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Exchange Rates, Interest Rates and the Global Carry Trade*

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Abstract

We empirically examine how the global carry trade affects the dynamics of spot exchange rates and interest rates across 13 countries from 2000, through the world financial crisis, until the end of 2011. Our model identifies the weekly carry trade position in each currency by matching data on forex trading flows with the predictions of a dynamic portfolio allocation problem that exploits the predictability in excess currency returns (deviations from uncovered interest parity). Using these carry positions produce two surprising results: First, in nine countries carry trades are an economically significant driver of interest rate differentials (vs. U.S. rates). Second, the carry trade only affects the dynamics of spot exchange rates insofar as it is contributes to total forex order flow; (i.e., flows generated by the carry trade and all other trading motives). These findings contradict the conventional view that sudden large movements in exchange rates are attributable to the carry trade. They suggest, instead, that the effects of the global carry trade are primarily concentrated in bond markets.

Keywords: Exchange Rate Dynamics, Microstructure, Order Flow.
JEL Codes: F3; F4; G1.

1 Introduction

International capital flows generated by the carry trade are widely believed to affect the behavior of foreign currency (forex) and other financial markets. In particular, carry trade activity is thought to contribute to the steady strengthening of target currencies with high interest rates and a weakening of funding currencies with low interest rates — movements that are inconsistent with the predictions of uncovered interest parity (UIP). Moreover, abrupt depreciations in target currencies and appreciations in funding currencies are often attributed to the rapid unwinding of carry trade positions generated by changes in expectations, risk tolerance or funding constraints (see, e.g., Gagnon and Chaboud, 2007 and Brunnermeier et al., 2009). Indeed, the effects of the global carry trade appear as a prime suspect whenever exchange rates move away from the paths that appear supported by macro fundamentals.[1] More generally, speculative capital flows associated with various forms of the carry trade are thought to affect a wide range of asset classes, ranging from bonds to equities to real estate (Tse and Zhao, 2012 and Acharya and Steffen, 2015). So the rapid unwinding of carry trade positions are viewed as a source of instability to global financial markets.

In this paper we present new evidence on the effects of the carry trade. In particular we examine how carry trade activity affects the dynamics of spot exchange rates and interest rate differentials across twelve currency pairs between 2000 and 2011. The novel feature of this research concerns the identification of carry trade activity. Existing measures, based on international banking statistics and position data from the futures market have well-known limitations (see below), so researchers have found it hard to make precise inferences about the effects of the carry trade. Instead, we develop a model to estimate carry trade activity in each currency by matching data on forex order flows with the predictions of a dynamic portfolio allocation model that exploits the deviations from UIP characteristic of canonical carry trades.

This model-based approach has several appealing features: First it decomposes the weekly forex order flow in each currency into two components, a carry component and a non-carry component driven by other factors. Since forex order flows are known to be important proximate drivers of exchange rate movements, this decomposition allows us to study how

[1]The exchange rate effects of the carry trade are routinely discussed in IMF and BIS publications; see, e.g. IMF (1998) and Cairns and McCauley (2007).

the carry trade affects exchange rates via its impact on order flow.[2] Second, our approach recognizes that historical returns to carry trade strategies have been very high. We derive our estimates of carry trade activity from real-time attempts to maximize expected future returns. Third, our approach also provides us with multilaterally consistent estimates of the carry trade positions in each country because the positions are derived from the solution to a multi-country portfolio allocation problem. Finally, we are able to estimate the total value of assets committed to carry trades across currencies. This global measure of carry trade activity provides information about carry trade speculators' risk tolerance and access to funding.

We estimate Structural Vector Autogressions (SVARs) for the order flow components, nominal depreciation rates and interest differentials for 12 countries verses the United States (Australia, Canada, the Euro Area, Japan, Mexico, Norway, New Zealand, Sweden, Singapore, South Africa, Switzerland, and the United Kingdom), from the start of 2000 until the end of 2011. Summary measures of the effects of the carry trade on exchange rates and interest rates are provided by the variance decompositions based on the SVAR estimates. We also compute historical decompositions for the SVAR variables to examine how the carry component of order flow contributed to movements in exchange rate and interest differentials in particular periods.

Our SVAR analysis produces several striking results. First, we find no evidence that the carry component of order flow affects the behavior of exchange rates for any of the currencies pairs. This is true "on average", in the sense that order flow shocks driven by the carry trade make insignificant contributions to the variance of depreciation rates over horizons ranging from one to 26 weeks. It also appears true episodically. Our historical decompositions do not show any episodes where variations in exchange rates appear driven by the effects of the carry component in order flows. These findings contradict the conventional wisdom concerning the exchange-rate effects of the carry trade described above.

The second main result concerns the effect of the carry trade on interest differentials. We find that order flow shocks driven by the carry trade have economically significant effects on the interest differentials in nine countries. These shocks appear to be the dominant driver of the differentials between U.S. short-term interest rates and the rates in New Zealand,

[2]Recent surveys of the literature examining the effect of forex order flows on exchange rates include Osler (2009), Evans (2011) and Evans and Rime (2012).

Singapore and South Africa throughout the period we study. The interest-rate effects of the carry trade also appear significant over shorter periods lasting a few years in Australia, Canada, Japan and Switzerland. All of these countries have been cited as either a funding source or target for the carry trade at one time or another (see, e.g., Galati et al., 2007). We also find that the interest differentials between U.S. rates and the rates in the Euro area, Norway and Sweden have been largely unaffected by the carry trade.

Our results provide new perspectives on the scale and dynamics of the carry trade. Global carry trade activity followed a cyclical pattern between 2001 and 2011, with peaks in 2002, 2005 and 2007. These cycles affect both the size and direction of the carry components of order flows across currencies. The carry components of order flow produce large carry positions in individual currencies; positive positions when the currencies are targets, and negative positions when the currencies are funding sources. Furthermore, there are episodes where large positions are quickly unwounded. Thus, our estimates of carry trade activity exhibit the time series characteristics that are believed to affect exchange rates (e.g., via the rapid unwinding of carry positions), but we nevertheless are unable to find evidence that this is in fact the case.

Finally, our SVAR models provide a perspective on the drivers of the carry trade. By construction, the carry component of individual order flows reflect changing forecasts about future returns on carry positions in 12 currencies, so any factor affecting these forecasts can in principle drive changes in individual carry positions. In practice our SVAR model estimates show that exogenous shocks to the domestic interest differential account for almost all the changes in the carry trade positions in Japan, Mexico, New Zealand and Singapore. The drivers of the carry positions in other countries are less clear cut. Shocks to domestic interest rates appear important over short periods in some countries (Australia, Canada and South Africa), but elsewhere other factors dominate. Based on our analysis, there is no simple characterization of what drives carry trade activity across all countries.

The structure of the paper is as follows: Section 2 discusses how this paper relates to earlier research. We present our model in Section 3. In Section 4 we describe the data and present the estimates of carry trade activity. The effects of the carry trade on exchange rates and interest rates are analyzed in Section 5 and discussed in Section 6. Section 7 concludes.

2 Related Literature

The carry trade refers to a class of trading strategies that exploit predictable cross-country differences in returns. In its simplest form a canonical carry trade involves borrowing (going short) in a source country's bond market where interest rates are low and investing (going long) in a target country's bonds where interest rates are high. The expected net return from engaging in this strategy should be zero under UIP because the expected depreciation of the target currency equalizes the returns on the long and short positions when measured in terms of a common currency. However, in practice, realized returns are far from equal. Indeed, there is a vast literature on UIP deviations (see Lewis, 1995 and Engel, 1996, 2015 for surveys) showing that differences in returns on cross-country bond positions are forecastable. This forecastability provides part of the impetus driving the canonical carry trade.

Other carry trade strategies involve currency derivatives, equities, foreign currency loans, and the international banking system. For example, the canonical carry strategy described above can be executed via the forward purchase of a target currency when forward contracts are selling at a discount relative to the current spot rate. A similar strategy can be implemented with currency futures contracts. Hedged carry trade strategies mitigate the risk from adverse exchange rate movements through the use of currency options (see, e.g., Burnside et al., 2011). As an example of carry strategies involving equities, Cheung et al. (2012) examine the effects of borrowing in the Japanese bond market to fund speculative equity positions in Australia, Britain, Canada, New Zealand, and Mexico. Another form of the carry trade involves foreign currency loans. For example, Galati et al. (2007) and Beer et al. (2010) document the popularity of 2002 Swiss franc-denominated mortgages in some eastern european countries. Finally, Acharya and Steffen (2015) characterize eurozone banking flows during the 2007-2012 period as a carry trade involving long positions in peripheral country bonds and short positions in German bonds. Koijen et al. (2013) show that many asset classes, including commodities and US Treasuries, exhibit carry-like elements in their returns.

A large literature examines the returns on carry trade strategies. Lustig and Verdelhan (2007) were the first to build portfolios to study the properties of the returns to carry trading. Burnside et al. (2011) emphasize that the strategies generate returns with high Sharpe ratios, higher than the returns on equity portfolios. Nevertheless, Lyons (2001) questions whether they have been large enough for financial institutions to commit large amounts of their own capital to carry trade strategies. Bhansali (2007) and Menkhoff et al. (2012b) show that carry strategies produce poor returns when exchange rate volatility is high. The question of whether returns to the carry trade represent compensation for exposure to risk factors has been addressed by a number of recent studies; including Lustig and Verdelhan (2007), Lustig et al. (2011), Farhi and Gabaix (2016), Burnside et al. (2011), Menkhoff et al. (2012a) and Daniel et al. (2014) (see Burnside, 2012 for a review). In this paper we do not take a stand on the source of the predictability in carry trade returns. We simply use real-time out-of-sample regression forecasts for returns to identify the carry trade positions in our portfolio choice model.

Earlier research on the effects of the carry trade use several different activity measures. Klitgaard and Weir (2004), Nishigaki (2007) and Brunnermeier et al. (2009) measure carry trade activity by the net open positions in currency futures contracts held by noncommercial traders. Gagnon and Chaboud (2007) and Galati et al. (2007) use balance sheet information contained in the BIS international banking statistics (bank's cross-border positions in different currencies). The authors of these studies clearly acknowledge the limitations of these measures. In particular they note that the position data for the currency futures market are subject to the imperfect classification of commercial and noncommercial traders as speculators involved in the carry trade. Moreover, while futures contracts can be used to execute carry trades, the volume of over-the-counter trade in currency forward contracts is far larger and thus more likely to be representative of derivative-based carry trade activity. The BIS statistics also pose problems. Because banks' balance sheets exclude leveraged accounts that would be used to execute derivative-based carry trades, at best they can only capture trades executed in cash markets (e.g., in the spot foreign currency and bond markets). Moreover, it is impossible to distinguish carry trade positions from other positions in balance sheet data.

Lyons (2001) and Evans (2011) examine a third measure of carry activity, the order flows of leveraged financial institutions in the dollar-yen market. These order flows are computed as the difference between the U.S. dollar (USD) value of orders to purchase and sell Japanese yen received each day by Citibank from hedge funds and other leveraged investors. This is a cleaner measure of actual carry trading activity, at least activity executed in the cash market, but it is limited to the trades at one large bank and in a single currency pair. Menkhoff et al. (2016) use similar data from a different bank, covering several currencies, and study the predictive power of portfolios based on lagged customer order flow. Unfortunately, market-wide data on leveraged customer flows across many currencies is unobtainable. In contrast, the data on market-wide order flows from the interbank market is available, but unlike the Citibank data, the flows are anonymous; i.e., they do not identify when trades are made on behalf of leveraged customers. We use this order flow data in conjunction with our portfolio choice model to estimate carry trade activity.

A number of papers provide *indirect* evidence concerning the effects of the carry trade. Brunnermeier et al. (2009) find that positive interest rate differentials are associated with negative conditional skewness of exchange rate movements. This pattern is consistent with temporary changes in the availability of funding liquidity to speculators engaged in leveraged carry trades. In particular, reductions in funding could trigger the rapid unwinding of carry positions leading to abrupt movements in exchange rates. Other indirect evidence comes from the literature on hedge funds. Pojarliev and Levich (2008 and 2010) find that the returns reported by currency hedge funds are mostly correlated with popular carry strategies. Jylhä and Suominen (2011) show that returns from a particular carry strategy can explain a large fraction of various hedge fund index returns. They then relate changes in interest rates and exchange rates to variations in hedge fund assets under management.

Finally, our analysis is related to forex microstructure literature. Microstructure models emphasize the role of forex trading in the determination of equilibrium exchange rates, particular the role of order flows (see, e.g., Lyons, 2001 and Evans, 2011). Order flows are the proximate drivers of exchange rates in these models because they convey information to market participants about the aggregate demand for each currency, and hence the future level for the exchange rate consistent with efficient risk-sharing. This theoretical framework easily accommodates the effects of the carry trade. In particular, forex orders produced by speculators engaged in the carry trade will affect the exchange rate insofar as they contribute to order flow that conveys information to market participants. In fact, because there is no real-time public reporting of participation in the carry trade (i.e., participation is private information), this is the *only* mechanism through which carry trade activity can have an exchange rate effect. Our analysis exploits this theoretical insight by examining whether the forex order flows driven by the carry trade do in fact have measurable impacts on exchange rates and interest rates.

3 The Model

As we noted above, carry trade strategies can involve trades in many different cash and derivatives markets. Moreover, strategies can be implemented in a single pair of currencies, or across multiple currencies simultaneously. No single model can therefore hope to accurately represent all the diverse carry trade strategies that have been implemented historically. We choose, instead, to take the perspective of a representative U.S. based hedge fund. The fund's carry trading is modelled as the forex trades that support the outcome of a portfolio allocation across 13 currencies based on real-time forecasts for the excess returns on foreign bond positions. Thus our approach takes the deviations from UIP that underly the forecastability of excess returns as inputs to generate carry trade positions consistent with optimal portfolio choice.

3.1 Portfolio Choices and Trading Decisions

The representative U.S. based hedge fund invests in a portfolio of N (here 12) foreign currency bonds and U.S. bonds. All bonds are assumed default-free. Let A_t denote the USD value of the fund's assets at the start of period t, comprising the domestic value of U.S. bond holdings A_t^0; and foreign bond holdings, A_t^i, for $i = \{1, 2, ..N\}$. Thus, $A_t = A_t^0 + \sum_{i=1}^N S_t^i A_t^i$, where S_t^i is the USD price of currency i. Returns on the fund's assets are defined as follows. Let R_t^i be the (gross) nominal interest rate on one-period bonds in country i, for $i = \{0, 1, ...N\}$, where country 0 is the U.S. The USD return from holding foreign country i's bonds during period t, realized at the start of period $t+1$, is $(S_{t+1}^i / S_t^i) R_t^i$. We identify the share of country $i's$ bonds in the fund's assets by $w_t^i = S_t^i A_t^i / A_t$ for $i = \{1, 2, ..N\}$, so the return on the fund's period-t portfolio, realized at the start of period $t+1$, is given by

$$\begin{aligned} R_{t+1}^p &= \left(1 - \sum_{i=1}^N w_t^i\right) R_t^0 + \sum_{i=1}^N w_t^i (S_{t+1}^i / S_t^i) R_t^i \\ &= R_t^0 + \sum_{i=1}^N w_t^i \left[(S_{t+1}^i / S_t^i) R_t^i - R_t^0 \right] \\ &= R_t^0 + \sum_{i=1}^N w_t^i E R_{t+1}^i, \end{aligned}$$

where $ER^i_{t+1} = (S^i_{t+1}/S^i_t)R^i_t - R^0_t$ identifies the excess return on the bonds from country i.

We treat the portfolio problem in two parts: One part considers the fraction of the fund's total assets held in foreign bonds, $\lambda_t = \sum_{i=1}^{N} w^i_t$. The other considers the composition of the portfolio that comprises the N foreign bonds. The fraction of this risky portfolio held in country i 's bonds is $\alpha^i_t = \omega^i_t/\lambda_t$. Using λ_t and α^i_t we can rewrite the portfolio return above as

$$R^p_{t+1} = R^0_t + \lambda_t \alpha'_t ER_{t+1}, \tag{1}$$

where $ER_{t+1} = [ER^i_{t+1}]$ and $\alpha_t = [\alpha^i_t]$ are $N \times 1$ vectors of excess returns and risky asset shares, respectively. Clearly any choice for λ_t and α_t determines the portfolio shares w^i_t.

We assume that the portfolio shares are chosen to maximize the conditional Sharpe Ratio for the portfolio return,

$$SR(\Omega_t) = \frac{\mathbb{E}\left[R^p_{t+1} - R^0_t|\Omega_t\right]}{\sqrt{\mathbb{V}\left[R^p_{t+1} - R^0_t|\Omega_t\right]}},$$

where $\mathbb{E}[.|\Omega_t]$ and $\mathbb{V}[.|\Omega_t]$ denote the mean and variance conditioned on the information set available to the fund at the start of period t, Ω_t. This assumption insures that the fund's foreign bond holdings are mean-variance efficient. It pins down the risky portfolio shares in α_t given the conditional first and second moments of excess returns. This is easily seen by substituting for $R^p_{t+1} - R^0_t$ from (1) in the Sharpe Ratio to give

$$SR(\Omega_t) = \frac{\lambda_t \alpha'_t \mu_t}{\sqrt{\lambda^2_t \alpha'_t \Sigma_t \alpha_t}} = \frac{\alpha'_t \mu_t}{\sqrt{\alpha'_t \Sigma_t \alpha_t}},$$

where μ_t is an $N \times 1$ vector of conditional expected excess returns $\mathbb{E}[ER_{t+1}|\Omega_t]$, and Σ_t is the $N \times N$ conditional covariance matrix of excess returns, $\mathbb{V}[ER_{t+1}|\Omega_t]$. Clearly, α_t can be chosen to maximize $SR(\Omega_t)$ without regard to the determination of λ_t. Formally, then, we assume that the risky shares chosen by the fund in period t are

$$\alpha^*_t = \arg\max\{SR(\Omega_t)\}. \tag{2}$$

It is important to note that α^*_t is a function of the fund's period-t's information Ω_t. Through time, changes in Ω_t produce variations in μ_t and Σ_t, that induce changes in α^*_t. In words, our model allows for variations in the composition of the risky foreign bond portfolio as the fund updates the conditional first and second moments of excess returns. We describe how we compute these conditional moments below.

Our model makes no explicit assumption about the determination of λ_t, the fraction of the fund's total assets held in foreign bonds. Informally, one can think of λ_t being chosen to reflect the fund's preferences concerning risk and the return on assets R_t^p, but there is no need to specify how the values for λ_t are determined in order to examine the implications of the fund's portfolio choices for the forex trades that are the focus of our analysis.

To see why, let ΔX_t^i denote the fund's period-t order flow for currency i. Positive (negative) values for ΔX_t^i measure the USD value of foreign currency i purchased with (sold for) USDs by the fund at the start of period t. Order flow is defined as the difference between the USD value of the bond holdings implied by period-t's portfolio choice and the value of pre-existing holdings from period $t-1$, so $\Delta X_t^i = S_t^i \left(A_t^i - R_{t-1}^i A_{t-1}^i \right)$. Combining this expression with the definitions of the portfolio shares gives

$$\begin{aligned}
\Delta X_t^i &= S_t^i A_t^i - \left(\frac{S_t^i R_{t-1}^i}{S_{t-1}^i} \right) S_{t-1}^i A_{t-1}^i \\
&= w_t^i A_t - \left(\frac{S_t^i R_{t-1}^i}{S_{t-1}^i} \right) w_{t-1}^i A_{t-1} \\
&= \alpha_t^i \lambda_t A_t - \gamma_t^i \lambda_{t-1} A_{t-1} \qquad \text{with} \qquad \gamma_t^i = \alpha_{t-1}^i \left(S_t^i R_{t-1}^i / S_{t-1}^i \right) \qquad (3)
\end{aligned}$$

for $i = \{1, 2, ..N\}$. These equations identify the restrictions on the cross-country order flows implied by the fund's portfolio choices. Order flows reflect variations in the desired composition of the foreign bond portfolio via changes in α_t^i, the effects of capital gains/losses on pre-existing holdings via $S_t^i R_{t-1}^i / S_{t-1}^i$, and variations in the size of the foreign bond holdings via changes in $\lambda_t A_t$. Of course the latter changes are common to all the order flows.

It also proves useful to consider the fund's aggregate order flow. This is found by aggregating across the N order flows using the fact that $\sum_{i=1}^N \alpha_t^i = 1$:

$$\Delta X_t \equiv \sum_{i=1}^N \Delta X_t^i = \lambda_t A_t - \Gamma_t \lambda_{t-1} A_{t-1} \qquad \text{where} \qquad \Gamma_t = \sum_{i=1}^N \gamma_t^i. \qquad (4)$$

Rewriting (4) as a difference equation in $\lambda_t A_t$ and iterating backwards gives

$$\lambda_t A_t = \Delta X_t + \sum_{i=1}^{\infty} \left(\prod_{j=1}^{i} \Gamma_{t-j} \right) \Delta X_{t-i}. \tag{5}$$

Here we see that the value of the foreign bond portfolio $\lambda_t A_t$ can be found from the history of aggregate order flow, the α_t^i shares and USD returns on foreign bonds, $S_t^i R_{t-1}^i / S_{t-1}^i$. Together, equations (3) and (5) allow us to determine the individual period-t orders flows ΔX_t^i from current and past values for α_t and ΔX_t without knowledge of λ_t or the total fund's total assets A_t. We will use these equations below to estimate the contribution of the fund's order flows to the total order flows for each currency we observe in the data.

