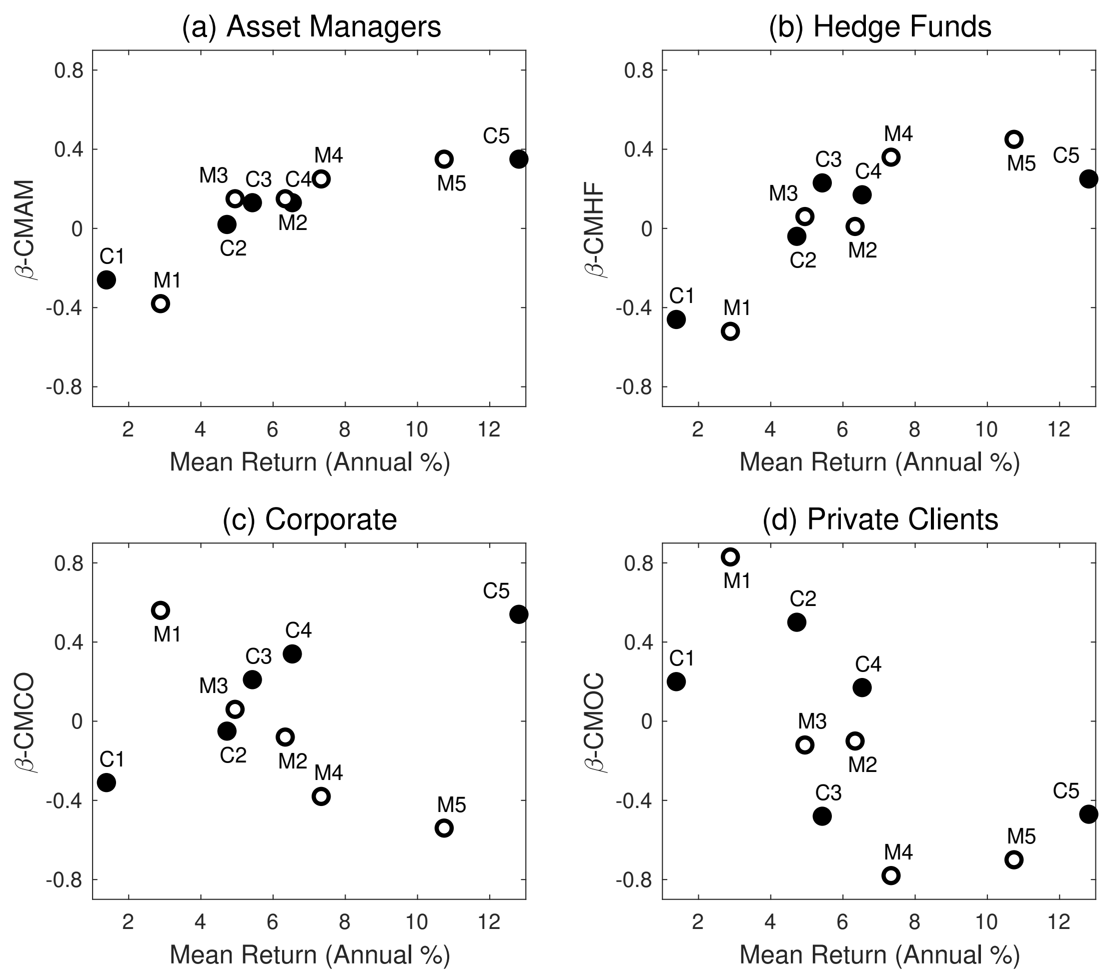


FIGURE 4

**Betas of Disaggregated Order-Flow Risk Factors**

This figure shows the betas of our ten currency portfolios, calculated with respect to the CMAM, CMHF, CMCO, and CMPC factors (when each factor is combined with DOL in a two factor model). The betas are plotted against the mean annualized excess returns of the portfolios: C1–C5 (black dots) and M1–M5 (rings).



# Appendix

## A. Data

Our data set consists of 20 of the most liquid currencies with the largest trading volume. Among these are the nine non-US G10 currencies: the Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), euro (EUR), British pound (GBP), Japanese yen (JPY), Norwegian krone (NOK), New Zealand dollar (NZD), and Swedish krona (SEK). The other 11 currencies are the Brazilian real (BRL), Czech krona (CZK), Hong Kong dollar (HKD), Hungarian forint (HUF), Korean won (KRW), Mexican peso (MXN), Polish zloty (PLN), Singapore dollar (SGD), Slovak koruna (SKK), Turkish lira (TRY), and South African rand (ZAR).

