FX Premia Around the Clock

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Ingomar Krohn* Philippe Mueller† Paul Whelan‡

ABSTRACT

We dissect return dynamics in the foreign exchange market into different components over the 24 hour day and revisit well-known trading strategies such as carry and momentum. Using high-frequency data on G10 currencies we show that positive average returns for going long foreign currencies are almost entirely generated during U.S. main trading hours. During U.S. overnight periods on the other hand, all but one (the Yen) depreciate versus the U.S. dollar. Returns from the carry and dollar carry strategies are largely generated intraday, while momentum strategies are most profitable overnight. This new evidence sheds light on our understanding of currency markets and has important implications for future theoretical and empirical work.

Keywords: foreign-exchange, carry trade, dollar carry trade, high-frequency data.

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*Warwick Business School, Coventry, CV4 7AL, UK, Email: Ingomar.Krohn.14@mail.wbs.ac.uk

†Warwick Business School, Coventry, CV4 7AL, UK, Email: Philippe.Mueller@wbs.ac.uk

‡Copenhagen Business School, Solbjerg Pl. 3, 2000 Frederiksberg, DK, Email: pawh.fi@cbs.dk

Empirical work on currency markets typically infers risk premia from strategies that compound daily close-to-close returns at the London fixing time (4:00 p.m. U.K. time).[1] Examples include the carry trade (long high interest rate currencies, short low interest rate currencies), the dollar carry trade (short the U.S. dollar when the average foreign interest rate is above the U.S. rate and go long the U.S. dollar otherwise), and currency momentum strategies (long currencies that have recently appreciated and short currencies that have recently depreciated).[2]

In this paper, we decompose the usual daily (or close-to-close) returns into different components and show that positive average returns for holding foreign currencies are almost entirely generated during U.S. trading hours when foreign currencies appreciate versus the U.S. dollar. On average, these returns largely reverse outside U.S. trading hours: Over our sample period, a portfolio that is long all foreign currencies returns less than 1% per annum using close-to-close returns whereas a split between intraday and overnight returns yields almost 5% intraday and almost -4% overnight, both highly significant. Hence, close-to-close returns may 'throw out the baby with the bathwater', distorting empirical tests and our economic understanding of FX dynamics. Revisiting the well-known trading strategies, we find that currency risk premia display distinct patterns around the clock: carry and dollar carry strategies are only profitable intraday, while the dollar and momentum portfolios exhibit a significant reversal from intraday to overnight resulting in an overall insignificant return. These findings have strong implications for economic theory and the design of empirical work, and shed light on our understanding of compensation for holding currency risk.

Currencies are traded globally and around the clock on OTC platforms both electronically and on the phone without predetermined opening and closing times. Prices fluctuate continuously from second to second, region to region, from bank to bank, 24 hours a day from 5:00 p.m. EST on Sunday until 5:00 p.m. EST on Friday. Of the estimated $6.6 trillion daily turnover, around $1.2 trillion are traded during U.S. opening hours, $2.4 trillion during London opening hours, with the remaining volume of $3.0 trillion distributed geographically across a large number of local markets (see BIS (2016)). Currency trading happens for a host of reasons and volumes are driven by hedging demands from businesses that operate in multiple countries, speculative demand from

[1] See, e.g., Thomson Reuters (2017).

[2] See, e.g., Lustig, Roussanov, and Verdelhan (2011), Lustig, Roussanov, and Verdelhan (2014) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012b).

day traders and investment funds and, last but not least, by central banks that trade in order to stabilize exchange rates.

Given the nature of currency markets, it is natural to study the exchange rate dynamics over the whole 24-hour trading period. Thus, we construct a panel of 5-minute spot returns around the clock using high-frequency data on a set of nine currencies vis-à-vis the U.S. dollar: the Australian dollar (AUD), the Canadian dollar (CAD), the euro (EUR), the Japanese yen (JPY), the New Zealand dollar (NZD), the Norwegian krone (NOK), the Swedish krona (SEK), and the Swiss franc (CHF). Our sample period spans January 1994 to December 2014 during which these pairs cover approximately 67% of the total daily turnover in the foreign exchange market (see BIS (2016)). The raw dataset is provided by Olsen & Associates. Complementing our high-frequency data we obtain daily spot and forward rates from WM/Reuters via Datastream. On the one hand, we need the forward rates to calculate excess returns (as opposed to using interbank rates to calculate the interest rate differentials for example), on the other hand we use the Datastream spot data to perform robustness checks for the daily results that we obtain from sampling our high-frequency data.

Our empirical design is focused on dissecting 24-hour currency returns. First, we construct conventional daily close-to-close returns based on changes in prices between 5:00 p.m. Eastern Standard Time (EST) on consecutive days. We take 5:00 p.m. EST as the closing time as we assume it marks the end of the main trading hours in New York and also coincides with the end of trading of currency derivatives on the Chicago Mercantile Exchange. Second, we build upon the approach in Breedon and Ranaldo (2013) and examine return dynamics during daily sub-periods. This means that close-to-close returns are then split into different intraday components based on the main trading hours in New York and three alternative local trading venues that are relevant for the currencies in our sample.

We consider up to four sub-periods for each currency pair based on geographically distinct trading regions, referring to these as overnight hours (from the perspective of a U.S investor), and U.S trading hours which we refer to as intraday hours. The 24-hour dissection we consider is (i) the first four trading hours after the Sydney open: 5:00 p.m. and 9:00 p.m. EST; (ii) the subsequent four hours which marks the open of the main trading venues in Southeast Asia (Singapore and Hong Kong): 9:00 p.m. and 1:00 a.m. EST; (iii) during the main trading hours in Europe: 1:00 a.m. and 8:30 a.m EST; and (iv) during the main trading hours in the United States: 8:30 a.m. and 5:00 p.m. EST. Following Lou, Polk, and Skouras (2017) we then aggregate daily intraday return components within each month, resulting in five monthly return series with 252 observations for every currency pair. Equipped with the different components of FX premia we proceed to document a number of novel findings.

G10 currency pairs display a systematic sequence of appreciations and depreciations marked by the opening and closing of four major trading venues: currency returns trace an *'W'* intraday pattern across the globe. First, after trading activity in New York has come to an end and the trading day in Sydney commences, currencies depreciate vis-à-vis the U.S. dollar. Second, between the start of the trading day in Southeast Asia (Singapore/Hong Kong) and Europe (London/Frankfurt) a reversal in the return patterns occurs. All G10 currencies show a strong appreciation vis-à-vis the U.S. dollar which lasts until the early morning hours of the next day. Third, coinciding with the opening of markets in Europe, foreign currencies depreciate until New York trading begins. This trend is particularly strong for European currencies, but it generally exists across the entire currency cross-section. With the beginning of trading activity in New York, a last significant return reversal can be observed and (almost) all foreign currencies exhibit a strong appreciation vis-à-vis the U.S. dollar. The relative increase in the value of foreign currencies against the dollar base currency lasts until New York trading activity ceases and, with the start of a new trading day, foreign currencies depreciate again. These systematic reversal patterns are striking in both economic and statistical terms.

Our results are consistent with the findings of Cornett, Schwarz, and Szakmary (1995) who document similar patterns using hourly data for the period 1977 to 1991. Breedon and Ranaldo (2013) confirm and extend the same result for the period 1997 to 2007 and link return patterns to order flow dynamics. With respect to these papers, our contribution is two-fold: First, we provide a granular dissection of close-to-close returns by daily sub-periods; Second, we make the connection that close-to-close returns, exclusively employed by the extant empirical literature, provide a distorted view of currency risk premia since they are the sum of potentially drastically different return dynamics. This point is made clear by noting that none of the average close-to-close returns are significantly different from zero at the 5% level, while all currency returns are highly statistically different from zero in sub-returns with the *'W'* shaped return pattern are statistically significant, albeit with opposite signs.

Second, we revisit the expectations hypothesis (Fama (1984)) that has been overwhelmingly rejected in the data using close-to-close returns. However, splitting up the daily returns into an intraday and an overnight component we show that the hypothesis that the slope coefficient β is equal to one cannot be rejected for any currency in our sample for the overnight period (although the intercept α is often significant). Using intraday data, however, the slope coefficient is strongly significantly different from one for all but two currencies.