3.2 Estimating Carry Trade Order Flows

Estimating the order flows driven by the carry trade involves two steps. First we estimate the conditional first and second moments of excess returns, μ_t and Σ_t, that are used to compute the vector of risky portfolio shares $\hat{\alpha}_t^*$ in (2). These estimates are derived from real-time forecasts that exploit the deviations from UIP characteristic of carry trade strategies. In the second step we use the $\hat{\alpha}_t^*$ vectors and data on actual order flows to estimate the flows attributable to the fund's carry trade strategy.

We compute estimates of the conditional first and second moments of excess returns from the real-time forecasts generated by a system of N regression equations. For consistency with the literature on UIP deviations, each equation in the system takes the form:

$$\frac{S_{t+1}^i - F_t^i}{S_t^i} = \eta_i + \beta_i \left(\frac{F_t^i - S_t^i}{S_t^i} \right) + \zeta_{t+1}^i \qquad \text{for} \qquad i = \{1, 2, ..N\}, \tag{6}$$

where F_t^i is the one-period forward rate for currency i. By covered interest party $F_t^i = R_t^0 S_t^i / R_t^i$, so the left-hand-side variable is proportional to the excess return on currency i; i.e., $(S_{t+1}^i - F_t^i)/S_t^i = ER_{t+1}^i / R_t^i$. The right-hand-side variable, the forward premium, is proportional to the interest differential; i.e., $(F_t^i - S_t^i)/S_t^i = (R_t^0 - R_t^i)/R_t^i$. Notice that these are forecasting regressions. When β_i differs from zero changes in the period-t forward premium forecast variations in the excess returns realized in period $t+1$.

The regressions in the form of (6) generally produce negative estimates of the slope coefficients β_i (see, e.g., Lewis, 1995 and Engel, 1996, 2015). This is consistent with the well-known fact that low-interest currencies tend, on average, to depreciate. For example, when the interest rate in country i falls relative to the U.S. rate, the rise in the forward premium $(F_t^i - S_t^i)/S_t^i$ is typically followed by a fall $(S_{t+1}^i - S_t^i)/S_t^i$ as currency i depreciates relative to the USD. Together, these changes generate lower excess returns because $(S_{t+1}^i - F_t^i)/S_t^i = (S_{t+1}^i - S_t^i)/S_t^i - (F_t^i - S_t^i)/S_t^i$, consistent with negative estimates for β_i.

We use recursive estimates of the system of regressions in (6) to generate real-time forecasts for excess returns.[3] Specifically, we compute the expected excess return on currency i conditional on period-τ information, $\hat{\mathbb{E}}[ER_{\tau+1}^i|\Omega_\tau]$, as $\left\{\hat{\eta}_{i|\tau} + \hat{\beta}_{i|\tau}[(F_\tau^i - S_\tau^i)/S_\tau^i]\right\} R_\tau^i$, where $\hat{\eta}_{i|\tau}$ and $\hat{\beta}_{i|\tau}$ are the coefficients estimated from the subsample of our data spanning periods $t = 1$ to τ. In words, the expected excess return is computed as R_τ^i times the predicted value for $(S_{\tau+1}^i - F_\tau^i)/S_\tau^i$ based on the estimates of (6) using data up to period τ. Because there is considerable correlation in the regression errors across equations, we estimate the coefficients by Seemingly Unrelated Regression (SUR). The vector of these expected excess returns, denoted $\hat{\mu}_\tau$ above, are used in computing the risky portfolio shares α_t^*.

The recursive regression estimates also provide us with estimates of the conditional covariance matrix for excess returns, $\Sigma_t = \mathbb{V}[ER_{\tau+1}|\Omega_\tau]$. The i, j 'th. element of this matrix can be written as $R_\tau^i R_\tau^j \mathbb{CV}[(S_{\tau+1}^i - F_\tau^i)/S_\tau^i, (S_{\tau+1}^j\text{-}F_\tau^j)/S_\tau^j|\Omega_\tau]$ because R_τ^i and R_τ^j are elements in Ω_t. We build an estimate of the covariance matrix, $\hat{\Sigma}_t$, element-by-element using the regression residuals to estimate the conditional covariance term, $\mathbb{CV}[.,.|\Omega_\tau]$. In particular, we compute the conditional covariance between the excess returns on currencies i and j as $R_\tau^i R_\tau^j \left\{\frac{1}{\tau}\sum_{t=1}^{\tau}(\hat{\zeta}_{t|\tau}^i \hat{\zeta}_{t|\tau}^j)\right\}$ where $\{\hat{\zeta}_{t|\tau}^n\}_{t=1}^{\tau}$ denote the residuals from the $n = \{i, j\}$ currency regression(s).

With these estimates of μ_τ and Σ_τ in hand, we numerically maximize the estimated conditional Sharpe ratio to find the risky portfolio shares:

$$\hat{\alpha}_\tau^* = \arg\max \left\{ \frac{\hat{\alpha}_\tau' \hat{\mu}_\tau}{\sqrt{\hat{\alpha}_\tau' \hat{\Sigma}_\tau \hat{\alpha}_\tau}} \right\}. \tag{7}$$

Several aspects of this estimation procedure deserve note. First, the period τ estimates of the conditional first and second moments of excess returns only use information that was

[3] Recursive estimation is chosen in order to use all available information.

available at the time (i.e., from the history of exchanges rates and interest rates at period τ). Second, we allow for the possibility that the statistical relationship between excess returns and the forward premium may have changed through time. Our procedure for computing $\hat{\mu}_\tau$ simply treats (6) as a forecasting equation that best represents the (linear) forecasting power of the forward premium for future excess returns in a sub-sample of the data. Similarly, our covariance matrix estimates allow for the presence of conditional heteroskedasticity in excess returns. As an alternative we could have allowed for heteroskedasticity by computing $\hat{\Sigma_\tau}$ from recursive estimates of a multivariate ARCH/GARCH model. However, our calculations revealed that the portfolio shares that maximize the conditional Sharpe ratio are relative insensitive to the use of different estimates for Σ_t. We therefore chose to use the simpler recursive estimator for Σ_t described above.

Finally, we should emphasize that these estimates for μ_t and Σ_t only use a subset of the information that was actually available to speculators following carry trade strategies at the time. It is possible that the portfolio decisions by speculators facing the same investment opportunity set and objectives were quite different from the decisions we identify using $\hat{\mu}_t$ and $\hat{\Sigma}_t$. However, our aim is not to estimate the decisions of any individual speculator engaged in the carry trade. Rather it is to identify the forex order flows consistent with the decisions of a representative hedge fund that seeks to exploit the forecasting power of the forward premium for excess currency returns.

Next, we use the portfolio shares computed in (7) to estimate the contribution of the carry trade to forex order flows. We use tick-by-tick transaction data to compute the weekly order flow for currency i, OF_t^i. These flows comprise two components: the carry trade flows generated by our hedge fund during week t, ΔX_t^i, and the flows generated by all other market participants, ξ_t^i. Using equations (3) and (4) we write the week-t order flow for currency i as

$$\begin{aligned} OF_t^i &= \Delta X_t^i + \xi_t^i. \\ &= \alpha_t^i \lambda_t A_t - \gamma_t^i \lambda_{t-1} A_{t-1} + \xi_t^i, \\ &= \left(\alpha_t^i \Gamma_t - \gamma_t^i\right) \lambda_{t-1} A_{t-1} + \alpha_t^i \Delta X_t + \xi_t^i, \qquad \text{for} \qquad i = \{1, 2, ..N\}, \end{aligned} \tag{8}$$

where $\Gamma_t = \sum_{i=1}^N \gamma_t^i$ with $\gamma_t^i = \alpha_{t-1}^i \left(S_t^i R_{t-1}^i / S_{t-1}^i\right)$.

We use equation (8) to estimate the aggregate carry trade order flow ΔX_t each period. Specifically, we find the value for ΔX_t each period that minimizes the contribution of the non-carry trade order flows to the cross-section of N order flows OF_t^i, given the portfolio shares $\hat{\alpha}_t^* = [\hat{\alpha}_t^{i*}]$ that maximize the conditional Sharpe ratio in (7).

Formally, we estimate ΔX_t as

$$\Delta\widehat{X}_t = \arg\min_{X_t} \sum_{i=1}^{N} \phi_i(\hat{\xi}_t^i)^2, \qquad \text{with} \qquad \hat{\xi}_t^i = OF_t^i - (\hat{\alpha}_t^{i*}\hat{\Gamma}_t - \hat{\gamma}_t^i)\hat{\lambda}_{t-1}\hat{A}_{t-1} - \hat{\alpha}_t^{i*}\Delta X_t, \quad (9)$$

where $\hat{\Gamma}_t = \sum_{i=1}^{N} \hat{\gamma}_t^i$ with $\hat{\gamma}_t^i = \hat{\alpha}_{t-1}^{i*}\left(S_t^i R_{t-1}^i / S_{t-1}^i\right)$. The $\hat{\xi}_t^i$ term identifies the non-carry component of order flow given the fund's portfolio decisions and the aggregate carry trade order flow. We choose the value for $\Delta\hat{X}_t$ to minimize the weighted sum of these squared components using the ϕ_i weights. As we discuss below, our data for some of the order flows may be less representative than others of the flows across the entire forex market, so we use different weights ϕ_i to check the robustness of our ΔX_t estimates. Notice, also, that the $\hat{\xi}_t^i$ term includes the estimated value of the fund's foreign bond portfolio in period $t-1$, $\hat{\lambda}_{t-1}\hat{A}_{t-1}$, which we denote by $\hat{W}_{t-1}$. This estimate is computed recursively from (4) as

$$\hat{W}_{t-1} = \hat{\Gamma}_{t-1}\hat{W}_{t-2} + \Delta\widehat{X}_{t-1}. \quad (10)$$

To initiate this recursion we need a value for $\hat{W}_0$. We find this value jointly with the sequence for $\Delta\hat{X}_t$ over the first 26 weeks covered by our flow data that minimize the sum of the weighted squared non-carry components, $\sum_{t=1}^{26}\sum_{i=1}^{N} \phi_i(\hat{\xi}_t^i)^2$.

The procedure above produces an estimated decomposition for the weekly order flow in each currency i:

$$OF_t^i = \Delta\hat{X}_t^i + \hat{\xi}_t^i \qquad \text{where} \qquad \Delta\hat{X}_t^i = \hat{\alpha}_t^{i*}\hat{W}_t - \hat{\gamma}_t^i\hat{W}_{t-1}. \quad (11)$$

We use the estimates of carry-trade order flows $\Delta\hat{X}_t^i$ to study the impact of the carry trade on interest rates and exchanges rates in Section 5 below.

4 Data

Our empirical analysis uses weekly data from January 2000 to November 25 2011 on interest rate differentials, exchange rates and order flows for 12 countries against the US dollar

(USD): Australia (AUD), Canada (CAD), the Euro Area (EUR), Japan (JPY), Mexico (MXN), Norway (NOK), New Zealand (NZD), Sweden (SEK), Singapore (SGD), South Africa (ZAR), Switzerland (CHF), and the United Kingdom (GBP).[4] The spot rates and one week forward rates, all mid-point rates measured relative to the USD, are the 4:00 pm "fixing rates" published by the WM company every Friday available from Datastream.[5][6] We take the one week USD eurocurrency deposit rate (again the mid-point of the bid and offer rates, as reported by the Financial Times/ICAP/Thomson Reuters on Datastream) as the risk-free rate, R_t^0. One-week interest rates in other currencies are computed using covered interest parity, i.e., $R_t^i = R_t^0 S_t^i / F_t^i$.

We construct a measure of weekly order flow from the Reuters Tick History database. This databased contains the transaction records from spot currency trading on the Reuters D2000-2 trading system, one of the principal electronic forex trading systems used by banks and large institutional investors. Our measure for the weekly order flow in currency i is computed as the difference between the number of buyer-initiated trades for currency i (i.e., trades at the ask-quote) and the number of seller-initiated trades (i.e. trades at the offer-quote) from 01:00 GMT to 18:00 GMT each weekday (i.e., excluding weekends). Unfortunately, the Tick History database does not contain information on the size of every forex trade, so our order flow measures assume a standard trade size of 2 million USD. Since variations in the size of individual trades are far smaller than the variations in the weekly imbalances between the number of buyer- and seller-initiated trades, our order flow measure should closely track actual weekly order flow on the Reuters system.[7]

Using order flow from the interdealer market warrants some explanation. Although access to the Reuters trading system was originally confined to banks, sophisticated end-users such as large hedge funds could also trade on the system via Prime Brokerage accounts during our sample period. Carry trades made by these end-users are directly reflected in the order

[4]We use data starting on October 27 1997 to produce forecasts, portfolio weights, and initiate the aggregate carry trading.

[5]For the EUR, no forward from the WM Company exists pre-December 28, 1998. Before this date we use the Thomson Reuters spot and forward rates, which are rates where "... market close is set at 21:50 GMT when the latest rate received is snapped and mapped as a close price."

[6]We use mid-point rates because our primary focus is to measure carry trading activity. Other papers have shown that carry trade strategies are profitable even when taking account of the bid-ask spread.

[7]Information on the size of individual forex trades is very rarely available, so measures of order flow base on a standard trade size are standard in the literature; see, e.g., Evans (2011). More formally, the ξ_t^i term in equation (8) can accommodate measurement error in OF_t^i.

flow data. With regard to the trades of other end users, we assume that banks act primarily as intermediaries passing their trades on to the interdealer market. This is a reasonable approximation because the half-lives of banks' inventory positions are typically measured in minutes, whereas we consider order flows at a weakly frequency. Our use of the order flow data also assumes that the carry trades contribute to liquidity demand in the interdealer market. This assumption is consistent with the evidence in Bjønnes and Rime (2005) that banks use market orders in the interdealer market to eliminate large inventory imbalances, such as those that would arise from the unwinding of carry positions by end users.

Table 1 reports summary statistics for the 12 order flows. The statistics in panel A show that the flows are generally very volatile, with standard deviations measured in the hundreds of millions of USD. However, the flows for the CHF, JPY, NOK and SEK prove exceptions to this general pattern. Notice, also, that average flows are far from zero for seven currencies. In these cases there appears to have been a secular change in forex holdings verses the USD. Our model allows for the factors driving these changes via the non-carry-trade terms ξ_t^i. Table 1 also shows that both the cross-correlations between flows (panel B) and serial correlation for individual flows are weak. The first-order autocorrelation coefficients reported in the right-hand-column of panel A are general positive but typically below 0.3. From Panel B we see that the cross-correlations between flows are on balance positive, but all are below 0.5 in absolute value (except AUD/NZD).

Although the Reuters D2002 system is one of the principal forex trading venues for banks and large financial institutions, it is not the only system where forex trades take place. In particular, EBS, an electronic limit order book owned by ICAP, has a dominant market share CHF, JPY and possibly also EUR. This fragmentation of the market means that the order flows we study are representative of market-wide flows, rather than accurate aggregation of buyer- and seller-initiated trades across the entire forex market. This is reasonable for at least 8 of the 12 flows we study, because the lion's share of trading in these currencies takes place through the Reuters system. However, for currencies like CHF, JPY, NOK and SEK, it is possible that the cross-sectional pattens in our data for these flows with the other currencies are unrepresentative of the patterns across the market.[8] We consider this possibility when estimating aggregate carry trade order flow, $\Delta\hat{X}_t$. In particular, in the appendix we examine

[8]EUR also has EBS as its primary trading platform. There is, however, sufficient volumes on the Reuters platform to warrant treating the EUR different from the JPY and CHF currencies.

Table 1: Summary Statistics for Order Flows

	Mean	Std. Dev.	Percentiles			ρ
			5	50	95	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
A:						
AUD	520.620	1641.300	-2444.800	574.000	3121.600	0.229
CAD	-366.520	1215.200	-2785.800	-186.000	1379.200	0.254
CHF	-5.828	51.656	-84.000	-2.000	62.000	0.229
EUR	130.430	815.260	-1041.200	56.000	1535.800	0.250
GBP	560.170	1590.200	-2105.200	614.000	3200.800	0.137
JPY	9.763	262.700	-403.600	0.000	401.200	0.114
MXN	-277.080	580.590	-1268.200	-228.000	594.800	0.269
NOK	0.791	36.441	-44.200	0.000	46.000	0.039
NZD	157.220	647.660	-870.400	114.000	1336.800	0.047
SEK	-2.696	34.780	-42.000	0.000	35.000	-0.082
SGD	-192.280	449.730	-974.700	-142.000	438.100	0.291
ZAR	-332.360	555.670	-1505.200	-200.000	363.000	0.319

B:

	AUD	CAD	CHF	EUR	GBP	JPY	MXN	NOK	NZD	SEK	SGD
AUD											
CAD	0.213										
CHF	0.051	0.132									
EUR	0.319	0.137	0.223								
GBP	0.451	0.238	0.154	0.394							
JPY	0.095	0.017	0.150	0.172	0.083						
MXN	0.086	0.221	0.023	-0.120	0.026	-0.052					
NOK	-0.082	-0.051	-0.010	-0.072	-0.057	-0.043	-0.025				
NZD	0.510	0.255	0.043	0.164	0.303	0.053	0.114	-0.041			
SEK	0.094	0.043	-0.028	-0.021	0.068	0.043	0.024	0.064	0.004		
SGD	0.314	0.255	0.088	0.224	0.244	0.199	0.184	0.016	0.227	0.099	
ZAR	0.369	0.309	0.029	0.192	0.267	0.033	0.233	-0.128	0.188	0.085	0.378

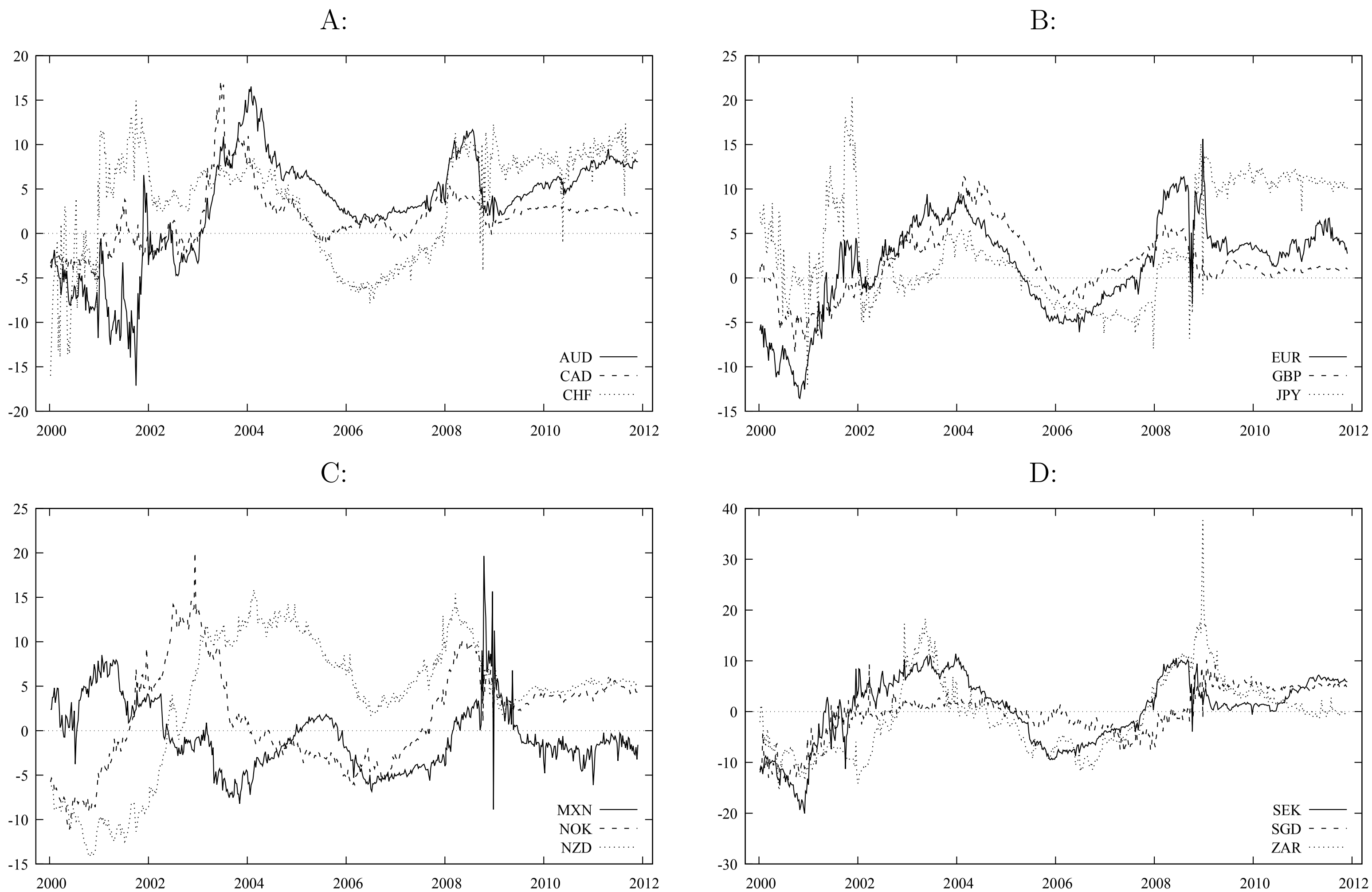
Notes: Panel A reports sample statistics for the forex order flows listed in the left hand column. The right-hand column reports the sample autocorrelation coefficient ρ. Panel B shows the sample correlation across the 12 flows. Order flows are measured in millions of USD (assuming a 2 million average trade size) the robustness of our estimates for $\Delta\hat{X}_t$ to the use of a weight ϕ_i equal to zero on these four flows in (9).