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 FCUs per USD. The weekly and daily spot exchange rates are obtained from WM/Reuters (via Datastream). Weekly one-week forward rates are available from the same source. One-week log excess returns, defined in equation (1), are measured using the average of the bid and ask forward and spot rates.

We use a unique data set, 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—asset manager (AM), corporate clients (CO), hedge funds (HF) and private clients (PC)—for nine currencies (EUR, JPY, GBP, CHF, AUD, NZD, CAD, SEK, NOK). Asset managers and hedge funds are recognized as financial customers. Corporate and private clients are recognized as nonfinancial 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 indicates net buying of foreign currency.

## B. Measures of Coskewness

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

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

where $\varepsilon_{t+1}$ 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

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

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

# Foreign Exchange Order Flow as a Risk Factor

Craig Burnside, Mario Cerrato, and Zhekai Zhang

**Supplemental Material**

## Estimates of the DOL-HMLC Model

In Table 1 we present the decomposed betas for the DOL-CM model that are referred to in Section IV.

## Estimates of the DOL-HMLC Model

In Table 2 we estimate a model based on the DOL and HMLC factors proposed by Lustig et al. (2011). Qualitatively, the results are in line with what has been documented in the existing literature. The SDF parameter ($b$) for the HMLC factor is positive, although only statistically significant at around the 12% level. The associated risk price ($\lambda$) is positive and statistically significant at the 7% or 1% level depending on the procedure used to compute standard errors. For the DOL factor both parameters are positive, but neither is statistically significant.

The cross-sectional fit of the model is modest, with an $R^2 = 0.39$. The modest fit of the model can also be seen in Figure 1 which plots the model-predicted expected returns against the sample average returns of the ten test assets. While the model does quite well in fitting the carry portfolios (C1–C5), it does rather poorly in explaining the momentum portfolios (M1–M5). In fact, it predicts that the M5 portfolio should have a lower expected return than the M1 portfolio. This is not puzzling: As we saw above, the M1 portfolio has a much larger exposure to HMLC risk than the M5 portfolio does.

While the model passes the Hansen-Jagannathan specification test (p-value of 0.16), it is rejected based on the Fama-MacBeth specification test (p-value of 0.01). The KP test strongly rejects the null of reduced rank.

## Estimates of the DOL-DVOL Model

Table 3 shows results for a model similar to the one used by Menkhoff et al. (2012), which includes DOL and DVOL as factors. Qualitatively, the results are in line with what has been documented in the existing 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 $\hat{b}_{\text{DVOL}}$ nor $\hat{\lambda}_{\text{DVOL}}$ is statistically significant at conventional significance levels, except when we use the Fama-MacBeth method.

The cross-sectional fit of the model is slightly better than that of the DOL-HMLC model, because the model fits the momentum portfolios somewhat better, and the carry portfolios almost as well. This is illustrated in Figure 2.

While the model passes the Hansen-Jagannathan specification test (p-value of 0.30), it is rejected based on the Fama-MacBeth specification test (p-value of 0.02). On the other hand, the KP test only rejects the null hypothesis of reduced rank at the 24% level. This may reflect the degree of imprecision with which the betas are estimated for the DVOL factor.

## Additional Currency Portfolios

In this section we consider several currency portfolios in addition to the ones we used as test assets in the main text.

### Carry Related Portfolios

- HMLC "High-Minus-Low Carry". Similar in spirit to the factor created by Lustig et al. (2011), and, as described in Section II.1, this is the return to being long portfolio C5 and short portfolio C1.

- HMLC-Alt. Similar to HMLC, this is the return to being long 50-50 in C4 and C5, and short 50-50 in C1 and C2.

- EWC "Equally-Weighted Carry". As in Burnside et al. (2011), if there are $N_t$ currencies available at time $t$, this portfolio goes long $1/N_t$ in each of the currencies with a positive forward discount and short $1/N_t$ in each of the currencies with a negative forward discount.

- DNC "Dollar-Neutral Carry". As in Daniel et al. (2017), this is formed in the same way as EWC except that the portfolio is long those currencies whose forward discount exceeds the median value in that time period, and short those whose forward discount is below the median value in that time period. This is similar to HMLC-Alt but doesn't exclude the currencies in C3, and is less leveraged (the sum of the absolute portfolio weights is 1 not 2).