Third, we show that sorting currencies into portfolios based on their forward discount as in Lustig, Roussanov, and Verdelhan (2011) leads to a significant spread between the high and the low interest rate portfolio during intraday periods only. Overnight, all portfolios depreciate against the dollar and there is no significant spread. Hence, the carry returns are almost exclusively earned during New York trading hours.

Fourth, the dollar portfolio, a portfolio that goes long a basket of foreign currencies and on average has a non-significant return, appreciates significantly during the day and reverses during the night, reflecting the general pattern of the individual currencies. In fact the intraday returns to the dollar portfolio are even larger than the returns to the dollar carry strategy from Lustig, Roussanov, and Verdelhan (2014) where the average forward discount serves as a signal to either go long or short the dollar portfolio. Unlike the dollar portfolio however, the dollar carry strategy does not reverse overnight but actually yields a small (and insignificant) positive return, leading to a positive return overall.

Finally, we also revisit the momentum strategies in Menkhoff, Sarno, Schmeling, and Schrimpf (2012b). While we do not find a significant momentum effect for our sample period and currency selection using close-to-close returns, we do find significant momentum returns for individual portfolios using intraday data only (and overnight, given the strong reversal from intraday to overnight). We also find a similar pattern as Lou, Polk, and Skouras (2017) who report strong reversals depending on whether the sorting is done based on past intraday or overnight returns, respectively. Moreover, we do find very strong time series momentum effects for all currencies when past returns are used as a signal to go long or short a particular currency. For momentum returns both intraday and overnight periods contribute roughly in equal parts. For some of the currencies in the sample (CAD, CHF, GBP) the intraday contribution is much higher whereas for others (NOK, NZD) the overnight contribution dominates strongly but there is no clear pattern emerging.

Overall, we find distinctly different foreign exchange return dynamics depending on whether we consider intraday or overnight periods within a 24-hour window. Some of the known results based on daily data are entirely due to what happens during the intraday or overnight periods, respectively. The rest of the paper is organized as follows. In Section I we describe the data, while Section II presents the empirical design and discusses how we choose the sub-periods over the 24 hour window. Section III describes the results with respect to currency risk premia during the intraday versus overnight period. Section IV summarizes an extensive set of robustness checks. Section V discusses intraday market characteristics such as volatility, liquidity, and trading costs which affect return dynamics differently during the course of the trading day. Section VI concludes the discussion.

I. Data

The empirical analysis is largely based on high-frequency foreign exchange data which allows us to dissect daily return patterns into different intraday components. Our sample period covers 20 years, from January 1994 to December 2014, and it comprises information at the tick-by-tick level. The raw dataset is provided by Olsen & Associates. It includes indicative spot rate quotes for Australia (AUD), Canada (CAD), Euro (EUR), Japan (JPY), New Zealand (NZD), Norway (NOK), Sweden (SEK), Switzerland (CHF), and the UK, vis-à-vis the U.S. dollar. These pairs belong to the most frequently traded currencies and, in aggregate, they cover approximately 67% of the total daily turnover in the foreign exchange market BIS (2016). We obtain data for the best bid and ask indicative quotes from the interbank market to the nearest even second such that we can construct returns based on mid prices as well as net returns, which take into account the bid-ask spread as a measure of transaction costs. After filtering the data for outliers, the price at each five-minute tick is obtained by linearly interpolating from the average of the bid and ask quotes for the two closest ticks. If no quote was submitted during a specific interval, we fill the gap with the most recent available price. Following previous studies (e.g. Andersen, Bollerslev, Diebold, and Vega (2003)) we exclude quotes that are submiited on days that are associated with low trading activity. We remove trading hours on weekends between Friday 5:00 p.m. and Sunday 5:05 p.m. (Eastern Time). Similarly we drop information around fixed holidays, Christmas (24-26th December), New Year (31st December - 2nd January), and fourth of July, and around flexible holidays, such as Good Friday, Easter Monday, Memorial Day, Labor Day, Thanksgiving, and the day after. While most currency pairs in the original data are denominated in U.S. dollar, we express all spot rates in U.S. dollar per foreign currency ($-\Delta s$). An increase of the exchange rate can be interpreted as an appreciation of the foreign currency vis-à-vis the U.S. dollar.

In addition to the intraday data, we obtain daily spot and forward rates from WM/Reuters via *Datastream* to construct currency excess returns.[3] Following previous studies (e.g. Menkhoff, Sarno, Schmeling, and Schrimpf (2012b), Mueller, Tahbaz-Salehi, and Vedolin (2017)), monthly foreign currency excess returns (rx_{t+1}) from a strategy that buys a currency at the forward rate in period t (fw_t) and sells it at the spot rate in period $t+1$ (s_{t+1}) is defined as $rx_{t+1} = fw_t - s_{t+1}$. To be able to account for return dynamics in distinct intraday periods, we construct excess returns in terms of the difference of the forward discount and the future change in the spot rate $rx_{t+1} = fw_t - s_t - \Delta s_{t+1}$. Based on this expression we can combine publicly available information spot and forward rate information from *Datastream* ($fw_t - s_t$) with intraday return dynamics constructed from high-frequency data (Δs_{t+1}).[4]

II. Empirical Design

In this section we discuss the definition of close-to-close returns and the dissection into different intraday components. Subsequently, we provide a comparison of these return series, illustrate their developments over the sample period, and uncover discrepancies and commonalities between returns that are generated during certain times of the day.

[3] As WM/Reuters data is only available from January 1997 onwards, we use Barclays BBI spot and forward rates for the periods January 1994 to December 1996.

[4] We explicitly assume that covered interest parity (CIP) holds and that the nominal interest rate differential between foreign (i^*) and domestic country (i) equals the forward discount: $i_t^* - i_t = fw_t - s_t$. As shown by Akram, Rime, and Sarno (2008), at lower frequencies CIP tends to hold for mahor currency pairs.

A. Intraday Return Dynamics

Equipped with equally-spaced 5-min spot rates for some of the most important currency pairs in the FX market, we define daily close-to-close spot returns (ΔS_d^{CTC}) as the change in the mid-price between 5:00 p.m.on day d and 5:00 p.m. (Eastern Time) on day $d-1$

$$\Delta S_d^{CTC} = \frac{p_d - p_{d-1}}{p_{d-1}} \tag{1}$$

Our choice of closing time differs from that used in most conventional data sources, in which the end of the currency trading day conventionally is defined at 4:00 p.m. London time; however, as we show in the robustness checks section, results for daily currency returns are almost identical if publicly available data from Datastream is employed.

Next we dissect daily currency returns into an intraday and an overnight component. While trading in currency markets takes place almost 24-hours a day, we take the perspective of a U.S. investor that is based in New York and we define the beginning and ending of the intraday period as 8:30 a.m. and 5:00 p.m. (Eastern Time), respectively. We assume they represent the most active trading hours in the spot market for New York based market participants. These trading hours also overlap with the opening hours of the Chicago Mercantile Exchange for currency derivatives, such that our definition of the intraday pariod accounts for commencing and ceasing trading activity of FX forwards, futures and options which is likely to have an impact on the price discovery process of currencies vis-a-vis the U.S. dollar in the spot market (Rosenberg and Traub (2009)).[5] In robustness tests we employ alternative intraday and overnight specifications, based on quote currencies' domestic trading hour (Breedon and Ranaldo (2013)), and results are qualitatively similar.