4.1 Forecasting Excess Returns

Table 2 summarizes the results from estimating the system of forecasting equations in (6). The left-hand-columns in panel A report the slope coefficients and their standard errors estimated by SUR over the entire sample period: i.e., from October 1997 to November 2011, a span of 732 weeks. Here we see that the slope estimates are negative for all but the CAD equation, and statistically significant at the one percent level in the CHF, EUR, JPY, MXN, SGD and ZAR equations. These findings are consistent with the results reported in the literature of UIP deviations. In columns (iii) - (v) we report percentiles for the empirical distribution of slope coefficients estimated recursively starting in January 2000 (based on 621 recursive estimates). Notice that the full sample estimates in column (i) fall in the right-hand-portion of these distributions. This indicates that our real-time forecasts generally placed a greater negative weight on the current forward premium than would pseudo forecasts computed using the full sample estimates. More generally, the dispersion of the empirical distributions makes clear that the statistical relation between future excess returns and the current forward premium varies with the estimation period.

Panel B of Table 2 reports summary statistics for the real-time excess return forecasts (measured in annual percent) between January 2000 and November 2011. Here we see that on average excess return forecasts are generally positive, but are also highly variable. The standard deviation of the forecasts over the 12 years range from three to more than seven percent. This high degree of variability is also apparent from the percentiles of the empirical distributions for the forecasts shown in columns (viii)-(x). For further perspective, Figure 1 plots the time series for each forecast. These time series have a good deal of low frequency persistence. At times, each plot displays a sizable amount of week-to-week volatility, but the forecasts also exhibit long swings lasting several years. These swings follow similar paths across multiple currencies for several years at a time. For example, the swings in the forecasts for the excess returns on the EUR, GBP and JPY are very similar between 2004 and 2006. On other occasions, the swings move in opposite directions (see, e.g., the forecasts for the NOK and NZD in 2003). These patterns suggest that there is no single common factor driving the long-term movements in the excess return forecasts across currencies.

Figure 1: Real-Time Forecasts of Excess Returns



Notes: Plots show the real-time forecasts for excess returns (measured in annual percent relative to the USD) computed as the one-week-ahead forecasts from the recursive SUR estimates of the equation system in (6).

Table 2: Summary Statistics for Excess Returns

	A: Slope Coefficients					B: Real-Time Excess Returns Forecasts				
	Full Sample		Real-Time Distribution Percentiles					Distribution Percentiles		
	Estimate	Std.Err.	5	50	95	Mean	Std.Dev.	5	50	95
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
AUD	-0.937	(1.106)	-7.314	-1.575	0.088	3.066	5.910	-8.615	4.013	11.433
CAD	0.692	(2.023)	-4.811	-1.693	0.718	1.818	3.295	-3.109	1.945	8.766
CHF	-4.605	(1.327)	-14.248	-4.196	-3.707	3.695	5.834	-5.932	5.742	10.697
EUR	-2.794	(1.056)	-4.110	-3.107	1.922	1.499	5.293	-9.058	2.815	9.426
GBP	-0.075	(1.641)	-3.381	-1.581	0.265	1.489	3.490	-4.351	1.053	8.632
JPY	-3.445	(1.370)	-7.244	-2.029	-0.471	3.339	6.003	-4.424	2.020	12.070
MXN	-1.674	(0.361)	-1.743	-1.584	-1.232	-0.662	3.835	-5.913	-1.331	6.725
NOK	-1.485	(0.891)	-3.272	-1.992	-1.437	1.578	5.497	-7.711	2.418	11.643
NZD	-1.252	(1.316)	-3.723	-1.786	0.751	3.777	7.483	-11.211	5.132	12.705
SEK	-2.028	(1.082)	-7.048	-3.019	-2.062	0.483	6.699	-12.200	1.516	9.433
SGD	-3.521	(0.792)	-4.132	-3.779	-3.486	-0.277	4.829	-10.766	0.352	5.604
ZAR	-3.274	(1.067)	-3.399	-2.846	-0.962	-0.777	7.425	-10.948	-0.909	12.696

Notes: Columns (i) and (ii) report the SUR slope coefficient estimates and standard errors from estimating the system of forecasting equations in (6) over the entire sample period: October 27 1997 to November 25 2011, 732 weekly observations. Columns (iii) - (v) report percentiles for the empirical distribution of the slope coefficients estimated recursively by SUR from January 1 2000 to November 25 2011. Panel B reports statistics for the real-time forecast of excess returns (in annual percent) over the same period.

4.2 Portfolio Allocations

Table 3 reports statistics for the risky-portfolio shares $\hat{\alpha}_t^{i*}$ that maximize the conditional Sharpe ratios in (7) between January 1, 2000 and November 27, 2011. Columns (i) - (vi) in panel A show the average, standard deviation, auto-correlation and percentiles for the distribution of shares during this period. For comparison, in column (vii) we also report the values for the shares that maximize the unconditional Sharpe ratio (i.e., the ratio computed from average excess returns and their covariance over the entire sample). The right-most column show the average interest differential for reference. Correlations between the shares $\hat{\alpha}_t^{i*}$ and $\hat{\alpha}_t^{j*}$ for $i, j = \{1, 2, ..12\}$ are shown in Panel B.

Table 3: Summary Statistics for Risky Portfolio Shares

	Mean	Std. Dev.	ρ	Percentiles			Uncond.	Mean int.diff.
				5	50	95		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
A:								
AUD	-0.030	0.518	0.910	-0.880	0.020	0.730	0.820	2.472
CAD	0.773	0.768	0.973	-0.123	0.556	2.523	0.093	0.183
CHF	0.536	1.727	0.908	-2.788	0.745	2.936	0.474	-1.600
EUR	-0.415	1.985	0.920	-2.942	-0.430	2.808	-0.093	-0.060
GBP	0.639	0.995	0.958	-0.434	0.287	2.732	-0.340	1.112
JPY	0.018	0.325	0.844	-0.473	0.013	0.438	0.743	-2.686
MXN	0.018	0.552	0.926	-1.067	-0.056	0.828	1.152	5.662
NOK	0.275	0.956	0.960	-1.158	0.120	2.702	1.062	1.230
NZD	0.532	0.917	0.953	-0.724	0.285	2.073	0.206	3.061
SEK	-0.771	1.139	0.956	-2.788	-0.356	0.521	-1.442	-0.055
SGD	-0.371	1.078	0.922	-2.801	-0.160	0.849	-1.851	-1.181
ZAR	-0.204	0.338	0.937	-0.882	-0.176	0.278	0.176	6.646

B:

	AUD	CAD	CHF	EUR	GBP	JPY	MXN	NOK	NZD	SEK	SGD
AUD											
CAD	-0.088										
CHF	0.190	-0.646									
EUR	-0.107	0.585	-0.920								
GBP	-0.101	0.676	-0.686	0.593							
JPY	0.465	-0.359	0.307	-0.223	-0.279						
MXN	0.140	-0.553	0.531	-0.381	-0.274	0.622					
NOK	-0.173	-0.056	0.103	-0.368	-0.085	-0.017	0.023				
NZD	-0.614	0.476	-0.600	0.603	0.538	-0.672	-0.451	-0.124			
SEK	0.062	-0.713	0.598	-0.605	-0.750	0.250	0.199	-0.014	-0.555		
SGD	0.042	-0.398	0.471	-0.555	-0.572	-0.110	-0.134	0.020	-0.395	0.425	
ZAR	-0.242	-0.481	0.150	-0.034	-0.461	0.070	0.058	-0.252	-0.046	0.487	0.091

Notes: In Panel A columns (i)-(iii) report the average, the standard deviation and the autocorrelation for each share α_t^{i*} that maximize the conditional Sharpe Ratio from January 1 2000 to November 25 2011. Columns (iv) - (vi) report percentiles for the empirical distribution of the conditional shares α_t^{i*} over the same period. Column (vii) reports the unconditional shares α_i^* that maximize the sharpe ratio using unconditional estimates of expected excess returns and their covariance. Column (viii) reports the average interest rate differential. Panel B reports the correlation matrix for the conditional shares α_t^{i*}.

As the table clearly shows, there is considerable time series variation in all the shares. Indeed, the percentiles in columns (iv) and (vi) imply that all the shares change sign at least once during the period. This means that our hedge fund borrows in all 12 foreign currencies at one time or another. The correlations in panel B provide information on the pattern of borrowing and lending across currencies. In particular, a strong negative correlation between $\hat{\alpha}_t^{i*}$ and $\hat{\alpha}_t^{j*}$, indicates the presence of a de facto bilateral strategy between currencies i and j where short positions in one currency fund long positions in the other. In our portfolio, the shares for the EUR and CHF are most strongly negative correlated, with a correlation of -0.92. Thus, increased holdings in the CHF are effectively financed by greater borrowing in the EUR, and vise-versa. Notice, also, that both the average and median values for the conditional shares α_t^{i*} are quite unlike their unconditional counterparts for many currencies. For example, the unconditional share for the AUD of 0.82 falls above the 95 percentile of the conditional share distribution, far from the median value of 0.02. The unconditional shares provide very little information about real-time portfolio choices in this setting because the forward premium is an important source of conditioning information.

Figure 2 provides further perspective on the role of conditioning information. In panel A we plot "annualized" Sharpe ratios that use the conditional and unconditional moments of excess returns.[9] The upper plot shows the conditional Sharpe ratio $\hat{SR}_t$ implied by the optimally chosen portfolio shares; while the lower straight line identifies the unconditional Sharpe ratio, $\hat{SR} = \max_\alpha \{\alpha'\hat{\mu}/\sqrt{\alpha'\hat{\Sigma}\alpha}\}$, where $\hat{\mu}$ and $\hat{\Sigma}$ are the unconditional first and second moments of excess returns estimated over the entire sample. These plots clearly illustrate the value of conditioning information. The conditional Sharpe Ratio is well above the unconditional ratio of 0.69 throughout the period, usually at least two to three times larger. Thus portfolios chosen to dynamically exploit the conditioning information in the forward premium have much more favorable ex ante risk-return characteristics than one using just unconditional information about excess returns.

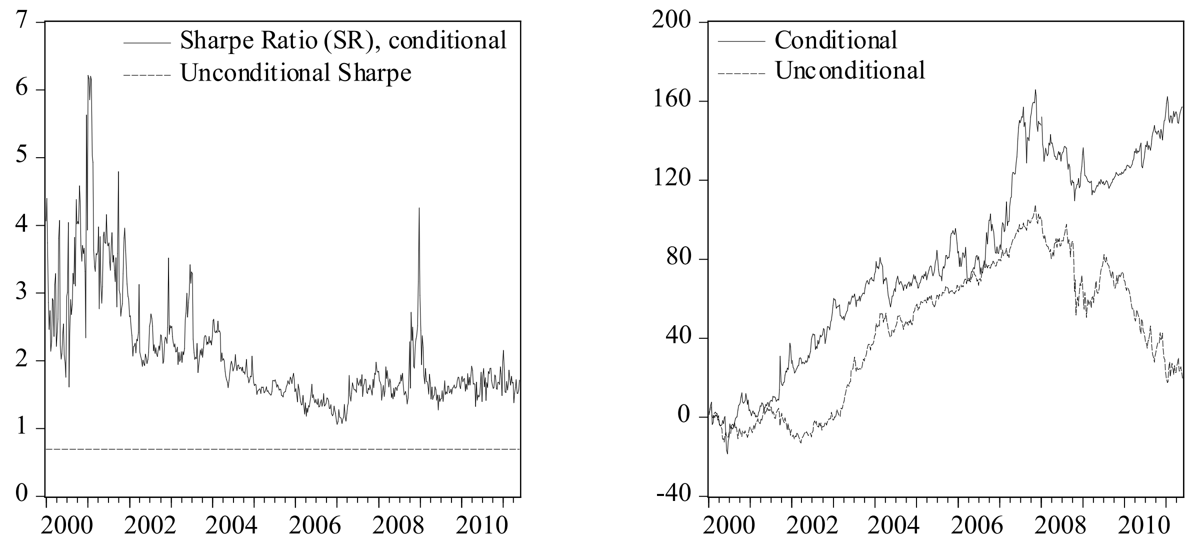
The plot for the conditional ratio, $\hat{SR}_t$, is also interesting in terms of its size and variability. Anecdotal evidence from market participants indicate that Sharpe ratios are a widely used metric to judge the performance of a trading strategy. Furthermore, capital is typically only committed to a strategy when the ratio exceeds a certain threshold, somewhere

[9] We follow the common practice of multiplying each ratio by $\sqrt{52}$ to allow for the fact that excess returns are computed at a weekly rather than annual frequency.

Figure 2: Expected and realized return on carry portfolio

A: Ex-ante Sharpe Ratios

B: Cumulative returns



Notes: Panel A plots for the (annualized) conditional Shape Ratio (SR) and the Unconditional Sharpe Ratio (constant, 0.69). Panel B plots cumulated returns (in percent) on the foreign bond portfolio using conditioning information in the forward premium (conditional), and returns using portfolio shares from Jan 1, 2000 (unconditional) .

between 0.5 and 1. Clearly $\hat{SR}_t$ is always well above this threshold. This suggests that the strategy followed by our hedge fund is one that would have actually been considered for implementation in real time.

We can also assess the value of conditioning information from the ex post performance of the portfolio. To this end, panel B of Figure 2 plots the cumulative realized return from January 1, 2000 on the optimally chosen portfolio using the conditioning information in the forward premium. Specifically, we plot $cr_t^* = 100\sum_{i=1}^{i=t} r_i^*$, where $r_t^* = \ln\left(\sum_{i=1}^{N} \hat{\alpha}_{t-1}^{i*}(S_t^i R_{t-1}^i / S_{t-1}^i)\right)$ is the log return on the fund's foreign bond portfolio that uses the optimally chosen shares $\hat{\alpha}_t^{i*}$. We also plot the cumulative return using the portfolio shares from January 1, 2000: i.e., $cr_t^0 = 100\sum_{i=1}^{i=t} r_i^0$, where $r_t^0 = \ln\left(\sum_{i=1}^{N} \hat{\alpha}_{t=0}^{i*}(S_t^i R_{t-1}^i / S_{t-1}^i)\right)$. Thus differences between the two plots represent the effects of new conditioning information after the start of 2000. As the figure shows, these differences are substantial. For example, by the start of 2003 conditioning information produced a roughly 40 percent higher cumulative return. In the next three years the benefits declined to the point in 2006 where the cumulative returns were equal. Thereafter, conditioning information produced much higher cumulative returns, rising to approximately 120 percent by the end of 2011. Over the whole period, the use of conditioning information produces an annual average return of 14.15 percent compared to the average cumulated return on U.S. bonds of 2.8 percent.

Finally, Table 4 compares summary statistics for the returns on three portfolios: the portfolios formed by maximizing the conditional and unconditional Sharpe ratios (described above) and a rank-based portfolio. Following Asness et al. (2013), the weights in the latter portfolio are based on the ranking of the forward discount for each currency pair (see appendix for details). The table shows that carry trades consistent with maximizing the conditional Sharpe ratio generate comparatively attractive returns when judged according to standard portfolio-performance measures like the Sharpe ratio, skewness and maximum draw-down statistics.

Table 4: Summary Statistics for Realized Portfolio Return

	Max Sharpe portfolios		Rank-portfolio
	Conditional	Unconditional	Conditional
Mean	13.768	1.733	-1.149
Median	23.531	7.991	-3.188
Standard deviation	176.370	138.950	109.610
Skewness	-0.614	-1.207	0.587
Ex.kurtosis	4.225	7.138	9.537
Sharpe Ratio	0.577	0.044	-0.178
Max. Draw Down	56.285	89.997	66.099

Notes: The table reports summary statistics for realized portfolio return, measured in annual percentage points, under different assumptions for portfolio formation, from January 1 2000 to November 25 2011. The first two columns show realized return from using either conditional or unconditional portfolio shares based on the approach where Sharpe Ratio is maximized. The right column report summary statistics using portfolio weights from ranking currencies based on their interest rate differential against the US. See appendix for details on our procedure for creating rank-based portfolio weights.

In summary, Figures 2 A and B and Table 4 show that the carry-trade strategy of our hedge fund is attractive from both an ex ante and ex post perspective. The conditional Sharpe ratios plotted in Figure 2 are well above the threshold typically required by market participants ex ante to risk capital in an investment strategy. And, ex post, the cumulative realized returns on foreign bonds are on average roughly five times higher than the returns on U.S. bonds.

4.3 Global Carry Trade Estimates

Table 5 reports summary statistics for the carry and non-carry trade components of the 12 order flows estimated between January 1 2000 to November 25 2011. These statistics show that our estimates of the carry components are highly variable, with standard deviations measured in the hundred millions of USD. Average order flows driven by the carry trade are very small by comparison, the sample means are generally on the order of a few million USD. Our estimates of the carry components exhibit weak negative autocorrelation across all the currencies. Table 1 showed that mean order flows for many currencies measured in the hundreds of millions of USD reflecting secular changes in forex currency holdings over the entire span of our data. The effects of these secular changes appear in the sample means of our estimated non-carry order flow components, which are sizable for many of the flows. Our estimates of the non-carry components are also generally more variable than their carry components but display less serial correlation.

One further result in Table 5 deserves particular comment; the correlation between the estimated carry and non-carry components of the flows reported in the right-hand column. Our estimation procedure makes no assumption about these correlations. However, as the table shows, the correlations are uniformly negative, and for the CHF, JPY and SGD flows they are below -0.9. It is important to recognize that these correlations are for estimated order flow components measured at a weekly frequency. Consequently, they reflect in part the effects of intra-week variations in spot rates on the order flow components. For example, carry trade order flow at the start of the week could induce a subsequent change in non-carry trade flow via its immediate impact on the spot rate. In particular, if some market participants unconcerned with the carry trade follow negative feedback trading strategies in which they sell (buy) currencies after they appreciate (depreciate), weekly carry and

Table 5: Summary Statistics for Order Flow Components

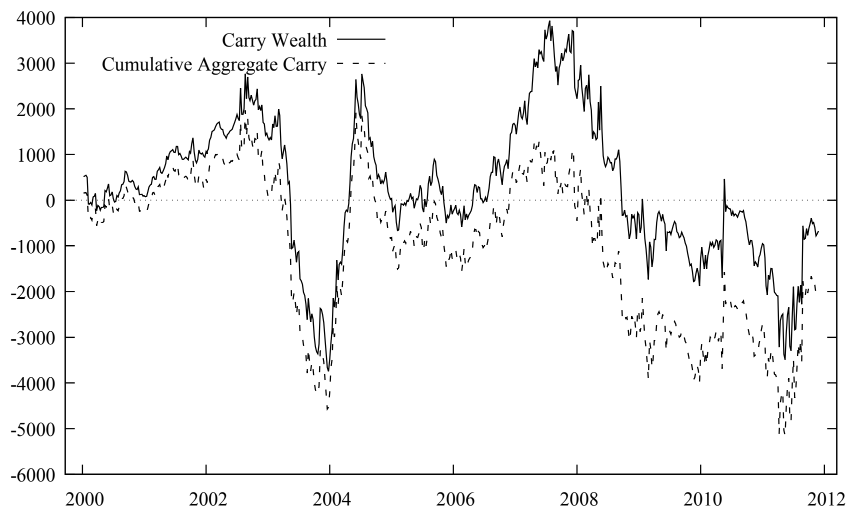
	Carry ΔX_t^i			Non-Carry ξ_t^i			
	Mean	Std. Dev.	AR(1)	Mean	Std. Dev.	AR(1)	Corr
AUD	-6.068	623.550	-0.381	603.320	1760.800	0.100	-0.267
CAD	-3.848	613.530	-0.091	-432.270	1309.400	0.212	-0.234
CHF	-8.837	1210.500	-0.079	10.036	1201.900	-0.066	-0.999
EUR	7.365	1191.300	-0.119	129.230	1266.200	-0.034	-0.809
GBP	2.541	676.140	-0.058	550.990	1627.700	0.082	-0.104
JPY	-3.036	490.550	-0.159	12.889	517.700	-0.131	-0.937
MXN	-0.016	567.140	-0.245	-331.750	767.490	-0.026	-0.685
NOK	11.131	226.970	-0.292	-4.548	45.612	-0.266	-0.863
NZD	0.098	756.800	-0.182	179.400	1053.100	-0.120	-0.745
SEK	-7.793	358.790	-0.214	6.038	308.550	-0.175	-0.847
SGD	-5.087	1055.000	-0.178	-191.030	1155.600	-0.077	-0.926
ZAR	2.615	312.860	-0.156	-353.250	675.010	0.190	-0.541

Notes: The table reports sample means, standard deviations and first-order autocorrlation coefficients for carry and non-carry components of order flows estimated between January 1 2000 to November 25 2011. The the right-hand column reports the sample correlation between the carry and non-carry components.

non-carry trade flow components will be negatively correlated.