- DDC "Dynamic Dollar Carry". As in Daniel et al. (2017), this portfolio goes long $1/N_t$ in every foreign currency if the median forward discount is positive, and short $1/N_t$ in every foreign currency if the median forward discount is negative.

- EWD "Equally Weighted Dollar Carry". As in Lustig et al. (2014), this portfolio goes long $1/N_t$ in every foreign currency if the median forward discount is positive, and short $1/N_t$ in every foreign currency if the median forward discount is negative.

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- HMLM "High-Minus-Low Momentum". This is the return to being long portfolio M5 and short portfolio M1.

- HMLM-Alt. This is the return to being long 50-50 in M4 and M5, and short 50-50 in M1 and M2.

- EWM "Equally-Weighted Momentum". If there are $N_t$ currencies available at time $t$, this portfolio goes long $1/N_t$ in each of the currencies with positive momentum and short $1/N_t$ in each of the currencies with negative momentum.

**Value Portfolios**

- Following Asness et al. (2013), we form three "value" portfolios from the G9 currencies, based on the magnitude of the real exchange rate of each currency with respect to the USD, measured against a benchmark of 60 months prior. These portfolios are labeled V1, V2, and V3 and are arranged in order from undervalued to overvalued.

- The V1, V2, and V3 portfolios are based on real exchange rates measured with price indices. This is why they have to be benchmarked against historical values. An alternative is to form five portfolios based on the value of the Big Mac Index (BMI) in each country. The BMI measures the USD price of a Big Mac in different countries and therefore provides a real exchange rate (however narrowly defined) with a direct interpretation. This requires us to drop Slovakia from consideration as data for Slovakia's BMI are not available during our sample period. Our five portfolios, labeled B1, B2, ..., B5 are arranged in increasing order of BMI in the previous calendar year.

- HMLB "High-Minus-Low Big Mac". This is the return to being long portfolio B1 and short portfolio B5.

- HMLB-Alt. This is the return to being long 50-50 in B1 and B2, and short 50-50 in B4 and B5.

**Currency Liquidity**

- LIQ. As in Mancini et al. (2013) this portfolio is long in the two most illiquid and short in the two most liquid currencies, where liquidity is measured by the size of the big-ask spread.

We use the model estimated in Section V to compute the model-predicted expected return for each portfolio. This is formed as $\hat{\beta}_p\hat{\lambda}$ where $\hat{\beta}_p$ is the portfolio's $1 \times 2$ vector of betas with respect to our factors (DOL and CM) and $\hat{\lambda}$ is the $2 \times 1$ vector of estimated risk premia presented in Table 12. The model-predicted expected return is then compared to the sample average of the return on the portfolio.

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Table 1: Decomposed Betas for the DOL-CM Model

| | (a) Currency Change | | | | (b) Forward-Discount | | | |
|---|---|---|---|---|---|---|---|---|
| | $\alpha$ $\times 100$ | $\beta$-DOL | $\beta$-CM | $\bar{R}^2$ | $\alpha$ $\times 100$ | $\beta$-DOL $\times 100$ | $\beta$-CM $\times 100$ | $\bar{R}^2$ |
| C1 | -0.01 | 0.60 | -0.25 | 0.62 | -0.03 | 0.03 | -0.20 | -0.003 |
| | (0.02) | (0.04) | (0.10) | | (0.00) | (0.09) | (0.41) | |
| C2 | -0.01 | 0.94 | 0.09 | 0.82 | 0.00 | 0.05 | 0.03 | -0.003 |
| | (0.02) | (0.03) | (0.07) | | (0.00) | (0.07) | (0.39) | |
| C3 | -0.02 | 0.94 | 0.21 | 0.83 | 0.02 | 0.06 | 0.17 | -0.002 |
| | (0.02) | (0.03) | (0.08) | | (0.00) | (0.08) | (0.44) | |
| C4 | -0.06 | 1.16 | 0.28 | 0.77 | 0.06 | 0.04 | 0.20 | -0.003 |
| | (0.04) | (0.07) | (0.12) | | (0.00) | (0.09) | (0.44) | |
| C5 | -0.04 | 1.04 | 0.38 | 0.55 | 0.19 | 0.23 | 0.95 | -0.001 |
| | (0.06) | (0.09) | (0.20) | | (0.01) | (0.26) | (1.28) | |
| M1 | -0.09 | 0.98 | -0.36 | 0.63 | 0.04 | 0.14 | 0.14 | -0.003 |
| | (0.04) | (0.07) | (0.15) | | (0.01) | (0.28) | (1.08) | |
| M2 | -0.01 | 1.00 | 0.13 | 0.78 | 0.03 | 0.03 | 0.74 | -0.001 |
| | (0.03) | (0.05) | (0.09) | | (0.00) | (0.17) | (0.67) | |
| M3 | -0.04 | 0.96 | 0.18 | 0.81 | 0.04 | 0.05 | 1.02 | 0.002 |
| | (0.03) | (0.03) | (0.09) | | (0.03) | (0.12) | (0.68) | |
| M4 | 0.00 | 0.89 | 0.34 | 0.76 | 0.05 | 0.02 | 0.00 | -0.004 |
| | (0.03) | (0.02) | (0.10) | | (0.00) | (0.17) | (0.77) | |
| M5 | 0.03 | 0.80 | 0.64 | 0.57 | 0.11 | 0.31 | -0.77 | -0.002 |
| | (0.04) | (0.05) | (0.16) | | (0.01) | (0.35) | (1.57) | |