While the intraday period coincides with the main spot trading hours in New York, the overnight period is defined as the time between 5:00 p.m. on day d and 8.30 a.m. on day $d+1$. This period includes the opening and closing times of major FX trading venues located outside of the U.S. (BIS (2016)). For example, it captures the period after trading in Sydney commences but before trading in the Southeast Asia's main trading venues - Singapore and Hong kong - has

[5] An overview of currency futures trading hours can be found at `http://www.cmegroup.com/trading-hours.html#fx`

started (5:00 p.m. to 9:00 p.m., Eastern Time). Furher, it includes the early trading hours in Southeast and East Asia (Tokyo), before trading in Europe commences (9:00 p.m. to 1:00 a.m.), and the main European trading hours, before markets in the U.S. are opening again(1:00 a.m to 8:30 a.m.). While the majority of our analysis focuses on the diverging patterns that occur during the day and over night, we provide summary statistics and discuss return movements related to sub-periods over night, when trading activity in major trading venue commences.[6]

More formally, following Lou, Polk, and Skouras (2017), we define intraday (ID) and overnight (ON) components in the following way:

$$\Delta S_d^{ID} = \frac{p_d^{5:00a.m.} - p_d^{8:30a.m.}}{p_d^{8:30a.m.}} \qquad \Delta S_d^{ON} = \frac{1+\Delta S_d^{CTC}}{1+\Delta S_d^{Intra}} - 1$$

such that our intraday and overnight return measures add up exactly to the close-to-close returns.[7] Next, we aggregate all daily returns within every months ($d \in t$) to the monthly monthly frequency

$$\Delta S_t^{CTC} = \prod_{d\in t}(1+\Delta S_d^{CTC}) \qquad \Delta S_t^{ID} = \prod_{d\in t}(1+\Delta S_d^{ID}) \qquad \Delta S_t^{ON} = \prod_{d\in t}(1+\Delta S_d^{ON})$$

and obtain 252 observations for CTC, ID and ON returns. Lastly, we log-atransform returns ($\ln\,\Delta S_t = \Delta s_t$) such that $\Delta s_t^{CTC} = \Delta s_t^{ID} + \Delta s_t^{ON}$. Equipped with these return series, the next section discusses different dynamics of intraday and overnight currency returns.

B. Intraday versus Overnight returns

To illustrate different return dynamics over the course of the trading day, we display the average cumulative returns at the 5-min frequency in Figure 1. The grey-shaded area (8:30 a.m. to 5:00 p.m.) marks the main trading hours in New York (intraday period) and the blue-dashed lines indicate the beginning of trading hours in Southeast Asia and Europe. As shown, all foreign currencies tend to appreciate after trading in New York ceased, and currencies reach their lowest

[6]According to BIS (2016), most of the daily turnover in the FX market is generated in the United Kingdom and the United States, followed by Singapore, Hong Kong, and Japan.

[7]Analogously, the overnight period can be split up into the three different sub-periods that capture activity at the time of the day when Sydney, Southeast Asia, and Europe trading venues open.

value around the opening hours of Singapore and Hong Kong. Subsequently, foreign currencies start to appreciate until trading in Europe commences (1:00 a.m. Eastern Time), before declining again until New York's trading venues are opening. During the intraday period all currencies, except the JPY, appreciate against the U.S. dollar. In particular the most liquid pairs - EUR, GBP, and CHFv- increase in value against the U.S. dollar between 8:30 a.m. and 5:00 p.m. Most of the other pairs exhibit a temporary drop between 11:00 a.m. and 12:00 p.m. (Eastern Time), which coincides with London fixing time. After New York closes, all foreign currencies depreciate again.

[INSERT FIGURE 1 HERE]

While a distinct W-shaped pattern of currency intraday returns is already indicated by the individual currencies, it becomes even more visible when considering the dynamics of an unconditional dollar portfolio where investors go long all foreign currencies. The 5-min cumulative intraday returns are shown in Figure 2. The solid black line represents an equally-weighted investment in all foreign currencies, while the red dashed line excludes the Japanese yen from the currency cross-section. Both lines show a W-pattern, that captures the appreciation of the U.S. dollar after New York closes, its appreciation when trading in Asia commences, a period of depreciation after London opens, and a almost persistent period of depreciation during the intraday period. Comparing the two lines, we note that a dollar portfolio that does not include the Japanese yen exhibits larger swings in the second half of the day, as the yen moves largely counter-cyclically to other currencies during the day.

[INSERT FIGURE 2 HERE]

Further, we summarize the average annualized returns for the overnight ($-\Delta s^{ON}$), intraday ($-\Delta s^{ID}$) and close-to-close ($-\Delta s^{CTC}$) period in Table I. In addition to these main periods of the day, we also provide a split of the overnight returns into three different sub-components. They capture return dynamics in the first hours after trading in Australia (5:00 p.m. to 9:00 p.m., $-\Delta s^{AUS}$), in southeast Asia (9:00 p.m. to 1:00 a.m., $-\Delta s^{SEA}$), and in Europe (1:00 a.m. to 8:30 a.m., $-\Delta s^{EU}$) begins.

[INSERT TABLE I HERE]

As shown, all foreign currencies depreciate against the U.S. dollar after trading venues in New York close. This trens is particularly distinct for the Australian (AUD: -7.31%) and New Zealand dollar (NZD: -8.91%), while negative returns of Scandinavian currencies are relatively modest during this period. Irrelevant of their magnitude, however, all averages are different from zero at least at the 1% level of significance. The next two columns also show a clear pattern. After trading in Southeast Asia commences, foreign currencies appreciate significantly against the U.S. dollar ($-\Delta s^{SEA}$), while most foreign currencies depreciate again during early European trading $-\Delta s^{EU}$. The exceptions to this last trend are the non-European currencies AUD, CAD, JPY, and NZD. While the returns for these currency pairs are negative, however, they are not significantly different from zero. Overall, overnight returns ($-\Delta s^{ON}$) are negative, implying that foreign currencies appreciate against the U.S. dollar. The returns are particularly low for the most liquid European currencies - CHF (-6.57%), EUR (7.02%), GBP (-8.22%), followed by the Scandinavian currencies, SEK (-5.22%) and NOK (-2.79%). With the beginning of trading in New York this trend reverses ($-\Delta s^{ID}$) and returns turn positive. Foreign currencies appreciate against the dollar, ranging between 8.54% (CHF) and 1.51% (CAD). The only exception to this trend is the Japanese yen which appreciates over night (1.73%) and depreciates during the day (-2.01%). The diverging return pattern between overnight and intraday periods results in small and insignificant close-to-close returns ($-\Delta s^{CTC}$). For the Japanese yen, CTC returns are slighty negative (-0.28%) and they increase to 1.97% fo the Swiss franc. For the dollar portfolio, Table I reflects the W-Shape pattern that we saw in Figure 2. Inspecting the sign of average returns during the overnight sub-periods, we note that the sign is changing in an alternate fashion. For CTC returns, the dollar portfolio generates an average annualized return of 0.35 with an associated t-statistic of 0.20.

[INSERT FIGURE 3 HERE]

Lastly, we show that the diverging pattern of the two intraday periods leads to significant differences over time. In Figure 3, we plot the cumulative monthly log returns over the entire sample period for CTC (blue), ID (red), and ON (yellow) returns. Clearly, the two intraday time series show a diverging trend for most of the currencies. The magnitude of the y-axis and the corresponding graphs can be interpreted in the following way. For example, if one would have invested one dollar in euros during the intraday period at the end of January 1994, one would have earned \$374 dollar in December 2014 from this investment. In contrast, the same trading approach with overnight positions would have let to approximately \$-77 at the end of our sample period. Returns from conventional close-to-close would generate to \$8.41. The biggest overnight and intraday spread is generated by the Swiss Franc, where \$500 and \$-75 are obtained from intraday and overnight investments, respectively.[8] Furthermore, while a discrepancy between intraday and overnight returns appear to be prevalent for European currency pairs during the entire sample period, a clear divergence between these series for AUD, CAD, and NZD only started in the early 2000s. In fact, for these currency pairs the plots move very closely to each other during the first six years or so of our sample. We note that the Japanese yen is again an exception to the trend.

III. Currency Risk Premia

As we established in the previous section that currency returns are strongly diverging during intraday and overnight trading periods, we next investigate the implications of these return discrepancies for well-known facts established in the foreign exchange literature which are commonly based on close-to-close returns. To this end, we begin our analysis and re-examine the expectation hypothesis by Fama (1984) for all three return series, and discuss the implication of diverging intraday dynamics for the forward discount anomaly. Following the time series regressions, we then employ conventional cross-sectional portfolio analysis to examine day-time dynamics of carry (Lustig, Roussanov, and Verdelhan (2011)), dollar carry (Lustig, Roussanov, and Verdelhan (2014)), and cross-sectional momentum (Menkhoff, Sarno, Schmeling, and Schrimpf (2012a)), and time series momentum (Moskowitz, Ooi, and Pedersen (2012)) trading strategies.