Our estimates also provide us with a perspective on the scale of the global carry trade. To this end Figure 3 plots the cumulated estimates of the aggregate carry-trade order flow $\hat{X}_t = \Sigma_{i=1}^t \Delta\hat{X}_i$ and the value of the foreign bond portfolio $\hat{W}_t$ between January 1 2000 to November 25 2011. Both series are measured in millions of USD. These plots display significant swings. Our estimate for initial wealth W_0 are close to zero so the series track each other closely for the first few years of the sample period. During this time aggregate carry trade order flow is generally positive so $\hat{X}_t$ and $\hat{W}_t$ steadily rise to a peak in mid 2002. Thereafter there is a sharp decline in both $\hat{X}_t$ and $\hat{W}_t$ until the start of 2004. During this period aggregate order flow driven by the carry trade is so strongly negative that the value of foreign bond holdings falls to approximately -4 billion USD. This figure represents the value of funds borrowed in foreign bond markets to fund holdings of U.S. bonds. In 2004 $\hat{X}_t$ and $\hat{W}_t$ quickly rebounding to the earlier peak levels. From this point onwards, cumulated returns on foreign bonds push $\hat{W}_t$ above $\hat{X}_t$. (Recall that $W_t = \Gamma_t W_{t-1} + \Delta X_{t-1}$ where $\Gamma_t = \Sigma_{i=1}^{N} \alpha_{t-1}^{i} (S_t^i R_{t-1}^i / S_{t-1}^i)$ so W_t will rise faster than X_t when $\Gamma_t > 1$.) This is particularly evident in 2006 and 2007 where $\hat{W}_t$ rises to a peak value of approximately 4 billion USD. After 2008 both $\hat{X}_t$ and $\hat{W}_t$ decline until the end of the sample period.

Figure 3: Carry Trade Order Flow and Wealth



Notes: Cumulated aggregate carry trade order flow ($\hat{X}_t = \Sigma_{i=1}^{t} \Delta \hat{X}_i$) and carry trade wealth ($\hat{W}_t$) (relative to its level at the start of 2000) in millions USD.

The series plotted in Figure 3 are estimated using equal weights on the 12 order flows in our data set. As noted above, this approach overlooks the fact that CHF and JPY order flows on the Reuters trading system are less representative of market-wide order flows than the other flows. To investigate whether our estimates are robust to the treatment of these flows, we computed alternative estimates for aggregate carry trade order flow, $\Delta \tilde{X}_t$, using a zero weight on either the CHF, JPY, NOK or SEK flows. The results are presented in the appendix. Reassuringly, the correlation between the alternative estimates, $\Delta \tilde{X}_t$ and $\Delta \hat{X}_t$, is greater than 0.9 and typically close to 0.99. Consequently, our estimates of W_t appear very robust to the treatment of the less representative flows.

Table 6 provides further insight into the properties of the carry trade. Panel A reports the estimates from regressing the change in each portfolio share on a constant and a change in the interest differential: $\Delta\alpha_t^i = c_{\alpha,i} + \delta_\alpha^i \Delta\left(R_t^0 - R_t^i\right) + \varepsilon_{\alpha,t}^i$. The large differences across the estimated slope coefficients and the low explanatory power of these regressions indicates that the portfolio shares are largely driven by multi-currency factors rather than changes in individual interest differentials. Panel B reports the estimates from regressing carry trade order flow for each currency on a constant and the change carry trade wealth: $\frac{\Delta X_t^i}{W_{t-1}} = c_{X,i} + \delta_X^i \frac{\Delta W_t}{W_{t-1}} + \varepsilon_{X,t}^i$. Once again there are large differences across the slope estimates and low levels of explanatory power for many of the currencies. Clearly, the carry trade order flows identified by our model are driven by a complex combination of interest differentials and the factors inducing changes in carry trade wealth.

Table 6: Regressions of portfolio weights and carry trading

	A: Portfolio weights			B: Carry Trading		
	Slope	Std.Err.	R^2	Slope	Std.Err.	R^2
AUD	-5.740	(2.601)	0.042	-0.086	(0.060)	0.062
CAD	3.482	(5.951)	0.006	0.639	(0.232)	0.431
CHF	-67.758	(15.696)	0.376	0.251	(0.260)	0.059
EUR	-9.487	(12.159)	0.005	0.169	(0.317)	0.026
GBP	5.855	(7.346)	0.008	0.916	(0.392)	0.523
JPY	-5.926	(1.180)	0.068	-0.018	(0.047)	0.005
MXN	-3.524	(0.513)	0.148	0.309	(0.239)	0.184
NOK	2.901	(6.988)	0.005	-0.071	(0.132)	0.015
NZD	-8.308	(3.306)	0.051	0.980	(0.417)	0.524
SEK	-30.569	(2.813)	0.288	-1.353	(0.558)	0.527
SGD	-31.693	(4.281)	0.386	-0.491	(0.500)	0.177
ZAR	-4.385	(0.748)	0.183	-0.246	(0.146)	0.307

Notes: Panel A in the table reports results from regressing change in portfolio weight on a constant and change in the interest rate differential. Panel B reports results from regressing (change in cumulative) carry trading on a constant and change in the aggregate carry wealth, both standardized by previous week's level of aggregate carry wealth. Regressions estimated between January 1 2000 to November 25 2011.

5 Effects of the Carry Trade

We now turn to the primary focus of this study, namely an examination of the carry trade's effect on exchange rates and interest rates.

Table 7 presents evidence on the impact of the carry trade on depreciation rates. The table reports the coefficient estimates from regressions of depreciation rates $(S_t^i - S_{t-1}^i)/S_{t-1}^i$, on the carry trade flow ΔX_t^i, order flow OF_t^i, and the (lagged) interest rate differential $R_{t-1}^0 - R_{t-1}^i$, at a weekly frequency between January 1 2000 and November 25 2011. The estimated coefficients on order flow and the interest differentials are similar to those found in earlier studies. The interest rate coefficients are generally not statistically significant (the EUR and ZAR are exceptions), while the order flow coefficients are positive and statistically significant for all the currencies except CHF, NOK and SEK. Our primary interest, however, is on the left hand columns which show the coefficients on the carry trade flow. Strikingly, for all but two of the currencies, the coefficient estimates are insignificant. The two exceptions appear in the regressions for CHF and SGD. In these instances the coefficients are significant but negative. By this measure, in the only cases where we can detect effects of the carry trade on depreciation rates (after controlling for the effects of order flow and interest differentials), the effects go in the "wrong" direction.

5.1 SVAR Specification

To further study the impact of the carry trade We now estimate SVARs for each of the 12 currency pairs with four variables: the first difference in the log spot rate, $\Delta s_t^i = \Delta \ln S_t^i$; the first difference in the log interest differential, $\Delta r_t^0 - \Delta r_t^i = \Delta \ln R_t^0 - \Delta \ln R_t^i$; standardized order flow, $of_t^i = OF_t^i / \hat{\mathbb{V}}(OF_t^i)^{1/2}$; and the standardized carry component of order flow, $\Delta x_t^i = \Delta \hat{X}_t / \hat{\mathbb{V}}(\Delta \hat{X}_t)^{1/2}$. Because the volatility of order flows varies considerably across currencies we divide the order flow series by their sample standard deviations, $\hat{\mathbb{V}}(.)^{1/2}$, to facilitate the interpretation of our results below. We include the first difference of the interest differential to accommodate the fact that the differential displays a far higher degree of serial correlation than the depreciation rate or order flows.[10]

Our SVAR impose both short- and long-run restrictions. Let $Y_t = [\Delta x_t^i \quad of_t^i \quad \Delta r_t^0 -$

[10] All our main results are robust to using the level of the interest rate differential instead of the first difference.

Table 7: Price-impact regressions

	Carry Trading		Order Flow		Interest diff.		R^2
	Slope	Std.Err.	Slope	Std.Err.	Slope	Std.Err.	
AUD	-0.010	(0.045)	0.954	(0.072)	-6.561	(3.678)	0.260
CAD	0.001	(0.021)	0.790	(0.099)	0.814	(3.858)	0.400
CHF	-0.142	(0.074)	0.058	(0.076)	-2.381	(1.815)	0.012
EUR	0.023	(0.031)	0.864	(0.049)	-9.705	(2.545)	0.381
GBP	0.027	(0.050)	0.797	(0.105)	1.223	(2.907)	0.384
JPY	-0.046	(0.053)	0.723	(0.066)	-1.448	(0.966)	0.286
MXN	-0.002	(0.039)	0.225	(0.081)	-0.063	(1.210)	0.026
NOK	0.167	(0.404)	-0.294	(0.399)	0.091	(1.561)	0.007
NZD	0.001	(0.060)	1.041	(0.142)	2.839	(3.739)	0.307
SEK	-0.179	(0.288)	0.041	(0.294)	-0.971	(1.749)	0.008
SGD	-0.039	(0.013)	0.283	(0.049)	-2.694	(1.784)	0.191
ZAR	0.092	(0.073)	1.160	(0.157)	-3.739	(1.570)	0.261

Notes: Table reports results from regressing the depreciation rate on Carry Trading, Order Flow and (lagged) interest rate differential. Both flows are standardized with its own standard deviation. Table reports robust standard errors. Estimated between January 1 2000 to November 25 2011.

$\Delta r_t^i \quad \Delta s_t^i]'$ denote the vector of variables in the SVAR

$$A(L)Y_t = \kappa + V_t,$$

where $A(L)$ is a finite-order matrix polynomial in the lag operator L, κ is a 4×1 vector of constants and V_t is a 4×1 vector of innovations (i.e., one-step-ahead prediction errors), with covariance matrix Σ. We assume that the innovations are related to a 4×1 vector of i.i.d. mean-zero structural shocks with unit variances U_t by $V_t = CU_t$. The C matrix is identified by restrictions on the VMA representation of the SVAR:

$$Y_t - \bar{Y}_t = A(L)^{-1}V_t = A(L)^{-1}CU_t = \Theta(L)U_t,$$

where $\bar{Y} = A(L)^{-1}\kappa$. The short run restrictions appear as zeros in the impact matrix

$$C = \Theta(0) = \begin{bmatrix} \theta_{11} & 0 & \theta_{13} & 0 \\ \theta_{21} & \theta_{22} & 0 & 0 \\ \theta_{31} & \theta_{32} & \theta_{33} & 0 \\ \theta_{41} & \theta_{42} & \theta_{43} & \theta_{44} \end{bmatrix}. \tag{12}$$

We identify the first structural shock in the U_t vector as the carry trade shock to order flow, u_t^x, and assume that it can immediately impact the other variables in the SVAR via the $\theta_{j,1}$ coefficients. The second structural shock, u_t^{of}, represents the unanticipated effects of all the non-carry factors affecting total order flow. This shock can also affect the interest differential and spot rate contemporaneously via the $\theta_{j,2}$ coefficients. The third shock, u_t^r ,represents the effects of unanticipated factors affecting the interest differential that are unrelated to order flows. We assume that this shock contemporaneously affects the exchange rate via θ_{43} and carry trade order flow via θ_{13}. The forth structural shock, u_t^s, represents the unanticipated effects of factors unrelated to the other shocks that affect the exchange rate.

One further restriction is required to exactly identify the structural shocks. For this purpose we impose a zero restriction on the sum of the VMA coefficient matrices:

$$\Theta(1) = \begin{bmatrix} \theta_{11}^{\infty} & \theta_{12}^{\infty} & \theta_{13}^{\infty} & \theta_{14}^{\infty} \\ \theta_{21}^{\infty} & \theta_{22}^{\infty} & \theta_{23}^{\infty} & \theta_{24}^{\infty} \\ \theta_{31}^{\infty} & 0 & \theta_{33}^{\infty} & \theta_{34}^{\infty} \\ \theta_{41}^{\infty} & \theta_{42}^{\infty} & \theta_{43}^{\infty} & \theta_{44}^{\infty} \end{bmatrix}.$$

Because the third variable in the SVAR is the first-difference of the interest differential, this zero restriction implies that non-carry trade shocks to total order flow have no long-run effect on the level of the differential. We view this as a plausible identification assumption because monetary policy is almost universally viewed as the proximate determinant of short-term nominal interest rates in the long run and there is no evidence that central banks take any account of order flows when setting policy.

Our identification assumptions depart from the assumptions employed by traditional VARs in two respects: First, we allow for the contemporaneous effect of interest rate shocks on the carry trade via the θ_{13} coefficient, and second we restrict the long run effects of non-carry trade shocks to order flow on the level of interest rates. Of course other identification schemes are possible. In principal interest rate shocks could contemporaneously affect total order flow via a non-zero θ_{23} coefficient in (12). To examine this possibility we also estimated SVAR models where the θ_{23} coefficient was left unrestricted and different additional long-run restriction were imposed (e.g., $\theta_{34}^{\infty} = 0$ and $\theta_{41}^{\infty} = 0$). These models produced estimates of θ_{23} that were insignificantly different from zero. Furthermore, as we will show below, the estimated variance contributions of interest rate shocks to total order flow based on our preferred SVAR specification are extremely small beyond the one week horizon. So, all-in-all, we find no evidence in our data that setting θ_{23} to zero is unduly restrictive.

Although our SVAR models are estimated in weekly data, we want to focus on the implications of the estimates for the effects of the carry trade on interest rates and exchange rate over macro-relevant horizons. For this reason, we err on the side of caution in choosing too many rather than too few lags to include in the SVAR specification. For each currency pair, we first examine the estimated impulse responses and variance decompositions from an SVAR with four lags. By standard metrics, such as information criteria and tests for serial correlation in the SVAR residuals, these specifications appear to adequately represent the time-series dynamics of all the variables in the SVARs. We then re-estimate the models with 13 lags and check whether the results from the four-lag specifications are robust. Here we pay special attention to the variance decompositions at the 13 and 26 week horizons. If the results are robust, as they are for six of the 12 currencies, we use the estimates from the four-lag specifications. For the six other currencies we check whether the 13-lag variance decomposition results are robust to the addition of one more lag. In all cases they are, so we use the estimates from the 13-lag specification for these six currencies. For perspective, our SVAR models are estimated using data from January 1 2000 to November 25 2011. The 593 week span of this sample is more than 45 times the length of the period covered by our 13-lag SVARs, so while these specifications may contain more lags than are strictly necessary, we retain plenty of degrees of freedom for reliable statistical inference.

5.2 Estimation Results

Table 8 reports the quasi maximum likelihood estimates of the short-run $\theta_{i,j}$ coefficients together with their associated asymptotic standard errors for all twelve currency SVAR models.[11] These estimates display several noteworthy features. Consider first the effects of interest rate shocks on carry trade order flow, identified by the θ_{13} coefficients in Panel I. The estimates of this coefficient are highly statistically significant in nine of the 12 models, but there is no clear pattern in their sign; six are positive and three are negative. When a carry trade strategy is applied to just a pair of currencies, ceteris paribus, order flow should be negatively correlated with the interest differential. Positive shocks to the interest differential (i.e., a rise in r_t^0 relative to r_t^i) make currency i a more likely source of funding in a carry trade strategy so the order flow for currency i falls. The negative estimates for θ_{13} support this bi-lateral carry trade interpretation for the AUD, MXN, and NZD. In contrast, the positive estimates for θ_{13} in the CAD, CHF, GBP, JPY, SEK and SGD models indicate that while the carry trade order flows react to interest rates shocks, they do so as part of a multilateral strategy where the order flows support speculative long and short trades across multiple currencies.

The estimates in Panel II of Table 8 show how shocks to the carry trade order flow affect the total order flow for each currency (θ_{21}). In 10 models the estimates of θ_{21} are statistically significant at the one percent level (at five percent level for NZD). This means that the effects of carry trade shocks u_t^x on total order flow are not completely offset by variations in the non-carry factors. Notice, however, that in eight models the positive estimates of θ_{21} are smaller than the estimates of the impact of carry shocks to carry trading (θ_{11}), so the effects are at least partially offset for most currencies. In the NZD, SGD and ZAR models the estimates of θ_{21} are negative, indicating that non-carry factors more than offset the effects of carry trade shocks on the total order flows for these currencies.

The estimated short-run effects on interest rates are shown in Panel III. Non-carry order flow shocks (captured by θ_{32}) are highly significant in all but the SGD model, while carry shocks (θ_{31}) have a significant short-run impact in all models except EUR, JPY and NOK. In all these cases the estimates of θ_{31} are larger in absolute value than the estimates of the θ_{32} coefficients. Carry trade shocks appear to have larger effects on interest differentials than the non-carry factors driving total order flows. In six cases the estimates of θ_{31} are significantly negative. So information about future excess returns that produce a positive shock to the carry trade order flow for currency i tends to raise the interest rate on currency i relative to the USD rate. Furthermore, in the JPY, NZD, and SGD models the estimates

[11] Models are estimated using the GRETL programming language.

Table 8: Short-Run SVAR Coefficients

Variable	I: Carry Trade: Δx^i		II: Order Flow: of^i		III: Interest Differential: $\Delta r^0 - \Delta r^i$			IV: Depreciation Rate: Δs^i				SVAR Order
Shock	u^x	u^r	u^x	u^{of}	u^x	u^{of}	u^r	u^x	u^{of}	u^r	u^s	
Parameter	θ_{11}	θ_{13}	θ_{21}	θ_{22}	θ_{31}	θ_{32}	θ_{33}	θ_{41}	θ_{42}	θ_{43}	θ_{44}	
AUD	0.608***	-0.746***	0.137***	0.974***	0.484***	-0.030***	0.470***	-0.042	1.115***	-0.192**	1.587***	4
	(0.217)	(0.176)	(0.039)	(0.028)	(0.137)	(0.003)	(0.141)	(0.096)	(0.072)	(0.085)	(0.045)	
CAD	0.694***	0.746***	0.219***	0.964***	-0.269***	0.060***	0.200***	0.293***	0.825***	-0.082*	0.971***	13
	(0.147)	(0.134)	(0.043)	(0.028)	(0.039)	(0.008)	(0.054)	(0.058)	(0.051)	(0.044)	(0.028)	
CHF	0.853***	0.645***	0.151***	1.041***	-0.394***	0.050***	0.398***	-0.139**	0.082	-0.080	1.526***	13
	(0.182)	(0.237)	(0.042)	(0.030)	(0.112)	(0.002)	(0.112)	(0.065)	(0.061)	(0.074)	(0.043)	
EUR	1.053***	-0.093	0.236***	0.936***	0.069	0.009***	0.513***	0.225***	0.882***	0.022	1.070***	13
	(0.034)	(0.168)	(0.038)	(0.027)	(0.084)	(0.001)	(0.018)	(0.056)	(0.050)	(0.043)	(0.030)	
GBP	0.589***	0.797***	0.424***	0.914***	-0.281***	0.130***	0.220***	0.400***	0.750***	0.004	1.052***	13
	(0.078)	(0.056)	(0.039)	(0.026)	(0.023)	(0.004)	(0.030)	(0.053)	(0.046)	(0.042)	(0.030)	
JPY	0.494	-0.858	-0.014	1.051***	0.577	0.025***	0.440	-0.018	0.799***	0.010	1.216***	4
	(2.569)	(1.478)	(0.043)	(0.030)	(1.317)	(0.005)	(1.728)	(0.066)	(0.054)	(0.053)	(0.034)	
MXN	0.605***	-0.783***	0.195***	0.958***	1.412***	-0.217***	1.010***	0.151**	0.242***	0.039	1.452***	4
	(0.169)	(0.129)	(0.043)	(0.027)	(0.219)	(0.044)	(0.308)	(0.060)	(0.055)	(0.062)	(0.041)	
NOK	1.035***	-0.013	1.017***	0.215***	-0.020	0.009***	0.589***	-0.108	-0.067	-0.142**	1.667***	4
	(0.029)	(0.009)	(0.030)	(0.006)	(0.024)	(0.002)	(0.017)	(0.067)	(0.067)	(0.067)	(0.047)	
NZD	-0.123	-1.002***	-0.105**	1.036***	0.557***	0.108***	-0.010	-0.004	1.136***	-0.028	1.634***	13
	(0.398)	(0.056)	(0.048)	(0.029)	(0.017)	(0.013)	(0.224)	(0.084)	(0.073)	(0.079)	(0.046)	
SEK	0.996***	0.077***	0.985***	0.230***	-0.063***	0.042***	0.489***	-0.133**	0.054	-0.116*	1.674***	13
	(0.028)	(0.010)	(0.029)	(0.007)	(0.020)	(0.001)	(0.014)	(0.067)	(0.067)	(0.067)	(0.048)	
SGD	0.095	1.046***	-0.118***	0.979***	-0.657***	-0.006*	-0.140	-0.095***	0.314***	-0.040	0.611***	4
	(0.350)	(0.043)	(0.040)	(0.028)	(0.050)	(0.003)	(0.218)	(0.031)	(0.026)	(0.031)	(0.017)	
ZAR	0.641***	0.802***	-0.145***	0.960***	-0.900***	-0.163***	0.536**	-0.092	1.278***	0.147*	2.032***	4
	(0.217)	(0.172)	(0.039)	(0.027)	(0.146)	(0.007)	(0.246)	(0.104)	(0.089)	(0.086)	(0.058)	

Notes: Quasi Maximum Likelihood estimates of the coefficients in C and asymptotic standard errors (in parenthesis). Statistical significance at the 1, 5, and 10 percent levels denoted by "***", "**" and "*", respectively. The right-hand-column reports the number of lags in each SVAR. Estimated between January 1 2000 to November 25 2011.

of θ_{33} (impact interest rate shocks) are statistically insignificant, indicating that we cannot reject the null that *all* of the short-run variations in these interest differentials are driven by order flows.