*Note*: We present estimates of the time series regressions

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

where $w_{it}$ is one of two component of $r_{it}^e$, the excess return of portfolio $i$ at time $t$, and $z_t$ is a vector of the two risk factors, DOL and CM. In part (a) $w_{it}$ is the component of the excess return due to the changing values of the spot rates of the constituent currencies. In part (b) $w_{it}$ is the component of the excess return due to the forward discounts of the constituent currencies. The portfolios are C1—C5 and M1—M5, described in the main text. Standard errors are reported in parentheses. We use weekly data, from the third week of January 2002 to the fourth week of March 2012.

Table 2: Estimates of the DOL-HMLC Model

| GMM Estimates | | | | |
|---|---|---|---|---|
| | DOL | HMLC | $R^2$ | HJ |
| $b$ | 3.85 | 5.93 | 0.39 | 11.73 |
| | (4.00) | (3.78) | | [0.16] |
| $\lambda$ | 0.10 | 0.18 | | |
| | (0.06) | (0.10) | | |
| **Fama-MacBeth Estimates** | | | | |
| | DOL | HMLC | $R^2$ | $\chi^2_{SH}$ |
| $\lambda$ | 0.10 | 0.18 | 0.39 | 19.26 |
| | (0.06) | (0.07) | | [0.01] |
| **KP Rank Tests** | | | | |
| | Stat. | d.f. | p-value | |
| Rank(0) | 273.6 | 20 | 0.00 | |
| Rank(1) | 206.0 | 9 | [0.00] | |

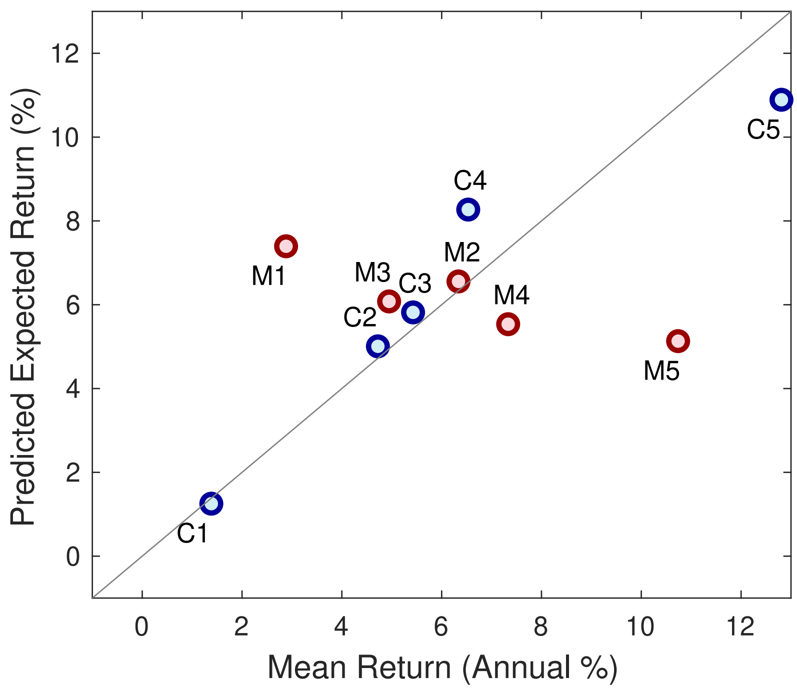
*Note*: We present estimates of the SDF and beta representations of the DOL-HMLC model, as well as KP reduced-rank tests. The test assets are C1 to C5, the five portfolios sorted on interest rate, and M1 to M5, the five portfolios sorted on momentum. The first panel shows the estimates of the SDF coefficients, $b$, from first stage GMM, corresponding risk prices, $\lambda$, the cross-sectional $R^2$ and Hansen-Jagannathan distance (HJ). Estimates of $\lambda$ are scaled by 100. The second panel shows estimates of $\lambda$ obtained using the Fama-MacBeth method with no intercept. A $\chi^2$ 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 last week of November 2001 to the fourth week of March 2012.