A. Intraday dynamics of the forward premium

To begin with, we follow the approach by Fama (1984) and we re-examine the forward discount anomaly, combining returns constructed from the high frequency data with commonly used spot and forward rates. We estimate the regression

$$\Delta s_{t+1} = \alpha + \beta(f_t - s_t) + \epsilon_{t+1} \tag{2}$$

[8] We transform cumulative log returns to compounded returns in the following way: $(e^{\frac{\Delta s_t}{100}} - 1) \times 100$

where $\Delta s_{t+1} = s_{t+1} - s_t$ refers to the exchange rate return, f_t denotes the 1-month log forward rate and s_t is the log spot rate in period t. We estimate three specifications of Equation (2) whereby we employ close-to-close, intraday, or overnight return data as dependent variable on the left-hand side, respectively. The forward discount on the right-hand side of the regression is constructed from conventional forward and spot rates that are obtained from *Datastream*. As widely discussed in the literature,[9] the intercept is expected to be zero ($H_0 : \alpha = 0$) and the slope coefficient to be significantly different from one ($H_1 : \beta = 1$). These hypotheses imply that the forward rate is an unbiased estimate of the future spot exchange rate. As rational agents drive the value of the forward rate to the price of the expected future exchange rate, profits from speculation in the forward market are non-profitable. In contrast, if the forward rate is higher (lower) than the expected spot rate, market participants earn a premium from buying (selling) a currency in the forward market. Deviations of the slope coefficient from unity can also be interpreted as a time-varying risk premium (Fama (1984)). Table II shows the regression results and test results from both hypotheses.

[INSERT TABLE II HERE]

As displayed in Table II, we find that for conventional close-to-close returns our results resemble regression outcomes from earlier assessments Fama (1984). For all nine currency pairs the intercept estimates are not significantly different from zero and they ranges between -0.37 (CHF) and 0.29 (AUD). Furthermore, the point estimate of the slope coefficient is almost always negative and the null hypothesis $H_0 : \beta = 1$ is rejected in only three cases (AUD, EUR, and SEK) at the 5% level of significance or higher. For CAD, evidence is weaker and we reject the null hypothesis only at the 10% level. Turning to intraday returns, we note that the intercept term is always negative and significantly different from zero in more than half of the cases. The slope coefficient ranges between -3.58 (CAD) and 1.30 (NZD) and is almost always significantly different from one. The only exceptions are the Norwegian krone (NOK) and the New Zealand dollar (NZD). For the other five currency pairs, we reject the null hypotheses at least at the 5% level. Interestingly, we find that the these dynamics reverse overnight, as shown in the bottom panel of Table II. First, all intercept terms are now positive and range between 0.04 (JPY) and 0.65 (CHF). Further, in four

[9] For an extensive survey, see for example Engel (1996).

out of nine cases the intercept term is significantly different from zero (CHF, EUR, GBP, SEK), and for the Australian dollar the null hypothesis $\alpha = 0$ can still be rejected at the 10% level. Second, while most of the slope coefficients are negative during the day, there is no clear pattern during the night. We find that the estimates for AUD, EUR, NOK, and NZD have a negative sign, while the magnitude of the coefficient for CAD, CHF GBP, JPY, and SEK increases and it turns positive. Third, and most importantly, we are not able to reject the null hypothesis $H_0 : \beta = 1$ in any of the nine cases at the 5% level or higher. Only for the Australian dollar we find weak evidence that the slope coefficient is significantly different from one.

Even though some of the overnight intercept estimates are significantly different from zero, our findings suggest that deviations from the expectation hypothesis regarding the slope coefficients are largely driven by return dynamics during U.S. trading hours. As the slope coefficient equals to one when overnight returns are employed, regression results point towards the existence of a risk premium that is only statistically different from zero during certain hours of the trading day. It implies that rational agents' expectations about the future path of the spot exchange rate are in line with the forward rate during overnight hours, but then deviate when trading in New York commences. The differences in expected and realized future spot rate generate room for a risk premium, which can only be earned during the day while speculation in the forward market remains unprofitable overnight. The diverging return dynamics of intraday and overnight returns, therefore, have a considerable impact for our understanding of the forward discount anomaly. Further, in the next section we show well-known FX trading strategies are impacted.

B. Carry Trade

As the previous results suggest that the forward rate converges to the expected future spot rate during overnight periods and risk premia occur largely during the day, we next examine its implications of these results for carry trade strategies. To this end, we follow Lustig and Verdelhan (2007) and Lustig, Roussanov, and Verdelhan (2011) and sort currencies' excess returns into portfolios based on their forward discount $fw_t - s_t$. At the beginning of each month, we allocate currencies into three portfolios, whereby portfolio 3 (P3) contains excess returns from currencies with the three highest forward discount, while currencies with the lowest implied interest rate differential are assigned to portfolio 1 (P1). Portfolio returns are based on the equally-weighted average of currency excess returns that are assigned to each portfolio. Following Lustig, Roussanov, and Verdelhan (2011) we also construct a high-minus-low portfolio from the difference between high (P3) and low interest rate portfolios (P1). Further, we report the returns from an unconditional dollar portfolio (dol) that captures returns earned from going long in all nine foreign currencies. Portfolios are held for one month and currencies are re-assigned at the end of the month. We apply the same portfolio ranking that we derive from the forward discount to close-to-close, intraday, and overnight returns and summarize annualized average excess returns and associated t-statistics in Table III.

[INSERT TABLE III HERE]

As displayed in Panel A, we first verify that our findings are in line with previous studies. Close-to-close average excess returns are monotonically increasing from -1.67% for P1 with low interest rate currencies to 3.37% for the high interest rate portfolio (P3). The high-minus-low portfolio earns 5.04% per year and is highly statistically significant.[10] The unconditional dollar portfolio generates a low return of 0.97% that is not significantly different from zero. Strikingly, Table III indicates that the majority of carry returns is generated in the intraday period, when main FX trading in New York is most active. The depreciation of the U.S. dollar leads to positive excess returns for all three portfolios. Portfolio returns increase monotonically from 2.43% (P1) to 5.95% (P3). The intraday high-minus-low portfolio generates a return of 3.52% and continuous to be significantly different from zero at the 1% level. This implies that almost 70% of the carry returns are generated during the day. The remaining 30% of close-to-close returns are produced overnight. During this period of the trading day, portfolio returns are negative and significantly different from zero. The lowest return is -4.37% (P2), while currencies associated with a high a interest rate differential produce a return of -2.52% (P3). It is worth noting that the results from this portfolio-based approach are in line with the time series regressions presented earlier. The carry trade strategy is more profitable during the intraday period, when expectations of the future spot rate and forward rate diverge from each other. As risk premia from the forward discount anomaly are low during over night, carry trade strategies are less profitable. Distinct return differences can also be observed for the dollar portfolio. While close-to-close excess returns are

[10] As a comparison, in Lustig, Roussanov, and Verdelhan (2011) the average annualized return for the high-minus-low portfolio for developed countries is 5.88% during the period November 1983 to December 2009.

positive but not statistically different from zero, the strategy earns 4.62% (t-stat: 3.92) intraday. In contrast, overnight returns are -3.62 (t-stat: -3.09), leading to a overall insignificant returns, when conventional close-to-close returns are employed.

Further, in Panel B and C we consider trading strategies that exploit the countercyclical return dynamics that occur during the day and over night. First, in Panel B we construct trading strategies that go long portfolios during intraday periods, and short the same set of currency portfolios overnight. For this strategy, almost all five portfolios generate positive and significant returns, ranging from 1.97% (P3-P1) up to 9.77% (P2). As shown in Panel C, however, the most profitable approach is a reversal trading strategy where an investor buys high interest rate currencies (P3) during the day, and sells low interest rate currencies (P1) in overnight periods. The average annualized return for such an approach is 10.02% (t-stat: 5.68). The return from the alternative reversal strategy ($P1^{Intra} - P3^{Over}$) is smaller, but with 5.00% it is of similar magnitude than returns from a conventional carry trade strategy.

We conclude results from the time series regression analysis of Equation (2) are mirrored in a cross-sectional currency portfolio exercise. We find carry trade returns are almost entirely generated during the day, while overnight speculation in the forward market appears to be not profitable.