Finally, the estimates of θ_{41} and θ_{42} in Panel IV show the short-run effects of the order flows on the exchange rates. Surprisingly, the estimates of the short-run impact of carry trade shocks via order flow (θ_{41}) are highly statistically significant in only the CAD, EUR, GBP and SGD models. Shocks to order flow driven by the carry trade do not appear to have an immediate impact on exchange rates across the majority of currencies we study. This is not to say that order flows are unimportant. On the contrary, the estimates of θ_{42} are highly statistically significant in nine models, and always larger than the estimate of θ_{41}. Many earlier studies have found that (aggregate) shocks to order flow have important immediate exchange-rate effects. Our results suggest that this effect is coming via the non-carry factors. We also note that that interest rate shocks have very little immediate impact on exchange rates. In only one case, the NOK model, is the estimate of θ_{43} statistically significant at the one percent level.

Overall, the estimates in Table 8 show that immediate effects of the carry trade on interest and exchange rates estimated by our SVAR models is rather different than the conventional wisdom. In particular these estimates do not provide direct support for the idea that forex trades generated by the carry trade are an important short-run driver of exchange-rate dynamics. On the contrary, they suggest that both carry and non-carry shocks driving order flow have most widespread short-term impacts on interest differentials. In the appendix we present results showing that these results are robust to ending the estimation prior to the global financial crisis.

We now examine the longer-term effects of the carry trade on interest rates and exchange rates. Table 9 reports variance decompositions for the level of the interest differential, $r_t^0 - r_t^i$, implied by the SVAR estimates at horizons ranging from one to 26 weeks.[12] Recall that the models impose a zero restriction on the θ_{34} coefficient so that exchange rate shocks cannot contribute to the variance of the interest differential at the one week horizon by construction. As the table shows, exchange rate shocks contribute little to the variability of the interest differential over longer horizons, except in the case of the CAD, MXN and NZD

[12] All of the variance decomposition results we report are representative of the contributions we compute for longer horizons, i.e. 52 weeks.

models. The contributions are strongest in the MXN case, rising to over 25 percent by 26 weeks, with contributions of 10 and 8 percent in the NZD and CAD models, respectively. Nevertheless, the broad pattern of our results shows that exchange rate shocks make only minor contributions to the variability of interest differentials at the six month horizon or less. This does not imply that unexpected movements in exchange rates have little affect on interest differentials. The exchange rate shocks in our SVAR models represent the factors driving unanticipated exchange rate changes that are unrelated (uncorrelated) with the carry and non-carry shocks driving order flows and interest rate shocks. The results in Table 9 show that these "other" factors driving exchange rates contribute little to interest-rate variability.

The left-hand column of each block in Table 9 reports the variance contributions of the carry order flow shocks. Carry trade order flow contributes significantly to the variance of the interest differential across horizons in all but three models. In the EUR model, carry-trade shocks make no economically significant contribution for short horizons, but the contribution rises to 11 percent by 13 weeks. For the SEK and NOK models the variance contributions are even smaller than for EUR. Across the other models, the estimated contributions of the carry trade are quite remarkable and suggest that order flows driven by the carry trade exerts a dominant economic effect on interest differentials at macro-relevant horizons. In all the remaining nine models the effect of carry trade exceed 50 percent, and are as high as 80-90 percent for the USD-NZD and USD-SGD differentials.

The interest-rate effects of the non-carry shocks driving order flow are very different. As the second column in each block of Table 9 shows, the variance contributions are very small across all horizons in every model. Recall that SVAR imposes the restriction that the non-carry trade shocks driving order flow have no long run impact on the level of the interest differential, so by construction the variance contribution must approach zero as the horizon lengthens. In principle, then, our estimates could have shown that non-carry shocks to order flow significantly affect interest differentials over short and medium horizons. In practice, the estimated contributions are very small in all models.

We now consider the exchange-rate effects of the carry trade. Table 10 reports variance contributions for the log level of each exchange rate at horizons ranging from one to 26 weeks. In contrast to the results above, the contribution of carry order flow shocks is small in every model across all horizons. Contrary to conventional wisdom, there is no evidence that forex transactions supporting carry trade strategies materially affect the behavior of spot exchange

Table 9: Variance Decompositions for the Interest Differential

	Horizon (weeks)	Shocks					Horizon (weeks)	Shocks			
		u^x	u^{of}	u^r	u^s			u^x	u^{of}	u^r	u^s
AUD	1	0.513	0.002	0.485	0.000	MXN	1	0.652	0.015	0.333	0.000
	4	0.463	0.002	0.527	0.008		4	0.518	0.008	0.281	0.193
	13	0.397	0.001	0.595	0.007		13	0.508	0.003	0.241	0.248
	26	0.371	0.001	0.621	0.007		26	0.505	0.002	0.231	0.262
CAD	1	0.624	0.031	0.345	0.000	NOK	1	0.001	0.000	0.999	0.000
	4	0.600	0.032	0.364	0.004		4	0.003	0.013	0.979	0.004
	13	0.459	0.025	0.477	0.039		13	0.003	0.006	0.985	0.006
	26	0.400	0.016	0.505	0.079		26	0.002	0.003	0.988	0.006
CHF	1	0.490	0.008	0.502	0.000	NZD	1	0.963	0.036	0.000	0.000
	4	0.585	0.007	0.402	0.006		4	0.946	0.032	0.003	0.018
	13	0.702	0.006	0.285	0.007		13	0.899	0.018	0.005	0.078
	26	0.766	0.003	0.227	0.004		26	0.861	0.008	0.002	0.129
EUR	1	0.018	0.000	0.982	0.000	SEK	1	0.016	0.007	0.977	0.000
	4	0.017	0.002	0.973	0.008		4	0.022	0.009	0.966	0.002
	13	0.115	0.003	0.871	0.011		13	0.051	0.006	0.941	0.002
	26	0.176	0.002	0.816	0.006		26	0.071	0.003	0.925	0.001
GBP	1	0.548	0.117	0.335	0.000	SGD	1	0.956	0.000	0.044	0.000
	4	0.506	0.098	0.385	0.010		4	0.945	0.005	0.046	0.004
	13	0.492	0.042	0.458	0.008		13	0.949	0.002	0.040	0.009
	26	0.489	0.019	0.482	0.010		26	0.949	0.001	0.038	0.011
JPY	1	0.632	0.001	0.367	0.000	ZAR	1	0.721	0.024	0.255	0.000
	4	0.643	0.001	0.349	0.006		4	0.693	0.016	0.279	0.013
	13	0.629	0.001	0.353	0.018		13	0.681	0.007	0.298	0.014
	26	0.627	0.000	0.352	0.020		26	0.680	0.004	0.302	0.014

Notes: Each cell reports the variance contribution of the shock listed at the head of each column to the interest differential at the horizon shown in the left-hand column of each block. Zero values imposed by the identification scheme are identified by "*". u^τ, u^x, u^r and u^s denote the structural shocks to the carry trade, order flow, interest differential and depreciation rate, respectively. Sample: January 1 2000 to November 25 2011.

rates. Shocks to order flow driven by non-carry factors, on the other hand, have economically significant effects on spot rates in eight models, with variance contributions ranging from approximately 20 to 50 percent. The four exceptions appear in the CHF, NOK, MXN and SEK models. We note, however, that in these four models both carry and non-carry order flow shocks account for very small fractions of the exchange rate variance. Table 10 also shows that interest rates shocks contribute little to the variance of the exchange rates in all models at any horizons.

Tables 9 and 10 report variance decompositions based on our SVAR model estimates without standard errors. In principle we could compute standard errors with the bootstrap. This would be consistent with the VAR literature but is impractical here for two reasons. First, the combination of short- and long-run restrictions in our SVAR models necessitates the use of an iterative estimation method, so repeated estimation as part of bootstrap procedure would be far more computationally demanding than is the case in a standard VAR. Second, our SVAR models include the carry component of order flow estimated at an earlier stage of our analysis. To fully account for the sampling variation in the carry components we would need to bootstrap both the first-stage estimation of the carry components and the nonlinear SVAR estimation. We decided not to attempt this extremely complex task. We have, however, endeavored to evaluate the statistical significance of our results in another way. For this purpose we compute the contribution of the structural shocks to the unconditional variance of changes in the interest differentials and exchange rates over different horizons. As we explain in the appendix, these statistics are closely related to the conditional variance contributions reported in Tables 9 and 10, but computing standard errors is much more straightforward. We find that these alternate decompositions are numerically very similar to those reported in Tables 9 and 10, and that the standard errors are typically well below 0.10 (across horizons). These findings indicate that the differences between the variance contributions of the carry shocks to interest rates and exchange rates discussed above are statistically significant.

Overall, the variance decomposition results in Tables 9 and 10 provide a new perspective on the impact of the carry trade. Simply put, order flows that support the carry trade contribute much more to the dynamics of the interest differentials that they do to the behavior of exchange rates. In contrast, the non-carry factors driving order flow appear to affect exchange rates rather than interest differentials. These findings contradict the traditional view

Table 10: Variance Decompositions for Log Spot Rates

	Horizon (weeks)	Shocks					Horizon (weeks)	Shocks			
		u^x	u^{of}	u^r	u^s			u^x	u^{of}	u^r	u^s
AUD	1	0.000	0.327	0.010	0.663	MXN	1	0.010	0.027	0.001	0.962
	4	0.011	0.334	0.009	0.646		4	0.016	0.025	0.006	0.952
	13	0.015	0.303	0.017	0.665		13	0.010	0.010	0.010	0.970
	26	0.016	0.291	0.018	0.674		26	0.007	0.005	0.010	0.978
CAD	1	0.050	0.396	0.004	0.550	NOK	1	0.004	0.002	0.007	0.987
	4	0.020	0.470	0.005	0.505		4	0.002	0.001	0.004	0.993
	13	0.019	0.450	0.013	0.518		13	0.001	0.001	0.012	0.986
	26	0.011	0.511	0.007	0.471		26	0.000	0.001	0.013	0.985
CHF	1	0.008	0.003	0.003	0.986	NZD	1	0.000	0.326	0.000	0.674
	4	0.008	0.001	0.011	0.981		4	0.001	0.317	0.003	0.680
	13	0.017	0.005	0.023	0.955		13	0.005	0.285	0.001	0.708
	26	0.010	0.004	0.030	0.956		26	0.003	0.276	0.003	0.718
EUR	1	0.026	0.394	0.000	0.580	SEK	1	0.006	0.001	0.005	0.988
	4	0.034	0.364	0.004	0.598		4	0.003	0.003	0.013	0.981
	13	0.020	0.424	0.036	0.520		13	0.003	0.021	0.043	0.933
	26	0.028	0.438	0.021	0.513		26	0.001	0.035	0.048	0.916
GBP	1	0.087	0.307	0.000	0.605	SGD	1	0.019	0.205	0.003	0.773
	4	0.091	0.342	0.003	0.564		4	0.021	0.211	0.003	0.765
	13	0.092	0.282	0.020	0.606		13	0.031	0.200	0.001	0.767
	26	0.084	0.278	0.020	0.618		26	0.032	0.192	0.001	0.775
JPY	1	0.000	0.301	0.000	0.698	ZAR	1	0.001	0.282	0.004	0.713
	4	0.000	0.313	0.001	0.686		4	0.003	0.308	0.026	0.664
	13	0.001	0.333	0.000	0.665		13	0.005	0.347	0.039	0.610
	26	0.001	0.339	0.000	0.660		26	0.005	0.366	0.040	0.589

Notes: Each cell reports the variance contribution of the shock listed at the head of each column to the log spot rate at the horizon shown in the left-hand column of each block. Zero values imposed by the identification scheme are identified by "*". u^τ, u^x, u^r and u^s denote the structural shocks to the carry trade, order flow, interest differential and depreciation rate, respectively. Sample: January 1 2000 to November 25 2011.

that forex transactions driven by the carry trade are important drivers of exchange rates, at least in any systematic fashion. We discuss how these results relate to existing research on the exchange-rate effects of the carry trade in Section 6.

It is also worth stressing that carry-trade order flow used in our SVAR models is not mechanically linked to either the future paths for exchange rates or interest rates. We used real-time forecasts of excess currency returns, a portfolio choice model and order flow data to estimate the carry-trade order flow series used in each model. The innovations in this series therefore represent the effects of new information on the excess return forecasts and/or the forex trading decisions embedded in the order flow data. Neither of these factors *need* have any relevance for the behavior of interest differentials or exchange rates. Indeed, this is largely what we find in the case of the NOK model estimates. But across the other 11 models there appears to be a consistent pattern of findings concerning the effects of carry and non-carry shocks to order flow on interest differentials and exchange rates.

5.3 Historical Decompositions

The variance decompositions in Tables 9 and 10 provide a simple statistical summary of how the carry and non-carry shocks driving order flows affect interest differentials and exchange rates at different horizons. To compliment this information we also compute historical decompositions for the variables in the SVARs. That is to say, we construct hypothetical time series for each variable under the assumption that only one of the structural shocks was present. In so doing we can examine whether the effects of a structural shock were concentrated in a particular episode - information that is not available from the variance decompositions presented above. In a series of figures we plot the actual series, driven by all four shocks, and the most relevant hypothetical series out of the four shock series carry, non-carry, interest rate differential and exchange rate ($\hat{X}_t^{i,n} = \sum_{j=0}^{t} \Delta \hat{X}_j^{i,n}$ for $n = \{x, of, r, s\}$).

5.3.1 Carry Trade Positions

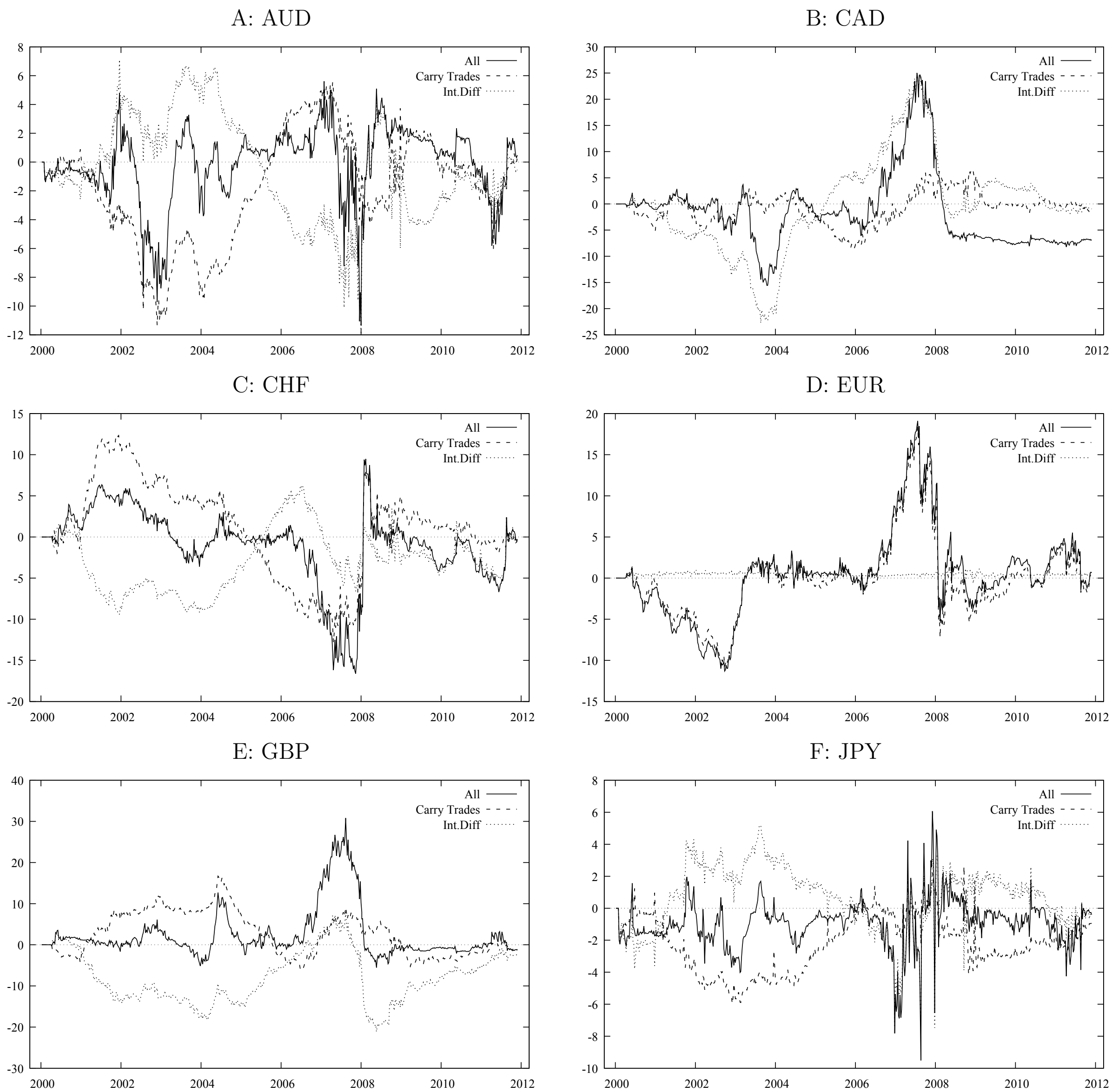
Figure 4 plots historical decompositions for cumulated carry trade order flow in each of the 12 currencies. The figures plot the actual series, $\hat{X}_t^i = \sum_{j=0}^{t} \Delta \hat{X}_j^i$, driven by all four structural shocks, and the hypothetical series $\hat{X}_t^{i,x}$ and $\hat{X}_t^{i,r}$ driven by the carry and interest rate shocks, respectively. As the figure shows, there are considerable swings in all the plots for $\hat{X}_t^i$. These swings signify the accumulation of large carry-trade positions, either long or short, at different points in the sample period. Many of the largest swings occur in between the start of 2006 and 2009, but for some currencies there are sizable swings in earlier periods. We also note that the swings in X_t^i after 2006 are in different directions across currencies. For example, $\hat{X}_t^i$ rises in the CAD plot and falls in CHF plot between 2006 and mid-2007. These movements signify the building of long positions in the CAD and short positions in the CHF.

A comparison of the plots for X_t^i with the hypothetical series provides us with information about the relative importance of the factors driving changes in carry trade positions. By construction, changes in carry-trade positions are driven by changes in (real-time) forecasts of future excess returns across the twelve foreign currencies, and changes in total assets committed to the carry trade (i.e. changes in the value of the foreign bond portfolio). Comparing the plots for $\hat{X}_t^i$ with $\hat{X}_t^{i,r}$ shows how much of the changing carry trade position in currency i can be linked to changes in the domestic interest differential that are unrelated to the feedback effects of order flow on the differential. Figure 4 shows that the plots for $\hat{X}_t^i$ with $\hat{X}_t^{i,r}$ are very similar in the case of the JPY, MXN, NZD and SGD throughout the sample period. Exogenous changes in domestic interest differentials account for most of the variations in the carry-trade position for these currencies.

In other cases, the domestic interest differential appears as a sporadic driving force. For example, the differential appears to be a primary driver of the CAD carry-trade position before 2005, and for the ZAR position between 2006 and 2009. Outside these episodes, excess return forecasts and changes in the carry trade assets that drive the positions are largely unrelated to domestic interest rate shocks. Our SVAR models attribute these drivers to the carry, non-carry order flow shocks and exchange-rate shocks.