Table 3: Estimates of the Volatility (DOL-DVOL) Model

| GMM Estimates | | | | |
|---|---|---|---|---|
| | DOL | DVOL | $R^2$ | HJ |
| $b$ | 0.58 | -0.98 | 0.50 | 9.54 |
| | (5.31) | (0.90) | | [0.30] |
| $\lambda$ | 0.10 | -24.61 | | |
| | (0.11) | (22.47) | | |
| **Fama-MacBeth Estimates** | | | | |
| | DOL | DVOL | $R^2$ | $\chi^2$ |
| $\lambda$ | 0.10 | -24.61 | 0.50 | 18.67 |
| | (0.06) | (10.25) | | [0.02] |
| **KP Rank Tests** | | | | |
| | Stat. | d.f. | p-value | |
| Rank(0) | 375.4 | 20 | 0.00 | |
| Rank(1) | 11.6 | 9 | [0.24] | |

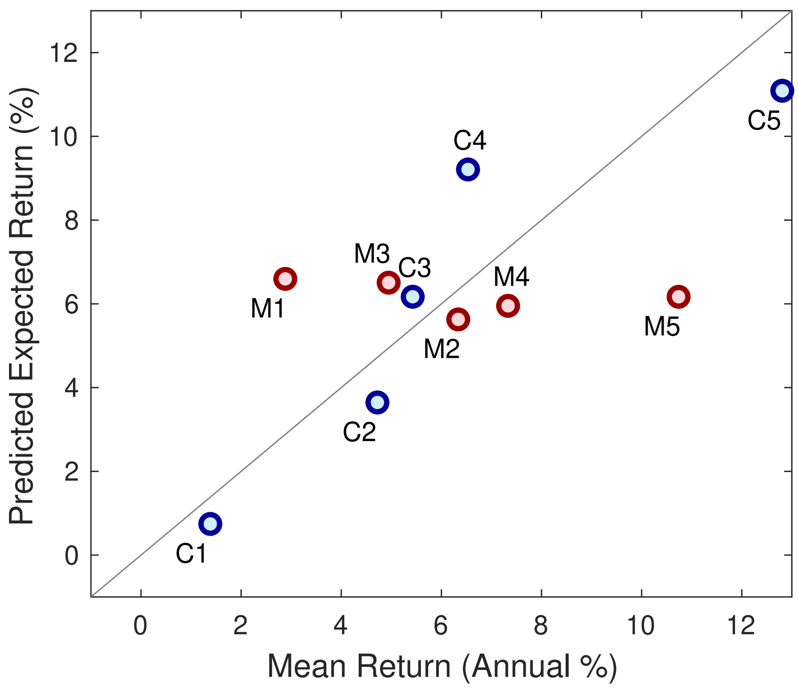
*Note*: We present SDF and beta representation estimates for the DOL-DVOL model, as well as KP reduced-rank tests. The test assets are C1 to C5, the five portfolios sorted on interest rate, and M1 to M5, the five portfolios sorted on momentum. The first panel shows the estimates of the SDF coefficients, $b$, from first stage GMM, corresponding risk prices, $\lambda$, the cross-sectional $R^2$ and Hansen-Jagannathan distance (HJ). Estimates of $\lambda$ are scaled by 100. The second panel shows estimates of $\lambda$ obtained using the Fama-MacBeth method with no intercept. A $\chi^2$ 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 last week of November 2001 to the fourth week of March 2012.