C. Dollar Carry Trade

The unconditional dollar portfolio in Table III already points towards potential profits that can be earned from buying and holding U.S. dollar during certain parts of the day, unconditional of the movements of the forward discount. As a next step, we further examine potential trading profits that can be exploited by conditioning the direction of the trade on the average implied interest rate, or equivalently, average forward discount (AFD). Following Lustig, Roussanov, and Verdelhan (2014), we construct dollar-carry trade portfolios, which are based on the sign of the AFD defined as

$$\bar{fw}_t - \bar{s}_t = \frac{1}{N} \sum_{i=1}^{N} fw_t^i - s_t^i \tag{3}$$

where $\bar{fw}_t - \bar{s}_t$ is the average monthly forward discount, and fw_t^i and s_t^i are the one-month forward rate and spot rate for country i in month t, respectively. We use the AFD as an end-of-month signal to allocate the nine currency excess returns into different portfolios. We follow a trading strategy where we invest in foreign currencies if the AFD takes positive values, and we sell the quote currencies otherwise. Again, we analyse the dynamics for monthly close-to-close, intraday, and overnight returns. The results are shown in Table IV. The column "ADF ≤ 0" refers to months in which we short the foreign currencies following a negative signal, but do not trade otherwise. The column "ADF > 0" applies the alternate strategy, whereby we invest in foreign currencies following a positive ADF, but do not trade in the remaining months. We obtain a signal to invest in foreign currencies in 149 months, and to short foreign currencies in the remaining 103 months. The column "dollar-carry" refers to returns from a dynamic trading strategy during which we buy and sell foreign currencies in every month, depending on the signal that we obtain from the ADF. As a comparison, we report the return of "ADF ≤ 0 (excl. 0)" and "ADF > 0 (excl. 0)" if we exclude the months, in which no trade is conducted, and returns of the unconditional dollar portfolio.

[INSERT TABLE IV HERE]

In contrast to the unconditional dollar portfolio constructed in the previous section, the dollar-carry portfolio based on close-to-close returns generates a significant and positive return of 4.72% (t-stat: 2.73).[11] Further, we note that dollar carry returns are largely generated during New York trading hours. Table IV shows that intraday dollar carry trade return is 3.78% (t-stat: 3.16). This equals almost 80% of the total close-to-close returns earned from the conventional dollar carry trade. A large fraction of this return can be attributed to intraday long positions in foreign currencies (4.20%), as the dollar tends to depreciate during New York trading hours in New York. Shorting positions during the day only generates 0.42%. Conversely, we find opposite return dynamics for the overnight period during which returns are negative. Moreover, returns of 0.95% from the overnight dollar carry portfolio are not statistically different from zero. Yet, it is worth noting that the returns are positive, contrasting the unconditional dollar portfolio, for which returns are negative in the overnight period. The difference between the two strategies can

[11] As a comparison, Lustig, Roussanov, and Verdelhan (2014) report an average annualized raw return of 5.60% for the dollar carry strategy for developed countries for the period November 1983 to June 2010

be attributed to the overnight return that is obtained from shorting foreign currencies outside of New York's main trading hours. This trading approach generates a net return of 2.28% for the dollar carry, while it enters negatively to an investor's portfolio that only holds long positions of foreign currencies.

In Panel B and C, we examine overnight minus intraday returns, as well as different reversal strategies that exploit the diverging return trends between these two periods. In Panel B, almost all strategies generate positive returns that are statistically different from zero at the 5% level or higher. Returns from this simple trading approach lie in the range of 2.70% (Dollar Carry) and 8.22% (dol) for all 252 months. Furthermore, we find that the AFD can be used as a signal to build reversal trading strategies (Panel C). A trading approach that shortens foreign currencies over night and buys them during the day ($AFD^{Intra} > 0 - AFD^{Over} <$) generates a return of 6.48% with a t-statistic of 5.62. These results suggest that returns from a conventional dollar carry trading strategy can be enhanced by exploiting intraday return movements.

D. Momentum Trading

The previous section points toward significant differences between intraday and overnight returns from well-know trading strategies, that derive trading signals for the portfolio allocations from the forward discount. In this section, we consider strategies that are solely based on the exchange rates' own historical performance. For one, we seek to understand if the return generating process for momentum trading strategies are also different during the day and over night. Further, we aim to examine if inferences for momentum trading diverge from the previous trading strategies if ranking signals are based on currencies' own return dynamics instead of interest rate differential or funding constraints.

To begin with, we follow the approach by Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) and construct currency portfolios at the beginning of each month based on their lagged excess returns. We assume investors hold portfolios for one month (formation and holding period both equal 1) and subsequently re-consider the portfolio choice. Portfolio 3 (P3) contains currencies with high previous excess returns, while currencies with low previous performance are allocated to portfolio 1 (P1). We apply three different sorting strategies, as summarized in Table V. First, we follow the literature and rank currencies according based on cumulative close-to-close excess returns (left Panel). Second, we construct rankings based on intraday (middle panel) and, third, rankings are based on overnight returns (right panel).

[INSERT TABLE V HERE]

Beginning the analysis of momentum returns in the left panel of Table V, we note that CTC returns are low and range between -0.29% (P1) and 1.48% (P3). The high-minus low portfolio generates an annualized return of 1.32% but the low t-statistic of 0.78 suggests returns are not significantly different from zero. In contrast to previous studies of currency momentum (e.g. Menkhoff, Sarno, Schmeling, and Schrimpf (2012a)), however, we cover a comparably short time series period and much smaller cross-section of currencies. Therefore, risk diversification benefits from only three portfolios is relatively small. Focusing on intraday and overnight return dynamics, we note a diverging pattern between the two intraday periods similar to previous trading strategies. We find that intraday returns are positive and significant for all three portfolios. Portfolio returns range between 3.80% (P1) and 5.74% (P2). Returns for the overnight period are negative. In contrast to carry and dollar carry trading trading approaches, however, returns from momentum high-minus-low strategies are low and only generate 0.24% and 1.53% for the intraday and overnight period, respectively. In both periods, high-minus-low returns are not statistically different from zero.

Focusing on alternative portfolio rankings, which are based on intraday (rx^{ID}) and overnight (rx^{ON}) excess returns, we find that individual portfolios generate positive returns during the day while returns are negative during the overnight period. For example, when sorted by (rx^{ID}) portfolios generate between 0.72% and 6.57% during the day, while overnight returns range between -2.21 % and -5.25%. Interestingly, we also observe the same pattern for the high-minus-low portfolio. When portfolios are sorted according to previous intraday returns, the difference between P3 and P1 is positive (5.58%) and significant (t-stat: 5.19), while it is negative and significant for the overnight period (-3.04%). Alternatively, if returns are sorted by previous overnight returns (rx^{ON}) the high-minus-low portfolio (-3.74%) generates negative intraday returns but positive overnight returns (3.27%). The reversal between intraday and overnight periods are in line with the findings in Lou, Polk, and Skouras (2017), highlighting the persistent return pattern that exists for both intraday periods.

Further, the distinct returns discrepancies between intraday and overnight return dynamics suggest possible benefits from day trading strategies. Panel B and C illustrate potential returns of trading approaches that go long momentum portfolios during the day and that take short positions overnight. As shown, these trading apporaches can be highly profitable and even exceed returns from conventional trading strategies. For example, focusing on individual portfolios of intraday minus overnight strategies the minimum return is 2.92% and while the maximum reaches 11.63%. Almost all portfolio returns of this trading strategy are statistically different from zero. In similar fashion, reversal momentum strategies can generate positive returns of up to 8.51%. For these strategies we invest in past winners during the day, and short past losers over night. Irrelevant of the portfolio sorting approach, all returns of this strategy are different at the 1% level of significance.

As a last trading approach, we examine return patterns of a time series momentum trading strategy, following Moskowitz, Ooi, and Pedersen (2012). At the beginning of each month we either buy or sell a currency dependent on its own previous performance over the previous 12 months. In every month we go long a currency if the cumulative excess returns over the previous year is positive, and we short it otherwise. We hold the currency for one month before re-allocating currencies at the beginning of the next month. Average annualized returns for close-to-close, intraday, and overnight returns are shown in Table VI.