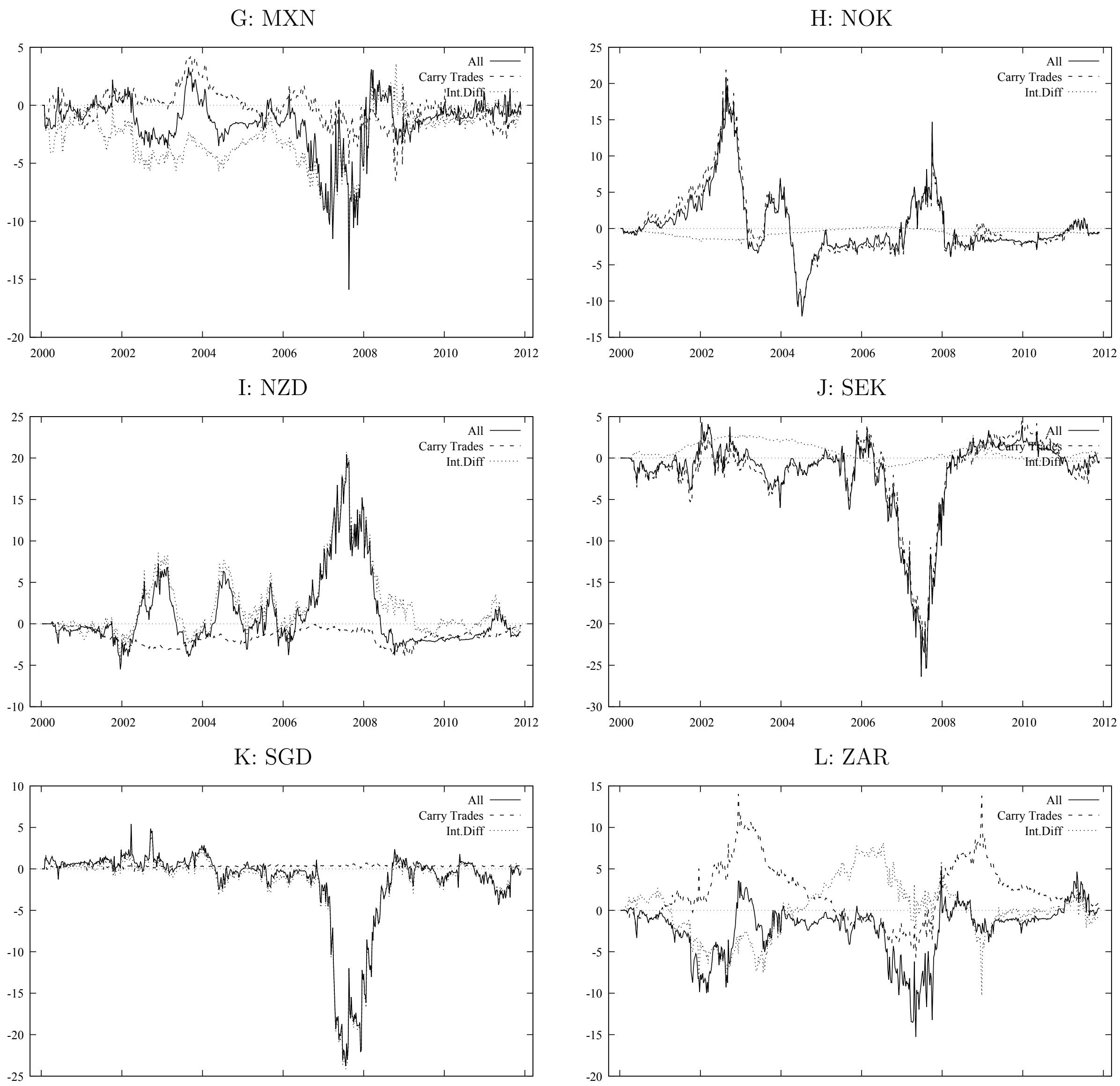
The effects of the carry shocks are depicted by the plots for the $\hat{X}_t^{i,x}$ series. As the figure shows, these series exhibit considerable swings in all cases except the JPY, NZD and SGD. Shocks to carry trade order flow that are unrelated to changes in interest differentials account for significant portions of the changes in the carry-trade positions of many currencies. Indeed these shocks appear as the dominant driver of the position changes for the EUR, SEK and NOK. In other cases, the effects of the carry shocks offset the effects of the interest rate shocks; see, e.g., the AUD, CAD CHF and GBP plots. Economically, the carry shocks represent the effects of unexpected revisions in excess return forecasts and assets committed

Figure 4: Historical Decompositions for the Carry Trade



Notes: Plots show de-trended paths for cumulated carry trade order flow driven by: (i) all shocks, (ii) carry trade shocks, and (iii) interest differential shocks. Order flow shocks and FX shocks not shown in order to improve exposition.

Figure 4: Historical Decompositions for the Carry Trade (Cont.)



Notes: Plots show de-trended paths for cumulated carry trade order flow driven by: (i) all shocks, (ii) carry trade shocks, and (iii) interest differential shocks. Order flow shocks and FX shocks not shown in order to improve exposition.

to the carry trade that are independent of interest rate shocks. The sizable variations in the X_t^x series show that non-interest factors are important drivers of the carry trade for many currencies.

Exchange-rate and non-carry shocks (not shown) also contribute, but to a lesser extent, to the carry-trade positions indirectly through their effects on expectations.[13] For AUD, CAD, EUR, GBP and ZAR there are periods where these shocks contribute to carry positions consistent with forecasts of excange rate changes against the USD. In particular for AUD before 2009, and CAD between 2005 and 2010. The effects of the non-carry order flow shocks on the carry-trade positions are similar.

In sum, the plots in Figure 4 show that there have been sizable changes in the carry-trade positions for many currencies over the sample period. Moreover, while changes in the bilateral interest differentials are the principal drivers behind the position changes for some currencies (notably the JPY and NZD), in most currencies other drivers are also import. So if there have been occasions where carry trade order flows had a significant impact on exchange rates, we should expect to see it below in the historical decompositions for exchange rates.

5.3.2 Exchange Rates

Figure 5 plots historical decompositions for the 12 log exchange rates. Again the figures plot the actual series, s_t^i, driven by all four structural shocks, and in this case the hypothetical series $s_t^{i,x}$ and $s_t^{i,of}$ driven by the carry and non-carry shocks, respectively. In all but one case, the path for the log spot rate driven solely by the carry shocks, $s_t^{i,x}$, remains close to zero and displays none of the sizable swings exhibited by the actual log spot rate, s_t^i. The CHF plot shows the one exception. Here there is an approximate 10 percent deprecation in the $s_t^{i,x}$ series around the beginning of 2008 that overlaps with the actual depreciation in the CHF that starts in mid 2007. Aside from this single episode, there is no evidence from the plots in Figure 5 that order flow driven by the carry trade materially affected the behavior of exchange rates over this sample period.

In contrast, non-carry trade shocks to order flow appear to have had sizable exchange-rate effects on some currencies. In the case of the CAD and GBP, there are long episodes

[13] Recall that neither shock is assumed to have a direct contemporaneous impact on carry trade order flow in our SVAR models.

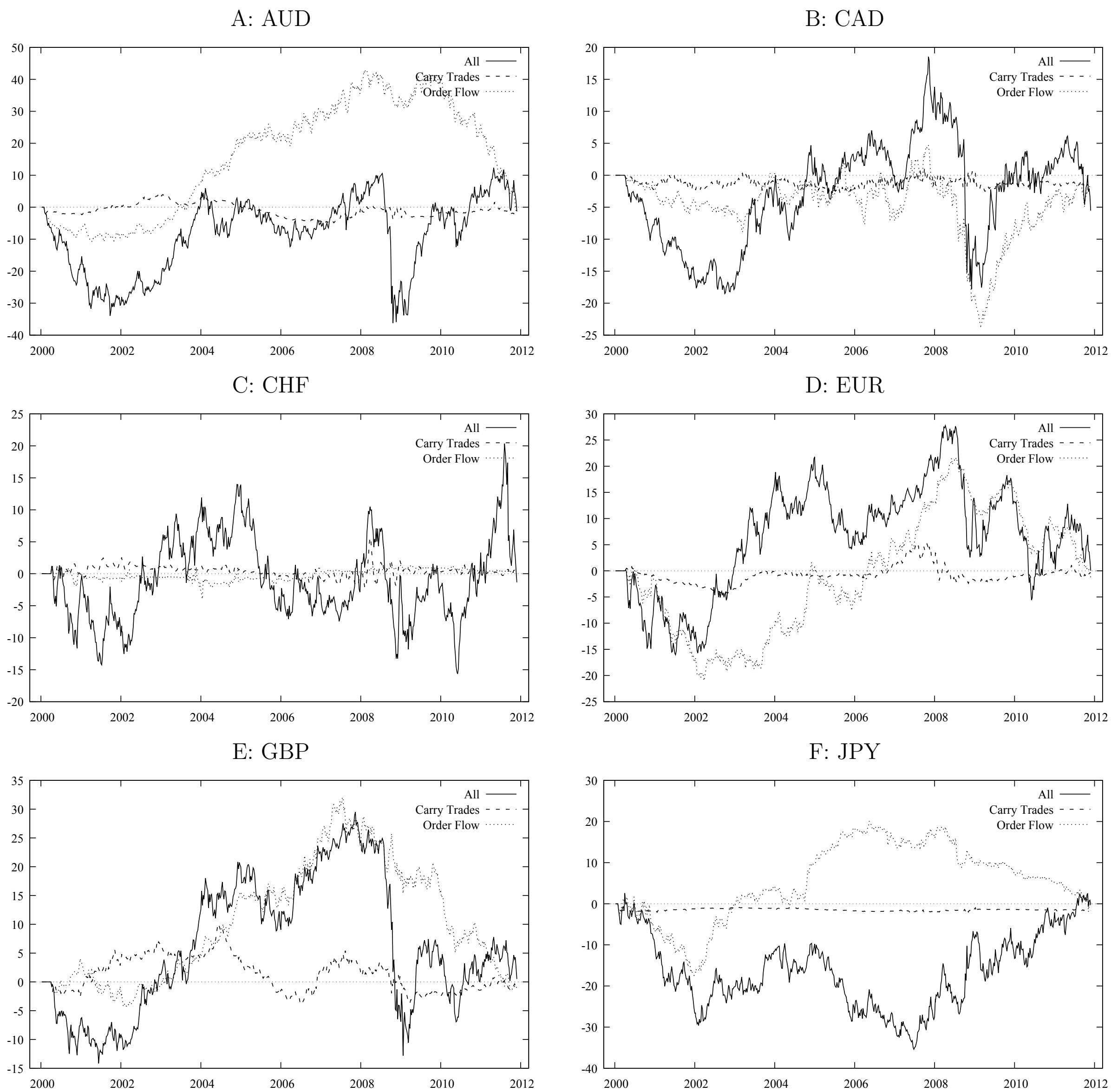
where the variations in the $s_t^{i,of}$ series are similar in scale and direction to those displayed by the actual spot rate. Interestingly, non-carry order flow shocks seem to have been the dominant driver of the CAD spot rate after 2007 whereas in the case of the GBP they appear to be dominant before 2008. In four currencies; the AUD, JPY, SGD and ZAR, the substantial exchange rate effects of non-carry shocks were offset by other factors (producing large differences between the plots for s_t^i and $s_t^{i,of}$). In principal interest rate shocks could be this offsetting factor. However, the $s_t^{i,r}$ series is described by very little variability and was dropped from figure to improve presentation. Instead it is the exchange-rate shocks (not shown) that offset the exchange rate effect of the non-carry order flows in these four currencies. Of course the exchange rate shocks derived from the SVAR models are really just the residuals from the depreciation rate equation of the model and have no precise economic interpretation other than the shocks that drive exchange rates uncorrelated to the other three structural shocks. In this respect our SVAR model does not resolve the well-known exchange-rate disconnect puzzle.

5.3.3 Interest Rates

Finally, we turn to the behavior of the interest differentials. Figure 6 plots historical decompositions for the twelve differentials, $r_t^0 - r_t^i$, and in this case only the hypothetical series $r_t^{0,x} - r_t^{i,x}$ driven exclusively by carry trade shocks.

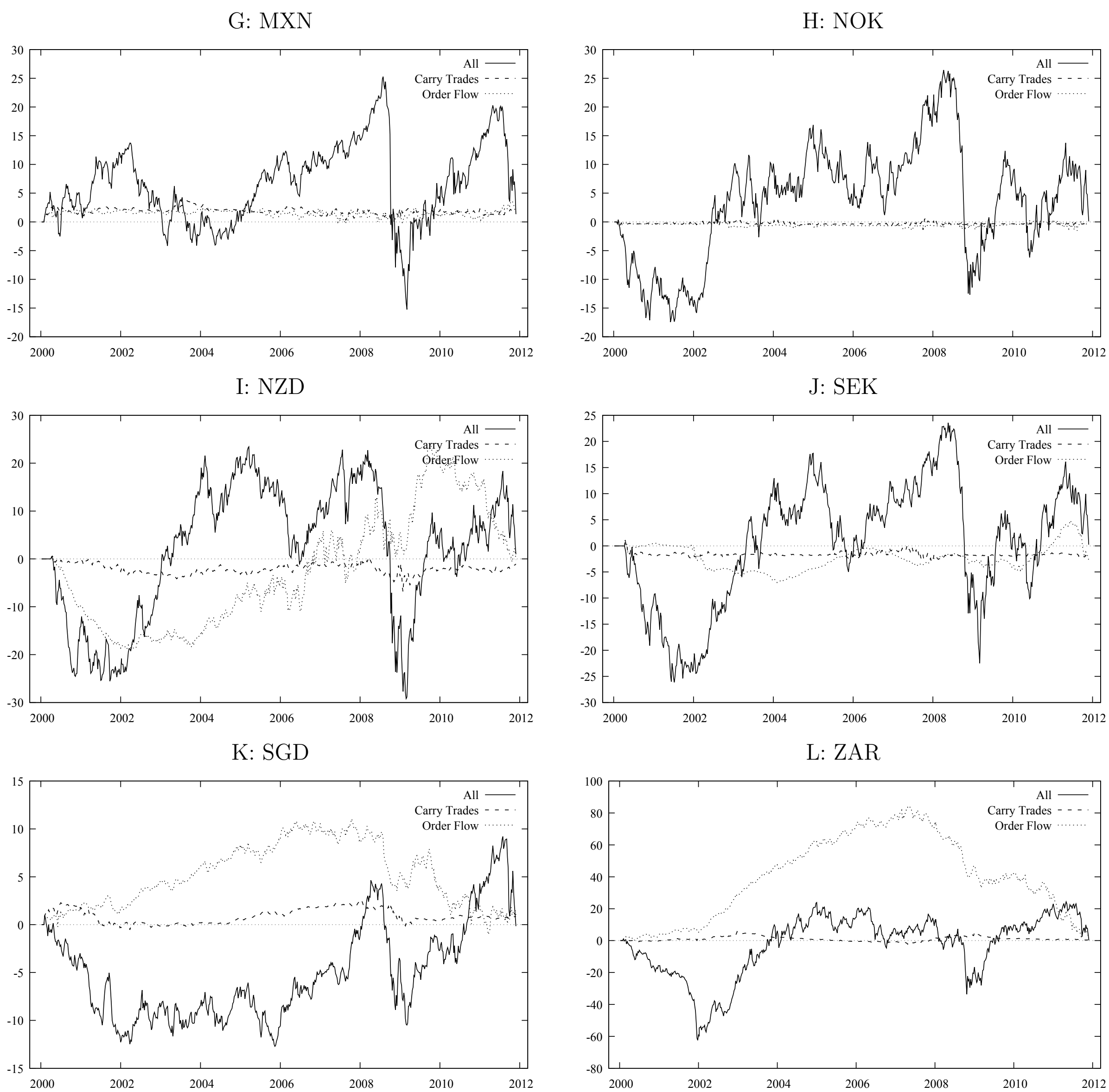
The key difference between the plots in Figures 5 and 6 concerns the role of the carry shocks to order flow. In nine cases, the sizable variations in the $r_t^{0,x} - r_t^{i,x}$ series indicate that carry trade shocks materially affect interest differentials. Indeed carry shocks appear to be the dominant driver of the JPY, SGD and ZAR interest differentials because the $r_t^{0,x} - r_t^{i,x}$ series closely track the actual differentials for the entire sample period. In the case of the AUD, CHF, GBP and NZD, the movements in $r_t^{0,x} - r_t^{i,x}$ and $r_t^0 - r_t^i$ are very similar over shorter periods. For example, carry trade shocks to order flow appear as the dominant driver of the NZD differential between mid-2006 and 2009. During other periods, the effects of the carry shocks are offset by other factors. For example, the effects of the carry shocks were offset by the interest rate shocks in 2006 and 2007 for both the CAD and GBP. In the case of the NZD, they were offset by exchange rate shocks in 2003 and 2004. More generally, for the AUD, CAD, CHF, GBP, MXN and NZD a complex combination of carry, interest rate and exchange rate shocks contribute the behavior of interest differentials in these countries.

Figure 5: Historical Decompositions for Log Spot Rates



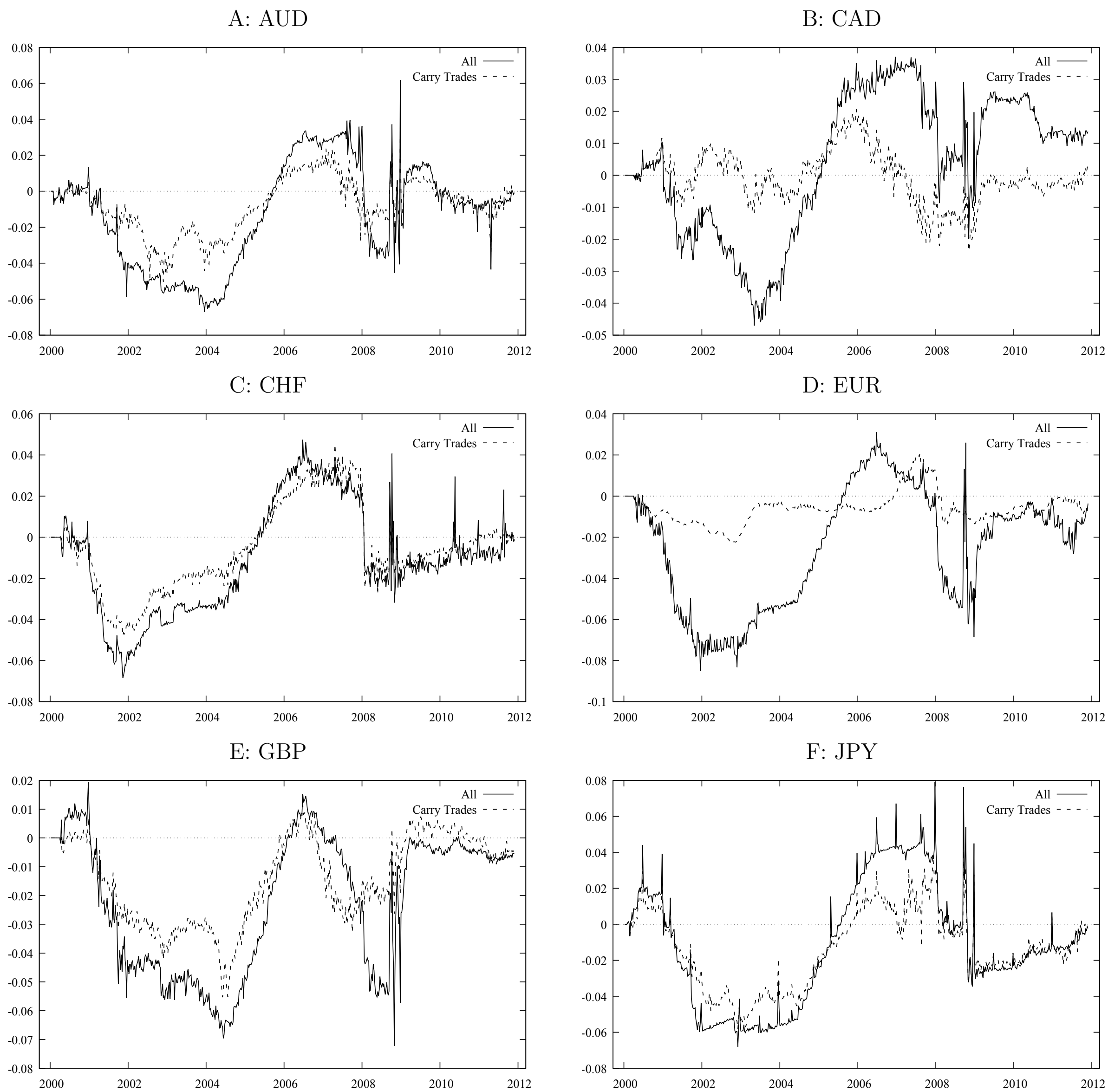
Notes: Plots show de-trended paths for the log spot rate driven by: (i) all shocks, (ii) carry trade shocks, and (iii) order flow shocks. Interest rate shocks and FX shocks not shown in order to improve exposition.

Figure 5: Historical Decompositions for Log Spot Rates (cont.)