Figure 1: Cross-Sectional Fit of the DOL-HMLC Model




*Note*: This figure illustrates the cross-sectional fit of the DOL-HMLC model (see Table 2). The model-predicted expected return is plotted against the mean annualized excess returns of the ten currency portfolios (C1–C5 in blue, and M1–M5 in red).

Figure 2: Cross-Sectional Fit of the DOL-DVOL Model

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In Table 2 we estimate a model based on the DOL and HMLC factors proposed by Lustig et al. (2011). Qualitatively, the results are in line with what has been documented in the existing literature. The SDF parameter ($b$) for the HMLC factor is positive, although only statistically significant at around the 12% level. The associated risk price ($\lambda$) is positive and statistically significant at the 7% or 1% level depending on the procedure used to compute standard errors. For the DOL factor both parameters are positive, but neither is statistically significant.

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Table 3 shows results for a model similar to the one used by Menkhoff et al. (2012), which includes DOL and DVOL as factors. Qualitatively, the results are in line with what has been documented in the existing 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.

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## Additional Currency Portfolios

In this section we consider several currency portfolios in addition to the ones we used as test assets in the main text.

### Carry Related Portfolios

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- Following Asness et al. (2013), we form three "value" portfolios from the G9 currencies, based on the magnitude of the real exchange rate of each currency with respect to the USD, measured against a benchmark of 60 months prior. These portfolios are labeled V1, V2, and V3 and are arranged in order from undervalued to overvalued.

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**Currency Liquidity**

- LIQ. As in Mancini et al. (2013) this portfolio is long in the two most illiquid and short in the two most liquid currencies, where liquidity is measured by the size of the big-ask spread.

We use the model estimated in Section V to compute the model-predicted expected return for each portfolio. This is formed as $\hat{\beta}_p\hat{\lambda}$ where $\hat{\beta}_p$ is the portfolio's $1 \times 2$ vector of betas with respect to our factors (DOL and CM) and $\hat{\lambda}$ is the $2 \times 1$ vector of estimated risk premia presented in Table 12. The model-predicted expected return is then compared to the sample average of the return on the portfolio.

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| | (a) Currency Change | | | | (b) Forward-Discount | | | |
|---|---|---|---|---|---|---|---|---|
| | $\alpha$ $\times 100$ | $\beta$-DOL | $\beta$-CM | $\bar{R}^2$ | $\alpha$ $\times 100$ | $\beta$-DOL $\times 100$ | $\beta$-CM $\times 100$ | $\bar{R}^2$ |
| C1 | -0.01 | 0.60 | -0.25 | 0.62 | -0.03 | 0.03 | -0.20 | -0.003 |
| | (0.02) | (0.04) | (0.10) | | (0.00) | (0.09) | (0.41) | |
| C2 | -0.01 | 0.94 | 0.09 | 0.82 | 0.00 | 0.05 | 0.03 | -0.003 |
| | (0.02) | (0.03) | (0.07) | | (0.00) | (0.07) | (0.39) | |
| C3 | -0.02 | 0.94 | 0.21 | 0.83 | 0.02 | 0.06 | 0.17 | -0.002 |
| | (0.02) | (0.03) | (0.08) | | (0.00) | (0.08) | (0.44) | |
| C4 | -0.06 | 1.16 | 0.28 | 0.77 | 0.06 | 0.04 | 0.20 | -0.003 |
| | (0.04) | (0.07) | (0.12) | | (0.00) | (0.09) | (0.44) | |
| C5 | -0.04 | 1.04 | 0.38 | 0.55 | 0.19 | 0.23 | 0.95 | -0.001 |
| | (0.06) | (0.09) | (0.20) | | (0.01) | (0.26) | (1.28) | |
| M1 | -0.09 | 0.98 | -0.36 | 0.63 | 0.04 | 0.14 | 0.14 | -0.003 |
| | (0.04) | (0.07) | (0.15) | | (0.01) | (0.28) | (1.08) | |
| M2 | -0.01 | 1.00 | 0.13 | 0.78 | 0.03 | 0.03 | 0.74 | -0.001 |
| | (0.03) | (0.05) | (0.09) | | (0.00) | (0.17) | (0.67) | |
| M3 | -0.04 | 0.96 | 0.18 | 0.81 | 0.04 | 0.05 | 1.02 | 0.002 |
| | (0.03) | (0.03) | (0.09) | | (0.03) | (0.12) | (0.68) | |
| M4 | 0.00 | 0.89 | 0.34 | 0.76 | 0.05 | 0.02 | 0.00 | -0.004 |
| | (0.03) | (0.02) | (0.10) | | (0.00) | (0.17) | (0.77) | |
| M5 | 0.03 | 0.80 | 0.64 | 0.57 | 0.11 | 0.31 | -0.77 | -0.002 |
| | (0.04) | (0.05) | (0.16) | | (0.01) | (0.35) | (1.57) | |