[INSERT TABLE VI HERE]

First, we note that CTC returns are positive and highly significant if decisions about the direction of the trade are based on the cumulative returns over the previous year. The lowest return is 5.10% for the euro and the highest return reaches 10.21% for the Japanese yen. Second, overnight returns of Asia-Pacific and Scandinavian currencies contribute more to the CTC returns than intraday time series momentum returns. The relative contribution of overnight returns ranges between 0.55 (SEK) and 0.68 (NZD). For the remaining European currencies and the Canadian dollar most of the CTC returns are generated during the day. This pattern is particularly strong for the Swiss franc (0.82). Third, we find that overnight and intraday returns are highly persistent. In Panel B, average intraday excess returns ($\bar{rx}^{ID}$) are highly significant and generate a large fraction of the CTC returns. In contrast more than half of the overnight returns are not significant and generate negative returns. The opposite pattern can be observed in Panel C. Here, average overnight excess returns ($\bar{rx}^{ON}$) are highly significant and range between 6.15% and 10.19%, while intraday returns are mostly insignificant or produce negative returns. We conclude that time series momentum appears to be the only trading strategy where long position during the day and over night contribute positively and often significantly to close-to-close returns. Further, exploiting persistent return patterns during the day and overnight allows to generate significant returns in both intraday periods.

IV. Robustness Checks

To confirm the robustness of our findings, we perform an extensive analysis employing publicly available exchange rate data from Datastream, using a smaller currency cross-section, considering an alternative intraday specification, conducting a sub-sample analysis, controlling for day-of-the-week effects, excluding FOMC announcement days, and separating crisis and non-crisis periods.[12]

A. Definition of the end of the trading day

To begin with, to alleviate concerns that our findings are driven by our definition of the FX market's closing time which coincides with the end of main trading activity in New York (5:00 p.m., EST), we construct summary statistics and replicate carry and dollar carry trading strategies with end of day spot rates obtained from Datastream. In contrast to the approach of our main analysis, these exchange rate series are sampled at 4:00 p.m. London time (which is equivalent 11:00 a.m or 12:00 p.m., EST). Employing these publicly available monthly time series, we find almost no differences compared to the summary statistics that we obtained with Olsen intraday data. The correlation coefficients between the Datastream series and our close-to-close returns is 0.99 for all nine currency pairs. Differences between the first four moments (mean, standard deviation, skewness, kurtosis) are rare and if they occur, they are very small in magnitude. Further, we find that the high-minus-low portfolio of the carry strategy and the dollar carry trading generate insignificantly different returns from those presented in Table III and IV . Based on the comparison of the two series, we conclude that our definition of the end of trading in the FX market is not a

[12]Results are available upon requests.

driver of our results.

B. Excluding the Yen

Second, since our previous analysis suggests that the Japanese yen moves largely counter-cyclically to other major currencies, we separately examine returns from carry and dollar carry trading strategies with a cross-section of only eight currencies and exclude the Japanese yen from an investor's portfolio choice. As one would expect, excluding a crucial funding currency has a significant impact on the return generating process of a carry trading strategy, while the effects on dollar carry are small. If the Japanese yen is excluded from the portfolio composition, close-to-close returns from carry trading decrease by around 1%, and returns are largely generated during the overnight period. We find that the carry trade strategy is less profitable during the day when investors are not able to short the Japanese yen, but more profitable during non U.S. trading hours, as investors go long only in currencies that move in the same direction over night. In line with this argument, returns from dollar carry and the unconditional dollar portfolio both increase if the yen is not considered for the portfolio construction. Annualized average returns increase from 4.53% to 4.76 % for the dollar carry portfolio and from 0.96 % to 1.43 % for the unconditional dollar portfolio. Overall, we conclude that results of our main analysis are robust to the choice of the cross-section of currencies, and changes to returns occur as expected if a strategy-relevant currency pair is excluded.

C. Local / Non-Local Dissection

First we consider the dissection of Cornett, Schwarz, and Szakmary (1995) who document similar patterns using hourly data for the period 1977 to 1991 and Breedon and Ranaldo (2013) who extend this study for the period 1997 to 2007. First, (almost) all G10 pairs appreciate against the U.S. dollar during New York trading hours. For European currencies there is an overlapping period when both markets are open. The appreciation starts when New York opens and continues until the main FX trading venue in the U.S. closes. During the period when both markets are closed, the appreciation during U.S. trading hours generally starts to reverse (or at least the further average appreciation is not statistically significant) with the Norwegian krona as the only significant deviation from this pattern. The reversal then continues once the local market opens up and continues during the local trading hours (and until New York opens in the case of the European currencies). The only exception to the general pattern is the Japanese yen that appreciates significantly versus the U.S. dollar during local trading hours and reverses during New York hours and when both markets are closed.

With respect to Cornett, Schwarz, and Szakmary (1995) and Breedon and Ranaldo (2013), our contribution is two-fold: (i) we provide a granular dissection of close-to-close returns by daily sub-periods; (ii) we make the connection that close-to-close returns, exclusively employed by the extant empirical literature, provide a distorted view of currency risk premia since they are the sum of potentially drastically different return dynamics. This point is made clear by noting that none of the average close-to-close returns are significantly different from zero at the 5% level, while all currency returns are highly statistically different from zero when consider local trading hours and U.S. hours separately, albeit with opposite signs.[13]

D. Sub-Sample Analysis

Third, we parsimoniously split our sample in half two sub-samples and repeat the analysis for each period. The first sub-sample covers the period January 1994 to December 2003 (120 months) and the second sub-sample includes all months between January 2004 and December 2014. For both periods we construct summary statistics and portfolios for the trading strategies. Overall, return currency dynamics are similar across both sub-samples, even though portfolio returns tend to be higher in the first period. Also, the unconditional dollar portfolio depicts periods of stronger appreciation and depreciation during the first half of our sample. This large swings have a strong impact on the dollar carry strategy. The annualized returned increases to 8.10% between January 1994 to December 2003, compared to only 1.33% for the January 2004 and December 2014 period. The diverging movements of intraday and overnight returns, however, remain the same. Further, even though the carry trade strategy appears to be less profitable in the second half of our sample, we find that high interest rate currencies always appreciate more during the day and depreciate less overnight, compared to low interest rate currencies. As overnight and intraday dynamics resemble the same diverging pattern in both sample periods, we conclude that results are not driven by the

[13]The only exception to this stylised fact is the USD/CAD currency pair where we cannot detect any significant pattern with respect to intraday versus overnight returns.

time series properties of our data or the choice of the sample period.

E. Day-of-the Week Effects

Fourth, we examine if close-to-close, intrayday, and overnight returns are affected by certain day-of-the-week effects. To this end, we construct monthly returns as described in the Data section, but we sequentially replace each weekday from Sunday to Friday and construct summary statistics for six different close-to-close and both intraday return series.[14] Comparing the returns, which each exclude a different weekday, we do not find any significant differences of average annualized returns. This indicates that trading dynamics at the start, middle, or end of the week do not cause a significant bias to the close-to-close, intraday, or overnight return series. We conclude that diverging return dynamics during the day and over night are not limited to specific days, but appear to be a constant phenomenon across the week.

F. FOMC Announcement Days

Fifth, we check to what extent average positive returns during the intraday period are positively skewed by scheduled FOMC announcement days. As documented in Mueller, Tahbaz-Salehi, and Vedolin (2017), foreign currencies tend to systematically appreciate on days, when monetary policy decisions are announced at approximately 2.15 p.m. (EST). To control for these abnormal return dynamics, we first identify all 168 scheduled FOMC announcement days between January 1994 and December 2014, exclude these dates from our sample, and then re-calculate average annualized returns for monthly overnight, intraday, and close-to-close returns. We find that excluding 168 out of 6353 days from the sample virtually does not have any strong effect on average annualized returns and, more importantly, it does not affect the spread between the two intraday sub-periods. For example, overnight returns continue to be negative and range between -8.22% and -0.92 for GBP and CAD, respectively, while they are largely positive during the day (CAD: 1.51%; GBP: 8.48%). Again, the only exception to this trend is the Japanese yen which shows countercyclical return dynamics compared to the rest of the sample. We conclude that the documented return differences between the intraday and overnight period do not arise because of abnormal returns during scheduled FOMC annnouncement days.

[14] Note that Saturdays have been excluded due to low trading activity as part of the data cleaning procedure.