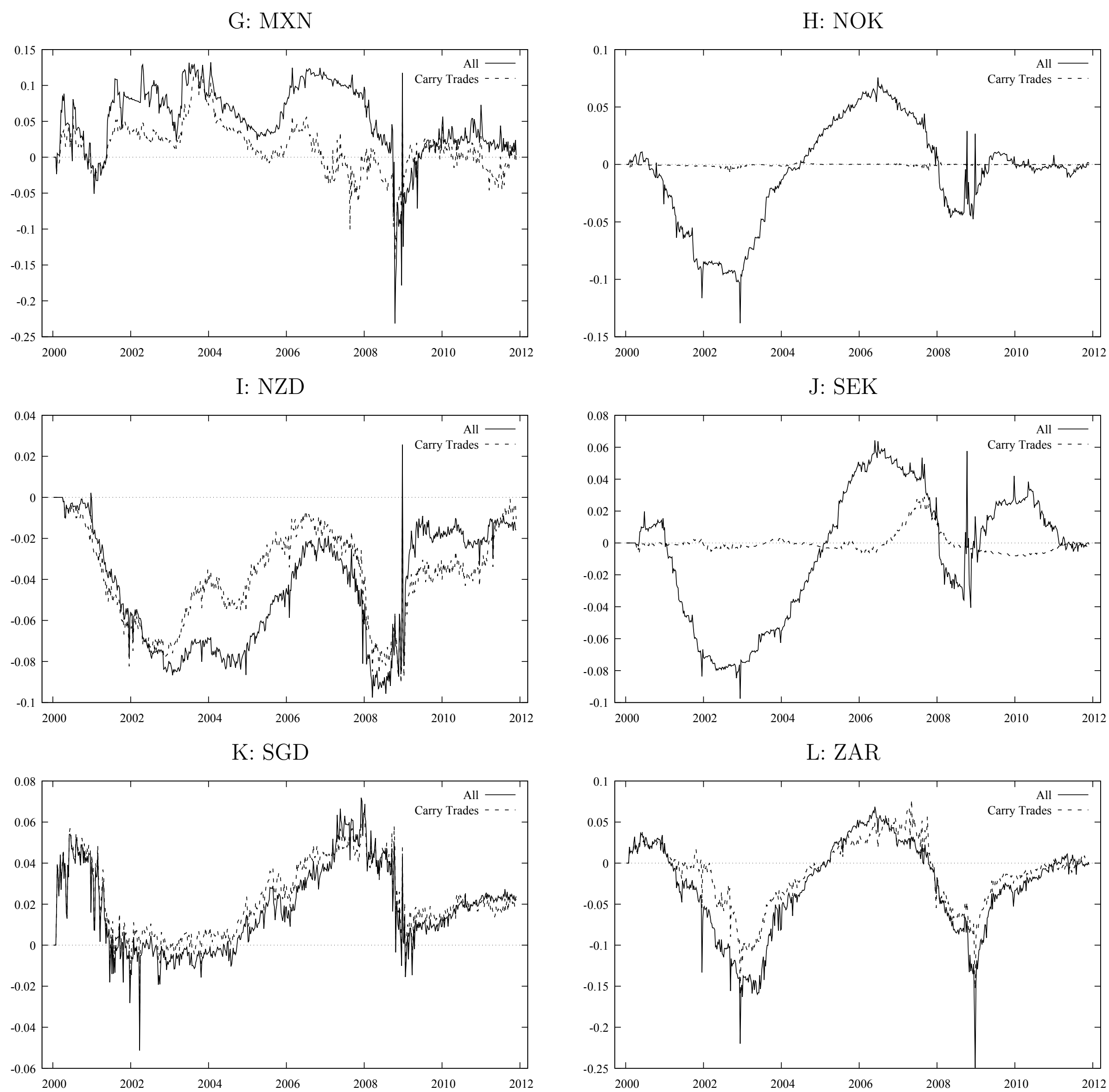
Notes: Plots show de-trended paths for the log spot rate driven by: (i) all shocks, (ii) carry trade shocks, and (iii) order flow shocks. Interest rate shocks and FX shocks not shown in order to improve exposition.

Figure 6: Historical Decompositions for Interest Differentials



Notes: Plots show de-trended paths for the interest rate differential driven by: (i) all shocks, and (ii) carry trade shocks. Order flow shocks, interest rate shocks and FX shocks not shown in order to improve exposition.

Figure 6: Historical Decompositions for Interest Differentials (cont.)



Notes: Plots show de-trended paths for the interest rate differential driven by: (i) all shocks, and (ii) carry trade shocks. Order flow shocks, interest rate shocks and FX shocks not shown in order to improve exposition.

Finally, we note that carry shocks have a negligible impact on the interest differentials for the EUR, NOK and the SEK. In all three cases interest rate shocks are the dominant drivers of the differentials over the entire sample period.

Non-carry shocks to order flows (not shown) have negligible effects on all twelve interest differentials: the $r_t^{0,of} - r_t^{i,of}$ series are very close to zero throughout the sample period. Finally, for some currencies the exchange rate shocks (not shown) have some influence, while others appear largely immune to the effects of exchange rate shocks.

6 Discussion

Several aspects of our results deserve further discussion. In this section we address the differences between our findings and others in the literature, the effects of estimation error in the order flow components, and the robustness of our findings to the use of alternative portfolio models.

6.1 The Absence of Exchange Rate Effects

In the introduction we noted that large exchange-rate movements that appear unrelated to changes in macro fundamentals are often attributed to the effects of the carry trade, and in particular, the rapid unwinding of carry trade positions. For example, unwinding of the carry positions involving the JPY are thought to lie behind the behavior of the USD/JPY rate in October 1998, May 2006 and February 2007 (see, e.g., Gagnon and Chaboud, 2007). In contrast our analysis found no effects of the carry trade on the UDS/JPY rate in 2006 and 2007 or any other year since 2001. This is not because our estimates of the JPY carry position remain stable. On the contrary, as Figure 4 shows, there are large swings in the estimated carry positions between 2006 and 2008. We failed to find exchange-rate effects of the carry trade in 2006 and 2007 because the order flows driven by carry trade shocks had no discernible effect on the USD/JPY rate. This finding is also consistent with earlier work that examined the exchange rate effects of order flows associated with the carry trade. When Lyons (2001) and Evans (2011) examined the JPY order flows received by Citibank in the weeks surrounding October 1998, they found that the significant ("once in a decade") appreciation of the JPY on October 7th and 8th was not accompanied by large (negative) flows from leveraged investors. Indeed, the order flow data indicate that these investors had significantly reduced their JPY borrowing five weeks earlier without any clear effect on the exchange rate.

This example illustrates a key distinction between our analysis and much of the existing research on the effects of the carry trade. Because the motives behind individual trades are not public information, trading decisions by speculators engaged in the carry trade can *only* affect an asset price insofar as they induce market participants to revise their view about future payoffs or the discount factor used to value them. In the case of exchange rates, forex order flow conveys this information. So if the carry trade is to affect a particular exchange rate, it must do so via order flow. It is this transmission mechanism that is the focus of our analysis. In contrast, results linking the behavior of exchange rates to indicators of carry trade activity such as interest differentials or futures positions provide *indirect* evidence on the existence of an operable transmission mechanism. For example, the predictive power of interest differentials for future skewness in exchange rate returns reported by Brunnermeier et al. (2009) is consistent with an operable carry trade effect, but it could also be attributable to another factor driving exchange rate behavior.

Our analysis reveals sizable swings in the cumulative carry order flows and yet those carry order flows have no discernible effect on exchange rates. If would be hard to make sense of this finding *if* the carry trade were the dominant driver of the total forex order flow for each currency. However, in reality, the carry trade is a relatively unimportant driver of order flow for most currencies. This is clearly seen in Table 11, which reports variance decompositions from the SVAR models for cumulated order flow, $\sum_{j=0}^{t} of_j^i$. Carry trade shocks account for very small fraction of the variance in order flow for ten currencies at all horizons. In these currencies it appears that non-carry factors swamp the effects of the carry trade on forex order flow. The NOK and SEK prove exceptions to this pattern. In these currencies carry trade shocks appear the dominant drivers of forex order flow, so ceteris paribus, we would expect to see exchange-rate effects of the carry trade for these currencies. This not what we find (see Table 10 and Figure 5). We suspect that this counterintuitive result reflects inaccuracy in our estimates of carry trade activity for the NOK and SEK, an issue we return to below.

Table 11: Variance Decomposition for the (cumulated) Order Flow

	Horizon (weeks)	Shocks					Horizon (weeks)	Shocks			
		u^x	u^{of}	u^r	u^s			u^x	u^{of}	u^r	u^s
AUD	1	0.019	0.981	0.000	0.000	MXN	1	0.040	0.960	0.000	0.000
	4	0.037	0.893	0.005	0.064		4	0.070	0.912	0.001	0.017
	13	0.056	0.682	0.013	0.249		13	0.095	0.862	0.000	0.043
	26	0.061	0.620	0.016	0.303		26	0.100	0.850	0.000	0.050
CAD	1	0.049	0.951	0.000	0.000	NOK	1	0.957	0.043	0.000	0.000
	4	0.021	0.969	0.003	0.007		4	0.935	0.055	0.000	0.010
	13	0.014	0.858	0.002	0.126		13	0.922	0.069	0.002	0.007
	26	0.007	0.663	0.001	0.329		26	0.919	0.072	0.002	0.007
CHF	1	0.021	0.979	0.000	0.000	NZD	1	0.010	0.990	0.000	0.000
	4	0.006	0.982	0.000	0.011		4	0.014	0.982	0.001	0.003
	13	0.005	0.987	0.002	0.006		13	0.010	0.934	0.014	0.041
	26	0.007	0.981	0.002	0.011		26	0.015	0.872	0.022	0.092
EUR	1	0.060	0.940	0.000	0.000	SEK	1	0.948	0.052	0.000	0.000
	4	0.069	0.924	0.000	0.006		4	0.937	0.061	0.001	0.001
	13	0.024	0.874	0.000	0.102		13	0.918	0.075	0.003	0.004
	26	0.017	0.766	0.000	0.217		26	0.919	0.071	0.008	0.002
GBP	1	0.177	0.823	0.000	0.000	SGD	1	0.014	0.986	0.000	0.000
	4	0.149	0.817	0.002	0.033		4	0.021	0.952	0.001	0.027
	13	0.098	0.730	0.023	0.149		13	0.024	0.867	0.000	0.109
	26	0.058	0.683	0.026	0.234		26	0.024	0.846	0.000	0.130
JPY	1	0.000	1.000	0.000	0.000	ZAR	1	0.022	0.978	0.000	0.000
	4	0.000	0.997	0.002	0.000		4	0.010	0.975	0.000	0.014
	13	0.000	0.995	0.004	0.001		13	0.006	0.946	0.001	0.047
	26	0.000	0.995	0.004	0.001		26	0.006	0.935	0.001	0.058

Notes: Each cell reports the variance contribution of the shock listed at the head of each column to the cumulated order flow at the horizon shown in the left-hand column of each block. Zero values imposed by the identification scheme are identified by "*". u^x, u^{of}, u^r and u^s denote the structural shocks to the carry trade, order flow, interest differential and depreciation rate, respectively. Sample: January 1 2000 to November 25 2011.

6.2 The Presence of Interest Rate Effects

If the carry trade is a minor driver of the forex order flows in most currencies, why do we find that carry trade shocks are important drivers of interest rate differentials?[14] Unfortunately, our SVAR models estimates provide little information on the transmission mechanism linking the forex trading decisions motivated by the carry trade with variations in interest rates. Nevertheless, prior research on the determination of interest rates in the U.S. Treasury market provides some guidance on the possible mechanism. Brandt and Kavajecz (2004), Green (2004) and Pasquariello and Vega (2007) report that order flows in the bond market account for a sizable fraction of the day-to-day variations in U.S. Treasury rates. Since the execution of a generic carry trade strategy requires trades in both bond and forex markets, our estimates of the carry component in forex order flow should be correlated with bond order flows driven by the carry trade in both the source and target currencies. So, if the carry trade makes a significant contribution to the bond order flows in either the source or target currency, it should affect the interest differential.

Our results show that carry trade shocks are dominant drivers of the JPY, SGD and ZAR interest differentials throughout the sample period. We interpret these results as evidence that shocks to the carry trade were an important source of order flow in the Eurocurrency (offshore) money markets in these three currencies. Carry trade shocks appear important drivers of the AUD, CHF, GBP and NZD differentials over shorter periods. In these cases we suspect that non-carry factors periodically overwhelmed the effects of the carry trade on money market order flows. Of course these interpretations are necessarily speculative because we do not have order flow data from the Eurocurrency money markets. However, we do note that we could find no evidence of significant carry trade effects on the differential between U.S. and E.U interest rates. These are exactly the money markets where non-carry factors driving order flows are likely to swamp the effects of the carry trade.

[14] We should also emphasize that the Eurocurrency interest rates we study are not the policy rates controlled by central banks. Obviously, the Eurocurrency rates are related to policy rates, but they are determined by market forces. For a further discussion of the distinction between the Fed Funds market and the Eurocurrency markets, see Lee (2003).

6.3 Estimation Error

Our examination of the SVAR model uses estimates of the carry trade component in order flow derived from a simple portfolio choice model rather than the forex trading records of every speculator engaged in the carry trade. As such, they undoubtedly contain some estimation error that is reflected in the variance and historical decompositions. The question is, could the presence of estimation error account for our findings? We do not find this plausible for three reasons: First, the estimates of aggregate carry trade activity shown in Figure 3 display a secular decline that just precedes the onset of the world financial crisis. This feature of our estimates arises from the ability of our model to match the cross-currency pattern of order flows rather than any assumption concerning portfolio choice. We view the decline in estimated aggregate carry trade activity after 2007 as premia facie evidence that our model tracks the major swings in carry trade activity for most currencies.

The second reason concerns the estimated contribution of the carry trade shocks to order flow. While there is surely some estimation error in the size of these shocks, the results in Table 11 imply that the true shocks would have to be at least an order of magnitude larger to swamp the effects of the non-carry shocks on total order flow. The lack of evidence we find for exchange-rate effects of the carry trade are more plausibly due to the importance of non-carry factors driving order flow than the presence of large estimation errors in the carry component.

Finally, our results show that the carry trade activity affects the interest differentials in many currencies. If our estimates of the carry component of forex order flow contained significant error, we would not expect them to be strongly correlated with any of the differentials. The fact that we find significant interest-rate effects of the carry trade for some currencies but not others undermines the notion that there is some mechanical link between differentials and our estimates of the carry components in the forex order flow. While it is true that our portfolio choice model uses forecasts for excess returns that are conditioned on interest differentials, the estimated carry components of the order flow are determined by matching the cross-currency pattern of order flows with the pattern of trades necessary to achieve optimal portfolio holdings. Consequently, there are a far more complex set of the factors determining the carry component of order flow in each currency than just a single interest differential.

6.4 Robustness

Our estimates of the carry trade component in forex order flow are derived from a portfolio choice model of a hedge fund that views the U.S. interest rate as (nominally) risk free. To ensure that our results are not dependent on this U.S. based perspective, we also estimated carry trade order flow components from the portfolio choice models of EUR and GBP based funds. When these alternative estimates of carry trade order flow are used to estimate the SVAR models will still find that carry shocks drive interest differentials while non-carry shocks drive exchange rates. Variance decompositions computed from these alternative SVAR models are reported in the appendix.

7 Conclusion

This paper presents a new and different perspective the carry trade. First, and foremost, our analysis provides no support for the widely held belief that carry trade activity is responsible for large movements in exchange rates that appear unrelated to macro fundamentals. While our model estimates identify sizable swings in carry trade positions across currencies, the forex transaction supporting these swings are swamped by other non-carry factors driving forex order flows. As a consequence, we find no evidence of a significant transmission channel linking carry trade activity to movements in the exchange rates. Nevertheless, our estimates do support the presence of significant carry trade effects on interest rates in some countries. We believe that these interest-rate effects are due to the greater importance of carry trade transactions in bond order flows. Future research using bond flows will determine whether this conjecture is correct.

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A Tables

Table A.1: Correlation between Carry trading using all flows vs. removing one flow

	CHF	JPY	NOK	SEK
AUD	0.9590	0.9997	0.9999	0.9996
CAD	0.9452	0.9994	0.9998	0.9998
CHF	0.9387	0.9995	0.9998	0.9997
EUR	0.9524	0.9994	0.9998	0.9996
GBP	0.9499	0.9994	0.9997	0.9997
JPY	0.9630	0.9998	0.9999	0.9998
MXN	0.9736	0.9997	0.9999	0.9997
NOK	0.9616	0.9997	0.9996	0.9997
NZD	0.9401	0.9996	0.9997	0.9996
SEK	0.9621	0.9995	0.9998	0.9995
SGD	0.9441	0.9997	0.9999	0.9996
ZAR	0.9760	0.9996	0.9999	0.9996

Notes: Table presents correlation between the carry trading in in currency i based on all flows when constructing aggregate carry trading, and the carry trading in currency i when the currency in the column headings is excluded from creation of aggregate carry trading. Sample: January 1 2000 to November 25 2011.

Table A.2: Comparing Short-Run SVAR Coefficients: Ratio of Full sample to pre-crisis

Variable	I: Carry Trade: Δx^i		II: Order Flow: of^i		III: Interest Differential: $\Delta r^0 - \Delta r^i$			IV: Depreciation Rate: Δs^i			
Shock	u^x	u^r	u^x	u^{of}	u^x	u^{of}	u^r	u^x	u^{of}	u^r	u^s
Parameter	θ_{11}	θ_{13}	θ_{21}	θ_{22}	θ_{31}	θ_{32}	θ_{33}	θ_{41}	θ_{42}	θ_{43}	θ_{44}
AUD	0.900 ***/**	0.915 ***/***	1.119 ***/***	-1.149 ***/***	-1.486 ***/***	0.547 ***/***	-2.558 ***/	-0.552 /	-1.096 ***/***	2.138 **/	1.400 ***/***
CAD	0.695 ***/***	1.228 ***/***	0.946 ***/***	1.100 ***/***	1.512 ***/***	1.512 ***/***	0.842 ***/***	1.277 ***/***	1.332 ***/***	1.355 */	1.260 ***/***
CHF	0.787 ***/***	1.330 ***/	0.998 ***/***	0.874 ***/***	1.475 ***/***	1.636 ***/***	1.777 ***/**	1.038 **/	1.186 /	0.495 /**	1.152 ***/***
EUR	0.922 ***/***	-10.799 /	0.913 ***/***	0.941 ***/***	-20.685 /	0.355 ***/***	1.475 ***/***	0.859 ***/***	0.975 ***/***	-1.914 /	1.209 ***/***
GBP	0.670 ***/***	1.232 ***/***	1.076 ***/***	1.044 ***/***	1.572 ***/***	1.582 ***/***	0.856 ***/***	1.265 ***/***	1.324 ***/***	-0.218 /	1.127 ***/***
JPY	3.642 /	0.802 /***	0.075 /***	0.931 ***/***	-1.049 /***	-0.452 ***/***	7.713 /	0.297 /	1.007 ***/***	0.124 /	1.137 ***/***
MXN	0.839 ***/***	0.917 ***/***	0.832 ***/***	1.121 ***/***	2.148 ***/***	1.210 ***/***	1.355 ***/***	0.818 **/***	0.744 ***/***	0.397 /**	1.610 ***/***
NOK	0.873 ***/***	1.243 /*	0.848 ***/***	1.636 ***/***	0.637 /	-0.427 ***/***	1.235 ***/***	0.828 /*	-7.951 /	0.920 **/**	1.128 ***/***
NZD	-1.591 /	0.895 ***/***	-1.205 **/*	1.048 ***/***	1.546 ***/***	-6.095 ***/***	-0.091 /	-0.019 /***	1.195 ***/***	-1.773 /	1.173 ***/***
SEK	0.884 ***/***	2.916 ***/***	0.847 ***/***	1.775 ***/***	0.831 ***/***	0.399 ***/***	1.558 ***/***	0.973 **/**	4.209 /	1.154 */	1.165 ***/***
SGD	0.130 /*	-1.153 ***/***	1.592 ***/**	1.298 ***/***	-2.343 ***/	-0.081 */***	-0.234 /***	6.370 ***/	1.007 ***/***	-0.616 /***	1.287 ***/***
ZAR	1.285 ***/**	0.777 ***/***	0.791 ***/***	1.266 ***/***	0.958 ***/***	0.776 ***/***	2.713 **/	0.383 /**	0.960 ***/***	0.654 */***	1.189 ***/***

Notes: Table presents a comparison of the short-run SVAR coefficients for two different samples. Numbers are ratio of full-sample coefficents to pre-crisis coefficients. The asterisks indicate the statistical significance in full sample and pre-crisis sample, respectively. Statistical significance at the 1, 5, and 10 percent levels denoted by "***", "**" and "*", respectively. Full sample is January 1 2000 to November 25 2011, while the pre-crisis sample ends in July 2008.