*Note*: We present estimates of the time series regressions

$$w_{it} = \alpha_i + z_t'\beta_i + \epsilon_{it}, \qquad t = 1, \dots, T,$$

where $w_{it}$ is one of two component of $r_{it}^e$, the excess return of portfolio $i$ at time $t$, and $z_t$ is a vector of the two risk factors, DOL and CM. In part (a) $w_{it}$ is the component of the excess return due to the changing values of the spot rates of the constituent currencies. In part (b) $w_{it}$ is the component of the excess return due to the forward discounts of the constituent currencies. The portfolios are C1—C5 and M1—M5, described in the main text. Standard errors are reported in parentheses. We use weekly data, from the third week of January 2002 to the fourth week of March 2012.

Table 2: Estimates of the DOL-HMLC Model

| GMM Estimates | | | | |
|---|---|---|---|---|
| | DOL | HMLC | $R^2$ | HJ |
| $b$ | 3.85 | 5.93 | 0.39 | 11.73 |
| | (4.00) | (3.78) | | [0.16] |
| $\lambda$ | 0.10 | 0.18 | | |
| | (0.06) | (0.10) | | |
| **Fama-MacBeth Estimates** | | | | |
| | DOL | HMLC | $R^2$ | $\chi^2_{SH}$ |
| $\lambda$ | 0.10 | 0.18 | 0.39 | 19.26 |
| | (0.06) | (0.07) | | [0.01] |
| **KP Rank Tests** | | | | |
| | Stat. | d.f. | p-value | |
| Rank(0) | 273.6 | 20 | 0.00 | |
| Rank(1) | 206.0 | 9 | [0.00] | |

*Note*: We present estimates of the SDF and beta representations of the DOL-HMLC model, as well as KP reduced-rank tests. The test assets are C1 to C5, the five portfolios sorted on interest rate, and M1 to M5, the five portfolios sorted on momentum. The first panel shows the estimates of the SDF coefficients, $b$, from first stage GMM, corresponding risk prices, $\lambda$, the cross-sectional $R^2$ and Hansen-Jagannathan distance (HJ). Estimates of $\lambda$ are scaled by 100. The second panel shows estimates of $\lambda$ obtained using the Fama-MacBeth method with no intercept. A $\chi^2$ 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 last week of November 2001 to the fourth week of March 2012.

Table 3: Estimates of the Volatility (DOL-DVOL) Model

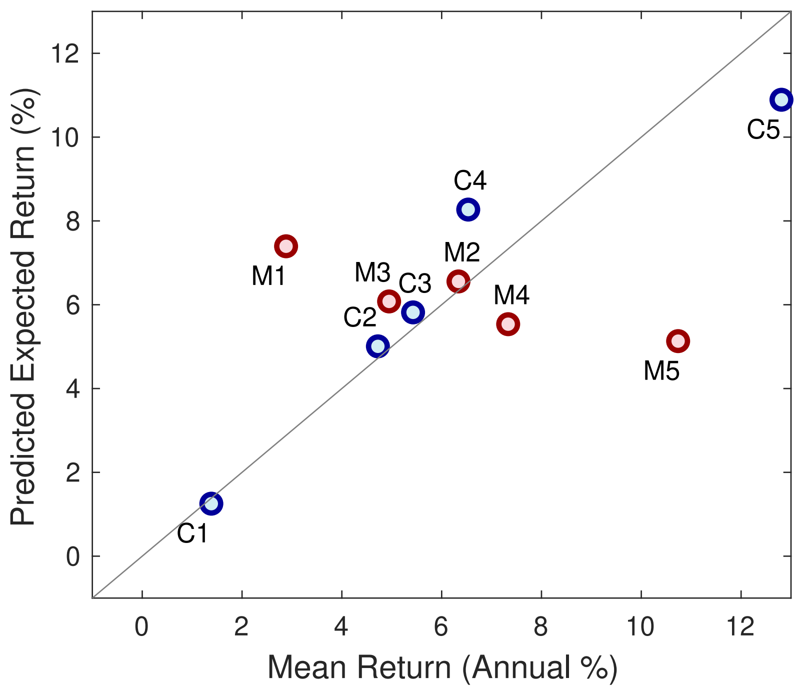
| GMM Estimates | | | | |
|---|---|---|---|---|
| | DOL | DVOL | $R^2$ | HJ |
| $b$ | 0.58 | -0.98 | 0.50 | 9.54 |
| | (5.31) | (0.90) | | [0.30] |
| $\lambda$ | 0.10 | -24.61 | | |
| | (0.11) | (22.47) | | |