G. Crises Periods

While the sub-sample analysis already indicates that the diverging intraday and overnight return pattern is a common characteristic across the entire sample, lastly, we explicitly examine if the intraday return patterns is driven by crises periods. To this end, we use NBER business cycle classifications to identify recession periods and we consider all months between March 2001 and November 2001, and between Decemeber 2007 and June 2009, as crises periods. We then re-construct and plot cumulative average 5-min returns over the trading day but explicitly distinguish between the 28 crisis-months and the remaining 228 months of the business cycle. We find that separating the return patterns of crises periods from the sample does not have a significant impact on the general intraday return pattern. Similar to the analysis that is based on the entire sample, we find that foreign currencies tend to depreciate during the beginning of the trading day, appreciate once trading in Singapore and Hong Kong commences, depreciate again during the early trading hours in Europe, and then strongly appreciate during the main trading hours in New York. During recession months, this pattern continues to exists for most of the currencies, but it is less consistent across the sample. In particular the point in time when currencies start to appreciate in the intraday periods appears to have shifted from 8:30 a.m. (EST) to the middle of New York's trading day. Overall, however, we conclude that the drift between overnight and intraday returns is not driven by crisis periods and, in fact, that it is more pronounced in non-crisis periods.

V. Alternatives

As the previous section indicates that our findings are robust to different return specification and alternatives definition of intraday periods, we next explore possible explanations for the diverging pattern between intraday and overnight returns. In particular, we analyse intraday volatility dynamics, currency intraday jumps and crashes, and liquidity conditions, and we discuss the impact of transaction costs, measured by the bid-ask spread, on average returns.

A. *Volatility*

A possible explanation for the diverging return patterns during the intraday and overnight periods could be that investors demand a higher compensation for buying or selling a foreign currency if the volatility in one periods is higher relative to the remaining time of the day. To control for this explanation, we conduct a simple variance decomposition of close-to-close returns in Table VII. For all currency pairs and different specifications of the dollar portfolio, the table shows the variance, which can be attributed to the intraday and overnight period, and the associated scaled covariance term. Numbers in squared brackets denote the fraction that each intraday component contributes to the overall total daily variance.

[INSERT TABLE VII HERE]

For most currency pairs, the intraday and overnight variances contribute approximately the same share to the total daily return variance. Exceptions to this observations are Asian Pacific currency pairs (AUD, JPY, NZD), for which overnight variance is larger in magnitude compared to intraday volatility. This difference might arise as these currencies are more likely to be actively traded during the main trading hours in Sydney, Singapore, and Hong Kong. For the other currencies, intraday return variances are at least as high as the variance over night. The only exception to this pattern is the British pound where the overnight variance is slightly higher compared to the intraday period. For the dollar portfolio, we note that intraday and overnight contribute exactly the same share to total close-to-close volatility (0.45). As differences between the two intraday periods are small, we suppose it is unlikely that return volatility is the main driver of the diverging intraday and overnight pattern.

To shed further light onto the intraday volatility pattern, we exhibit the average absolute percentage change at each five minute time-stamp over the trading day in Figure 4.

[INSERT FIGURE 4 HERE]

For all currency pairs we observe a spike of the intraday volatility at the end of the trading hours in New York, before volatility decreases significantly in the subsequent hours. Most currencies, in particular the Japanese yen, show an increase in the volatility pattern before trading commences in Singapore and Hong Kong, and it decreases subsequently until approximately 1:00 a.m.. At this point of the trading day, which coincides with the opening hours of trading venues in Europe, a sharp increase in volatility can be observed for all currency pairs. Again, volatility largely declines afterwards until it shows the largest spike when New York trading commences. Further, currencies remain volatile for the next three hours (approximately until 11:00 a.m. or 12:00 a.m. Eastern time which is the time of the London fix), then drops over most of the intraday period, and then spikes one last time when New York trading ceased.

B. Crash Risk

While the relative contribution of overnight and intraday volatility to total daily volatility appears to be very similar across currencies, we next analyse if currencies are prone to show sudden short-lived crashes, or return jumps, and if there are more likely to occur during one of the two intraday sub-periods. For example, Lee and Wang (2016) argue that jumps in the spot market are more likely around the opening and closing hours of large FX trading venues across the globe. Also, currency returns experience jumps in clusters so that the likelihood of jumps arriving is higher subsequent to the occurenece of an earlier jump. Further, Lee and Wang (2017) split the day in a 'Jump period', around Tokyo closing time, and 'No Jump period' and propose a modified carry trade strategy that account for currencies' sensitivity for negative jumps. As the jump sensitivity of funding currencies is larger than for investing currencies, the modified carry trade strategy that unwinds positions at certain times of the day outperforms the conventional carry trade approach.

To detect return jumps, we employ the jump test proposed by Lee and Mykland (2008) and account for return intra-week periodicity (Boudt, Croux, and Laurent (2011)). Figure 6 displays the relative number of times that jumps occur at each 5-minute time stamp. We explicitly distinguish between positive return jumps that imply a sudden appreciation of the foreign currency vis-a-vis the U.S. dollar (blue) and return crashes, which capture for a sudden depreciation of the foreign currency (yellow).

[INSERT FIGURE 6 HERE]

As illustrated by the graphs, currencies tend to exhibit more jumps and crashes after trading in New York ceases. This pattern is particular prevalent for European currenices and the Canadian dollar, while jumps of the Australian dollar, New Zealand dollar, and Japanese yen are less common. This observation points toward the close link between the occurence of jumps and liquidity dynamics, as latter currencies are likely to be more actively traded during the early hours of the new trading day. Therefore, they are less likely to exhibit jumps compared to European currency pairs whose main trading venues open at a later time of the day. Interestingly, it appears that the number of currency jumps and crashes are almost the same during the entire trading day. To investigate this observation more explicitly, Table VIII shows the absolute and relative number of jumps for each intraday subperiod.

[INSERT TABLE VIII HERE]

For all currency pairs, we find that jumps are relatively more likely to occur during the overnight period. For example, for the Australian dollar 64% of all jumps occur overnight, while only 36% of jumps occur between 8:30 a.m. and 5:00 p.m (intraday period). As indicated earlier, this pattern is even stronger for European currencies, for which up to 80% (CHF) of all jumps occur during the overnight period. This is to some extent unsurprising, however, as the overnight period encompasses 15.5 hours, while there are only 8.5 intraday hours. Important to note with respect to the return pattern, however, is that the occurrence of currency jumps and crashes is almost uniformly distributed in each sub-period and, therefore, over the entire trading day. As shown in the last three columns of Table VIII positive ($J > 0$) and negative ($J < 0$) jumps occur almost with the same likelihood. Yet, if the W-shaped intraday return pattern of currencies could be explained by currency crash risk, we would expect that the occurences of currency crashes and jumps differ during the intraday and overnight period. This would provide additional incentive to short and invest certain currency pairs at certain hours of the day.

C. Liquidity

Next, we examine FX market liquidity as a possible driver that impacts returns differently during the night and over the day. Following earlier literature, we measure market liquidity by the quoted bid-ask spread. An increase in the spread implies an increase in the cost of a transaction and possibly exacerbates or delays the execution of a trade (Brunnermeier, Nagel, and Pedersen (2009)). Hence, the market becomes more illiquid. In contrast, lower bid-ask spreads imply a higher degree of liquidity. In Table IX we compare the average bid-ask spreads at close-to-close time, and during intraday and overnight periods. In the bottom part of the panel we present the t-statistic of conventional t-tests, assessing if liquidity conditions are significantly different from each other across sub-periods.

[INSERT TABLE IX HERE]

The following observations are worth noting. First, comparing the three periods, market liquidity appears to be the lowest towards the enf of New York's main trading hours. At this time of the day, the average bid-ask spread ranges between 1.41 (EUR) and 4.58 basis points (NZD). It is on average higher at this point of the day than during overnight and intraday periods. Second, comparing liquidity conditions between intraday ($B\bar{A}S^{ID}$) and overnight ($B\bar{A}S^{OV}$) Table IX indicates that trading costs are lower during the day for all currency pairs, except the Australian dollar. In this case overnight bid-ask spreads are slightly higher compared to the intraday period. Third, the absolute difference between intraday and overnight bid-ask spreads ranges between 0.013 basis points (JPY) and 0.347 (NOK). Even though some of the differences are small in magnitude, the t-statistics in the bottom part of the table indicate that we strongly reject the null hypothesis for all currencies that liquidity dynamics across sub-periods are the same. As t-statistics are high irrelevant of the magnitude of the difference in averages indicates that the volatility of liquidity dynamics are high within each daily sub-period and over the span of our sample. To shed further light on liqudity conditions within each sub-period, we plot the bid-ask spread across all five minute intervals normalized by average daily bid-ask spread.