B Rank based portfolios

Following Asness et al. (2013) we build carry portfolios where the portfolio weights $\alpha_{i,t}$ in the risky part of the portfolio, are based on the rank-position of the forward discount. In particular, the weights are calculated as

$$\alpha_{i,t} = \begin{cases} c_t^{+}\text{rank}\left(fd_{i,t}\right) & \text{if } fd_{i,t} > 0 \\ c_t^{-}\text{rank}\left(fd_{i,t}\right) & \text{if } fd_{i,t} \leq 0 \end{cases} \tag{B.1}$$

where c_t^{+} and $c_t^{-}$are constants that assure that the weights sum to 1. Our approach differ from the one adopted by Asness et al. (2013) in two ways: First, while in the approach of Asness et al. (2013) one goes long in currencies with rank above the average rank, our reference point for going long is if the forward discount is positive or not (in line with the basic idea of the carry trade). Second, our weights on the foreign bonds sum to 1, while in Asness et al. (2013) weights are such that one are short and long equal amounts. The formula of Asness et al. (2013) is given below for reference:

$$\alpha_{i,t} = c_t \left(\text{rank}\left(fd_{i,t}\right) - \sum_i \frac{\text{rank}\left(fd_{i,t}\right)}{N} \right).$$

C Historical decompositions

We compute the hypothetical time series for each variable used in the historical decompositions from the VMA representation of the SVAR: $Y_t - \bar{Y}_t = \Theta(L)U_t$. In particular, for the carry component of order flow, change in interest differential and exchange rate we write

$$\begin{aligned}
\Delta x_t^i &= \overline{\Delta x_t} + \theta_{11}(L)u_t^x + \theta_{12}(L)u_t^{of} + \theta_{13}(L)u_t^r + \theta_{14}(L)u_t^s \\
&= \overline{\Delta x_t} + \Delta x_t^{i.x} + \Delta x_t^{i,of} + \Delta x_t^{i,r} + \Delta x_t^{i,s}, \qquad \text{(C.1)}
\end{aligned}$$

$$\begin{aligned}
\Delta r_t^0 - \Delta r_t^i &= \overline{\Delta r_t^0 - \Delta r_t^i} + \theta_{31}(L)u_t^x + \theta_{32}(L)u_t^{of} + \theta_{33}(L)u_t^r + \theta_{34}(L)u_t^s \\
&= \overline{\Delta r_t^0 - \Delta r_t^i} + (\Delta r_t^{0,x} - \Delta r_t^{i,x}) + (\Delta r_t^{0,of} - \Delta r_t^{i,of}) + (\Delta r_t^{0,r} - \Delta r_t^{i,r}) \\
&\quad + (\Delta r_t^{0,s} - \Delta r_t^{i,s}), \qquad \text{(C.2)}
\end{aligned}$$

$$\begin{aligned}
\Delta s_t^i &= \overline{\Delta s_t^i} + \theta_{41}(L)u_t^x + \theta_{42}(L)u_t^{of} + \theta_{43}(L)u_t^r + \theta_{44}(L)u_t^s \\
&= \overline{\Delta s_t^i} + \Delta s_t^{i,x} + \Delta s_t^{i,of} + \Delta s_t^{i,r} + \Delta s_t^{i,s}, \qquad \text{(C.3)}
\end{aligned}$$

where $\theta_{i,j}(L)$ pick out the i,j th. elements from the matrix polynomial $\Theta(L)$. Estimates for each hypothetical series are computed using the estimated coefficients in $\theta_{i,j}(L)$ and estimates of the structural shocks (i.e., $\hat{u}_t^x$, $\hat{u}_t^{of}$, $\hat{u}_t^r$ and $\hat{u_t^s}$). Figure 4 plots historical decompositions for $\hat{X}_t^i$ using $\hat{X}_t^{i,n} = \sum_{j=0}^t \Delta \hat{X}_j^{i,n}$ for $n = \{x, of, r, s\}$ where $\Delta \hat{X}_t^{i,n} = \Delta \hat{x}_t^{i,n} \hat{\mathbb{V}}(\Delta \hat{X}_t)^{1/2}$. Similarly, Figure 5 plots decompositions for $s_t^i = \sum_{j=0}^t \Delta s_j^i$ using $\hat{s}_t^{i,n} = \sum_{j=0}^t \Delta \hat{s}_j^{i,n}$ and Figure 6 plots $r_t^0 - r_t^i = \sum_{j=0}^t \Delta r_j^0 - \Delta r_j^i$ with $\hat{r}_t^{0,n} - \hat{r}_t^{i,n} = \sum_{j=0}^t \Delta \hat{r}_j^{0,n} - \Delta \hat{r}_j^{i,n}$.

To compute variance decompositions, we first cumulate equations (C.1) - (C.3) over h periods to give

$$\Delta^h x_t^i = \overline{\Delta^h x_t} + \Delta^h x_t^{i.x} + \Delta^h x_t^{i,of} + \Delta^h x_t^{i,r} + \Delta^h x_t^{i,s},$$

$$\begin{aligned}
\Delta^h r_t^0 - \Delta^h r_t^i &= \overline{\Delta^h r_t^0 - \Delta^h r_t^i} + (\Delta^h r_t^{0,x} - \Delta^h r_t^{i,x}) + (\Delta^h r_t^{0,of} - \Delta^h r_t^{i,of}) + (\Delta^h r_t^{0,r} - \Delta^h r_t^{i,r}) \\
&\quad + (\Delta^h r_t^{0,s} - \Delta^h r_t^{i,s}),
\end{aligned}$$

$$\Delta^h s_t^i = \overline{\Delta^h s_t^i} + \Delta^h s_t^{i,x} + \Delta^h s_t^{i,of} + \Delta^h s_t^{i,r} + \Delta^h s_t^{i,s},$$

where $\Delta^h z_t = z_t - z_{t-1}$. From these equations we obtain the variance decompositions

$$\mathbb{V}(\Delta^h x_t^i) = \mathbb{CV}(\Delta^h x_t^i, \Delta^h x_t^{i,x}) + \mathbb{CV}(\Delta^h x_t^i, \Delta^h x_t^{i,of}) + \mathbb{CV}(\Delta^h x_t^i, \Delta^h x_t^{i,r}) + \mathbb{CV}(\Delta^h x_t^i, \Delta^h x_t^{i,s})$$

$$\begin{aligned}\mathbb{V}(\Delta^h r_t^0 - \Delta^h r_t^i) &= \mathbb{CV}(\Delta^h r_t^0 - \Delta^h r_t^i, \Delta^h r_t^{0,x} - \Delta^h r_t^{i,x}) + \mathbb{CV}(\Delta^h r_t^0 - \Delta^h r_t^i, \Delta^h r_t^{0,of} - \Delta^h r_t^{i,of}) \\ &\quad + \mathbb{CV}(\Delta^h r_t^0 - \Delta^h r_t^i, \Delta^h r_t^{0,r} - \Delta^h r_t^{i,r}) + \mathbb{CV}(\Delta^h r_t^0 - \Delta^h r_t^i, \Delta^h r_t^{0,s} - \Delta^h r_t^{i,s})\end{aligned}$$

$$\mathbb{V}(\Delta^h s_t^i) = \mathbb{CV}(\Delta^h s_t^i, \Delta^h s_t^{i,x}) + \mathbb{CV}(\Delta^h s_t^i, \Delta^h s_t^{i,of}) + \mathbb{CV}(\Delta^h s_t^i, \Delta^h s_t^{i,r}) + \mathbb{CV}(\Delta^h s_t^i, \Delta^h s_t^{i,s}).$$

We estimate the contribution of the h-period change in the n'th. hypothetical component to the interest differential and exchange rate as the slope coefficients from regressions

$$\Delta^h \hat{r}_t^{0,n} - \Delta^h \hat{r}_t^{i,n} = \gamma + \gamma_h^r(\Delta^h r_t^0 - \Delta^h r_t^i) + \eta_t^r \qquad \text{and} \qquad \Delta^h \hat{s}_t^{i,n} = \gamma + \gamma_h^s \Delta^h s_t^i + \eta_t^s, \quad \text{(C.4)}$$

for $n = \{x, of, r, s\}$. Notice that the dependent variables in these regressions are computed from the SVAR model estimates and so contain estimation error. Under the assumption that this error is uncorrelated with the change in interest differentials and exchange rates (i.e. the independent variables in the regressions), the least squares estimates of γ_h^r and γ_h^s provide estimates of the variance ratios

$$\frac{\mathbb{CV}(\Delta^h r_t^0 - \Delta^h r_t^i, \Delta^h r_t^{0,n} - \Delta^h r_t^{i,n})}{\mathbb{V}(\Delta^h r_t^0 - \Delta^h r_t^i)} \qquad \text{and} \qquad \frac{\mathbb{CV}(\Delta^h s_t^i, \Delta^h s_t^{i,n})}{\mathbb{V}(\Delta^h s_t^i)},$$

respectively. Tables D.3 and D.4 report estimates of the slope coefficients for horizons $h = \{1, 4, 13, 26\}$ weeks. The tables also report heteroskedastic consistent Newey-West standard errors that allow for$MA(h-1)$ serial correlation that arises from the use of overlapping data when $h > 1$.

The variance contributions computed from the regression estimates in (C.4) differ from the decompositions usually computed from VAR estimates (reported in Tables 9 - 11). Those decompositions attribute the *conditional* variance of each variable to the different structural shocks rather that the *unconditional* variance. To make this distinction clear, we write the conventional variance decomposition for the change in the exchange rate as the slope coefficient from the regression:

$$\Delta^h \hat{s}_t^{i,n} - \hat{\mathbb{E}}[\Delta^h \hat{s}_t^{i,n} | Y_t] = \psi + \psi_h^s (\Delta^h s_t^i - \hat{\mathbb{E}}[\Delta^h s_t^i | Y_t]) + \eta_t^s,$$

where $\hat{\mathbb{E}}[.|Y_t]$ denotes forecasts computed from the SVAR estimates. For all the currencies we study $\hat{\mathbb{E}}[\Delta^h \hat{s}_t^{i,n} | Y_t]$ and $\hat{\mathbb{E}}[\Delta^h s_t^i | Y_t]$ are very close to zero, so the conventional variance decompositions for the depreciation rate reported in Table 10 are very close to the decompositions in Table D.4. In the case of the interest differentials, there is some variation in the SVAR forecasts, so the conventional decompositions in Table 9 are slightly different from those in Table D.3.

D Extra tables

Table D.3: Variance Decomposition for Interest Differential Changes

	Horizon (weeks)	Series									Horizon (weeks)	Series							
		dr_t^x		dr_t^{of}		dr_t^r		dr_t^s				dr_t^x		dr_t^{of}		dr_t^r		dr_t^s	
AUD	1	0.615	(0.023)	0.009	(0.005)	0.340	(0.028)	0.037	(0.011)	MXN	1	0.411	(0.022)	0.011	(0.003)	0.410	(0.023)	0.168	(0.020)
	4	0.617	(0.029)	0.003	(0.004)	0.374	(0.029)	0.007	(0.014)		4	0.343	(0.028)	0.013	(0.005)	0.387	(0.037)	0.257	(0.054)
	13	0.509	(0.070)	0.001	(0.002)	0.478	(0.070)	0.013	(0.009)		13	0.338	(0.051)	0.008	(0.005)	0.334	(0.082)	0.318	(0.103)
	26	0.516	(0.070)	0.002	(0.002)	0.488	(0.062)	-0.005	(0.013)		26	0.351	(0.073)	0.000	(0.003)	0.361	(0.103)	0.288	(0.098)
CAD	1	0.465	(0.029)	0.085	(0.023)	0.388	(0.019)	0.061	(0.019)	NOK	1	0.017	(0.011)	0.102	(0.052)	0.839	(0.055)	0.043	(0.015)
	4	0.481	(0.024)	0.056	(0.014)	0.401	(0.027)	0.064	(0.021)		4	0.004	(0.002)	0.041	(0.014)	0.939	(0.017)	0.016	(0.010)
	13	0.375	(0.046)	0.038	(0.013)	0.507	(0.066)	0.091	(0.035)		13	0.003	(0.002)	0.011	(0.007)	0.982	(0.011)	0.004	(0.008)
	26	0.331	(0.064)	0.044	(0.017)	0.543	(0.091)	0.098	(0.053)		26	0.000	(0.001)	0.006	(0.004)	0.994	(0.007)	0.001	(0.007)
CHF	1	0.094	(0.045)	0.009	(0.002)	0.854	(0.041)	0.043	(0.007)	NZD	1	0.689	(0.015)	0.141	(0.012)	0.016	(0.011)	0.153	(0.021)
	4	0.194	(0.080)	0.013	(0.003)	0.764	(0.075)	0.031	(0.007)		4	0.724	(0.032)	0.098	(0.013)	0.032	(0.009)	0.145	(0.030)
	13	0.341	(0.158)	0.006	(0.005)	0.631	(0.149)	0.020	(0.012)		13	0.753	(0.067)	0.054	(0.014)	0.031	(0.012)	0.170	(0.050)
	26	0.401	(0.151)	-0.001	(0.006)	0.589	(0.147)	0.006	(0.010)		26	0.717	(0.114)	0.038	(0.019)	0.035	(0.015)	0.223	(0.089)
EUR	1	0.039	(0.015)	0.010	(0.004)	0.942	(0.014)	0.010	(0.003)	SEK	1	0.035	(0.027)	0.026	(0.005)	0.918	(0.022)	0.020	(0.008)
	4	0.070	(0.018)	0.012	(0.005)	0.894	(0.019)	0.031	(0.008)		4	0.039	(0.016)	0.029	(0.006)	0.921	(0.017)	0.009	(0.006)
	13	0.098	(0.059)	0.014	(0.006)	0.880	(0.054)	0.022	(0.016)		13	0.063	(0.060)	0.010	(0.004)	0.918	(0.054)	0.006	(0.013)
	26	0.094	(0.076)	0.008	(0.004)	0.901	(0.077)	0.004	(0.009)		26	0.064	(0.093)	0.006	(0.003)	0.928	(0.088)	0.002	(0.017)
GBP	1	0.278	(0.020)	0.078	(0.007)	0.562	(0.023)	0.089	(0.019)	SGD	1	0.953	(0.009)	0.039	(0.010)	0.015	(0.014)	0.013	(0.006)
	4	0.218	(0.016)	0.069	(0.012)	0.662	(0.022)	0.057	(0.012)		4	0.949	(0.011)	0.028	(0.008)	0.015	(0.012)	0.024	(0.009)
	13	0.229	(0.066)	0.029	(0.011)	0.674	(0.084)	0.069	(0.030)		13	0.949	(0.019)	0.013	(0.006)	0.015	(0.014)	0.027	(0.019)
	26	0.238	(0.098)	0.013	(0.009)	0.681	(0.127)	0.066	(0.043)		26	0.940	(0.030)	0.007	(0.004)	0.020	(0.016)	0.040	(0.038)
JPY	1	0.954	(0.008)	0.023	(0.004)	0.009	(0.007)	0.014	(0.006)	ZAR	1	0.849	(0.044)	0.048	(0.009)	0.095	(0.046)	0.010	(0.004)
	4	0.957	(0.016)	0.016	(0.005)	0.010	(0.009)	0.018	(0.011)		4	0.836	(0.033)	0.038	(0.012)	0.101	(0.025)	0.025	(0.011)
	13	0.906	(0.025)	0.014	(0.003)	0.009	(0.007)	0.070	(0.021)		13	0.836	(0.054)	0.020	(0.011)	0.105	(0.042)	0.041	(0.015)
	26	0.880	(0.025)	0.005	(0.002)	0.012	(0.006)	0.104	(0.024)		26	0.850	(0.057)	0.004	(0.004)	0.106	(0.049)	0.042	(0.026)

Table D.4: Variance Decomposition for Exchange Rate Changes

	Horizon (weeks)	Series									Horizon (weeks)	Series							
		s_t^x		s_t^{of}		s_t^r		s_t^s				s_t^x		s_t^{of}		s_t^r		s_t^s	
AUD	1	0.042	(0.026)	0.332	(0.081)	0.019	(0.010)	0.609	(0.052)	MXN	1	0.016	(0.006)	0.034	(0.012)	0.018	(0.006)	0.932	(0.013)
	4	0.032	(0.025)	0.356	(0.057)	0.023	(0.013)	0.591	(0.036)		4	0.017	(0.016)	0.031	(0.018)	0.022	(0.010)	0.930	(0.012)
	13	0.032	(0.017)	0.239	(0.045)	0.043	(0.017)	0.684	(0.032)		13	0.003	(0.016)	0.023	(0.014)	0.027	(0.016)	0.947	(0.017)
	26	0.039	(0.018)	0.237	(0.043)	0.044	(0.016)	0.678	(0.045)		26	-0.002	(0.011)	0.023	(0.019)	0.038	(0.017)	0.941	(0.018)
CAD	1	0.111	(0.017)	0.387	(0.043)	0.032	(0.013)	0.470	(0.037)	NOK	1	0.008	(0.005)	0.017	(0.005)	0.032	(0.014)	0.944	(0.016)
	4	0.044	(0.010)	0.484	(0.035)	0.021	(0.009)	0.452	(0.038)		4	0.003	(0.003)	0.006	(0.003)	0.024	(0.015)	0.968	(0.015)
	13	0.034	(0.016)	0.536	(0.047)	0.022	(0.021)	0.408	(0.046)		13	0.002	(0.004)	0.001	(0.002)	0.050	(0.014)	0.947	(0.014)
	26	0.022	(0.014)	0.608	(0.063)	0.021	(0.015)	0.339	(0.054)		26	0.003	(0.005)	0.001	(0.002)	0.056	(0.021)	0.940	(0.023)
CHF	1	0.052	(0.024)	0.041	(0.019)	0.074	(0.039)	0.834	(0.044)	NZD	1	0.045	(0.020)	0.353	(0.041)	0.015	(0.008)	0.588	(0.044)
	4	0.099	(0.036)	0.008	(0.005)	0.102	(0.044)	0.787	(0.053)		4	0.046	(0.016)	0.371	(0.038)	0.013	(0.007)	0.572	(0.040)
	13	0.072	(0.050)	0.005	(0.008)	0.062	(0.030)	0.858	(0.057)		13	0.039	(0.011)	0.302	(0.063)	0.019	(0.011)	0.639	(0.060)
	26	0.064	(0.045)	0.005	(0.008)	0.062	(0.032)	0.869	(0.058)		26	0.033	(0.011)	0.276	(0.077)	0.028	(0.016)	0.667	(0.064)
EUR	1	0.038	(0.014)	0.297	(0.053)	0.109	(0.059)	0.561	(0.048)	SEK	1	0.020	(0.010)	0.045	(0.015)	0.111	(0.050)	0.831	(0.049)
	4	0.042	(0.015)	0.266	(0.040)	0.189	(0.056)	0.517	(0.044)		4	0.011	(0.006)	0.039	(0.012)	0.113	(0.030)	0.847	(0.031)
	13	0.032	(0.014)	0.337	(0.067)	0.104	(0.036)	0.574	(0.055)		13	-0.006	(0.008)	0.011	(0.013)	0.116	(0.035)	0.870	(0.037)
	26	0.030	(0.013)	0.357	(0.080)	0.090	(0.027)	0.574	(0.073)		26	-0.011	(0.008)	0.015	(0.014)	0.125	(0.050)	0.865	(0.049)
GBP	1	0.079	(0.014)	0.333	(0.050)	0.076	(0.026)	0.513	(0.047)	SGD	1	0.036	(0.011)	0.244	(0.024)	0.011	(0.006)	0.709	(0.024)
	4	0.083	(0.021)	0.349	(0.046)	0.087	(0.025)	0.486	(0.037)		4	0.031	(0.014)	0.270	(0.039)	0.013	(0.007)	0.686	(0.040)
	13	0.078	(0.020)	0.274	(0.077)	0.070	(0.020)	0.583	(0.064)		13	0.027	(0.030)	0.277	(0.069)	0.008	(0.008)	0.688	(0.083)
	26	0.087	(0.020)	0.302	(0.079)	0.066	(0.020)	0.553	(0.074)		26	0.042	(0.048)	0.255	(0.072)	0.000	(0.009)	0.704	(0.103)
JPY	1	0.020	(0.009)	0.242	(0.035)	0.003	(0.004)	0.734	(0.033)	ZAR	1	0.007	(0.004)	0.355	(0.041)	0.022	(0.006)	0.621	(0.038)
	4	0.007	(0.008)	0.263	(0.035)	0.010	(0.003)	0.721	(0.035)		4	0.004	(0.005)	0.380	(0.028)	0.057	(0.012)	0.563	(0.029)
	13	0.014	(0.011)	0.226	(0.073)	0.009	(0.005)	0.752	(0.067)		13	-0.005	(0.011)	0.390	(0.067)	0.089	(0.021)	0.524	(0.077)
	26	0.021	(0.010)	0.132	(0.103)	0.002	(0.006)	0.849	(0.096)		26	-0.019	(0.015)	0.442	(0.113)	0.097	(0.025)	0.476	(0.125)