| Fama-MacBeth Estimates | | | | |
|---|---|---|---|---|
| | DOL | DVOL | $R^2$ | $\chi^2$ |
| $\lambda$ | 0.10 | -24.61 | 0.50 | 18.67 |
| | (0.06) | (10.25) | | [0.02] |

| KP Rank Tests | | | |
|---|---|---|---|
| | Stat. | d.f. | p-value |
| Rank(0) | 375.4 | 20 | 0.00 |
| Rank(1) | 11.6 | 9 | [0.24] |

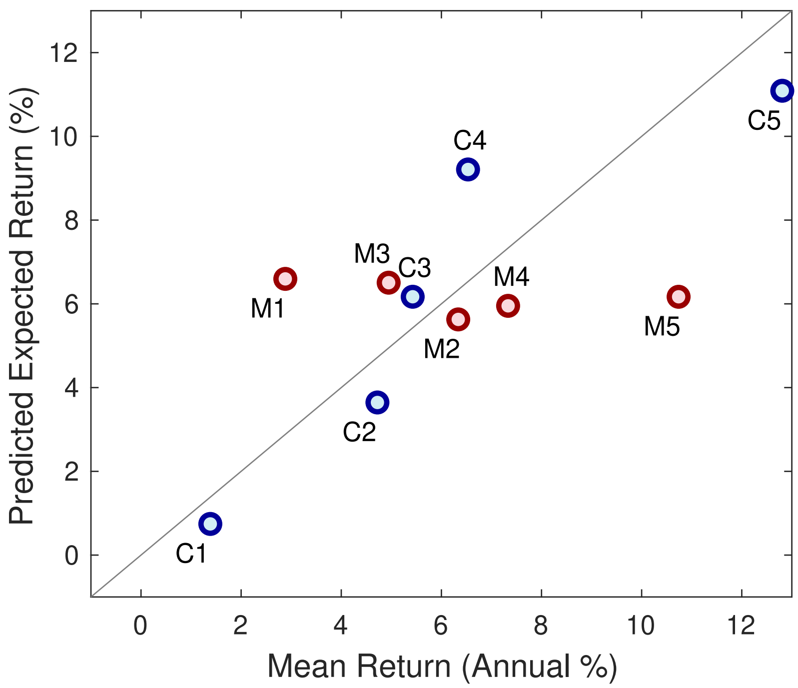
*Note*: We present SDF and beta representation estimates for the DOL-DVOL model, as well as KP reduced-rank tests. The test assets are C1 to C5, the five portfolios sorted on interest rate, and M1 to M5, the five portfolios sorted on momentum. The first panel shows the estimates of the SDF coefficients, $b$, from first stage GMM, corresponding risk prices, $\lambda$, the cross-sectional $R^2$ and Hansen-Jagannathan distance (HJ). Estimates of $\lambda$ are scaled by 100. The second panel shows estimates of $\lambda$ obtained using the Fama-MacBeth method with no intercept. A $\chi^2$ 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 last week of November 2001 to the fourth week of March 2012.

Figure 1: Cross-Sectional Fit of the DOL-HMLC Model




*Note*: This figure illustrates the cross-sectional fit of the DOL-HMLC model (see Table 2). The model-predicted expected return is plotted against the mean annualized excess returns of the ten currency portfolios (C1–C5 in blue, and M1–M5 in red).

Figure 2: Cross-Sectional Fit of the DOL-DVOL Model




*Note*: This figure illustrates the cross-sectional fit of the DOL-DVOL model (see Table 3). The model-predicted expected return is plotted against the mean annualized excess returns of the ten currency portfolios (C1–C5 in blue, and M1–M5 in red).