[INSERT FIGURE 5 HERE]

Starting in the left Panel of Figure 5, we note that liqudity conditions are relatively stable for AUD, NOK, and JPY between 8:00 p.m. and 4:00 p.m on the following day. While there exists an incrase in liquidity once European trading commences, intraday volatility stays reasonably constant over time. This changes, however, during the last hour of trading hours in New York. For all three currencies the plots displays a significant jump in illiquidity. Similar trends can be observed for the European currencies and the Canadian dollar. Across currencies liquidity conditions worsen towards the end of the intraday periods, and improve with the opening of alternative trading venues in the Asian-Pacific region. The decline in bid=ask spread, however, is less distinct as for the AUD, NOK, and JPY. In fact, intraday liquidity conditions for CHF, EUR, GBO, NOK, SEK, and CAD only significantly improve with increasing trading activity in Europe.

D. Trading Costs

While the analysis so far is based on returns constructed from the mid-price, this section takes into account transaction costs and employs currencies' ask and bid prices for intraday, overnight and close-to-close returns. As our trading strategy to buy and sell currency pairs twice a day, the spread may have a significant impact on the magnitude of net returns. We note, however, that intraday data is based on indicative quotes, which tend to have a wider bid-ask spread than firm transacted prices. Our findings, therefore, can be considered as lower bound and real returns are likely to be higher if firm transaction prices are used. We construct returns from long and short positions in the following way. For CTC returns we assume that investors buy (sell) at the beginning of each month and sell (buy) currencies at the end of the month if they hold a long (short) position. In this case, investors only conduct two trades a month and simply hold their position for most of the period. CTC returns for long and short positions are defined as

$$\Delta S_t^{CTC,L} = \frac{p_{t,end}^{b,5:00p.m.} - p_1^{a,5:00p.m.}}{p_{t,1}^{a,5:00p.m.}} \qquad \Delta S_t^{CTC,S} = \frac{-p_{t,end}^{a,5:00p.m.} + p_1^{b,5:00p.m.}}{p_{t,1}^{b,5:00p.m.}}$$

where the superscript L and S denote long and short position, b and a refer to bid and ask price, and subscript t, end and $t, 1$ refer to the last end first day within each month. In similar fashion net ID and ON returns are constructed, but in contrast to the previous analysis based on mid-prices their aggregate does not equal CTC returns. Long and short positions for ID and ON returns are defined as

$$\Delta S_d^{ID,L} = \frac{p_d^{b,5:00p.m.} - p_d^{a,8:30a.m.}}{p_d^{a,8:30a.m.}} \qquad \Delta S_d^{ID,S} = \frac{-p_d^{a,8:30p.m.} + p_d^{b,5:00p.m.}}{p_d^{b,5:00p.m.}}$$

$$\Delta S_d^{ON,L} = \frac{p_d^{b,8:30a.m.} - p_{d-1}^{a,5:00p.m.}}{p_{d-1,1}^{a,5:00a.m.}} \qquad \Delta S_t^{ON,S} = \frac{-p_{t,end}^{a,8:30p.m.} + p_1^{b,5:00p.m.}}{p_{t,1}^{b,5:00p.m.}}$$

aggregated to the monthly frequency and all series are log-transformed. Average annualized returns are summarized in Table X.

[INSERT TABLE X HERE]

As shown, conducting two trades during each intraday period has a substantial impact on currency returns. In particular for less frequently traded currency paros where bid-ask spreads are wider, positive returns are largely used up by transaction costs. Yet, for the most liquid pairs - CHF, EUR, GBP - Table X exhibits positive return patterns for short foreign currency positions overnight, and for long foreign currency positions during the day. When trading in New York takes place (ID), the returns of these three exchange rates are positive and significant at the 5% level, while significance is slightly less distinct overnight and returns for the Swiss franc are not statistically different from zero. Yet, an equally-weighted portfolio consisting of only these three currency pairs generates, on average, 3.29% after accounting for transaction costs. We interpret this as first evidence that investing and shorting foreign currencies based on the time of the day can be a profitable trading approach.

VI. Conclusion

In this paper we study currency risk premia around the clock for the G10 currencies. We find that most currencies (with the exception of the Japanese yen) appreciate against the U.S. dollar during New York trading hours (i.e., the intraday period) and depreciate during the rest of the 24 hour day (i.e., the overnight period). This seems to suggest that currency dynamics are distinctly different depending on the time of day (measured with respect to the U.S. trading day).

Thus, we revisit well-known results in the foreign exchange literature and find the following: (i) Running Fama (1984) regressions to test the expectations hypothesis we cannot reject that the β coefficient is equal to one for all currencies in the sample during the overnight period; (ii) carry returns and dollar carry returns are almost entirely earned during the intraday period; (iii) the dollar portfolio earns a significant positive return intraday but reverses equally strongly during the night; (iv) momentum returns are significant intraday and overnight respectively but not when measured close-to-close (for our sample period and selection of currencies); and (v) time series momentum is strong for all currencies and the contribution from intraday and overnight periods is roughly equally strong.

In summary, we present novel stylised facts with respect to the most important global currencies. The results suggest that the distinction between intraday and overnight periods is not only important in the equity markets as documented by Lou, Polk, and Skouras (2017) but also in the global foreign exchange market. This seems obvious given the global nature of the market and the fact that currencies are not only traded around the globe but also around the clock. While Lou, Polk, and Skouras (2017) attribute some of their results to the “overnight” versus “intraday” clienteles, geographical differences and local demand for currencies may play a more important role in the foreign exchange market.

VII. Appendix: Tables

Table I. Intraday Returns: By Main Trading Hours

This table reports annualized average returns for different intraday periods. $-\Delta s^{AUS}$ refers to returns after trading in Sydney commenced (5:00 p.m. to 9:00 p.m.); $-\Delta s^{SG/HK}$ refers to returns subsequent to the opening of the main trading venues in Southeast Asia (Singapore and Hong Kong, 9:00 p.m. to 1.00 a.m.); $-\Delta s^{EU}$ refers to returns during main trading hours in Europe (1:00 a.m. to 8.30 a.m); $-\Delta s^{ON}$ refers to the overnight returns from an U.S. investors perspective. It equals the sum of the first three columns $(-\Delta s^{AUS} + -\Delta s^{SEA} + -\Delta s^{EU})$. $-\Delta s^{ID}$ refers to the intraday returns during the main trading hours in New York (8.30 a.m. and 5.00 p.m.). $-\Delta s^{CTC}$ refers to daily close-to-close returns between 5.00 p.m. on day t and 5.00 p.m. on day $t+1$ ($-\Delta s^{CTC} = -(\Delta s^{Over} + \Delta s^{Intra})$). "dol" refers to the unconditional dollar portfolio that goes long all foreign currencies, and "dol (excl. JPY)" is the unconditional dollar portfolio that invests in all foreign currencies except the Japanese yen. Positive values imply the foreign currency appreciates versus the U.S. dollar. All times are measured in Eastern Standard Time, taking into account daylight saving changes in New York. The sample period is January 1994 to December 2014, comprising 252 monthly observations.

	$-\Delta s^{AUS}$	$-\Delta s^{SEA}$	$-\Delta s^{EU}$	$-\Delta s^{ON}$	$-\Delta s^{ID}$	$-\Delta s^{CTC}$
AUD	-7.31	3.30	1.45	-2.56	3.41	0.85
	(-6.70)	(3.70)	(0.88)	(-1.29)	(2.31)	(0.32)
CAD	-2.47	2.20	-0.65	-0.92	1.51	0.59
	(-4.84)	(5.31)	(-0.56)	(-0.70)	(1.09)	(0.34)
CHF	-2.76	3.00	-6.81	-6.57	8.54	1.97
	(-3.31)	(5.96)	(-5.21)	(-3.94)	(5.10)	(0.82)
EUR	-4.33	4.22	-6.91	-7.02	7.41	0.38
	(-5.68)	(8.83)	(-5.89)	(-4.76)	(4.86)	(0.17)
GBP	-5.74	3.08	-5.56	-8.22	8.48	0.26
	(-9.71)	(8.50)	(-4.73)	(-6.04)	(6.58)	(0.14)
JPY	-2.30	3.21	0.81	1.73	-2.01	-0.28
	(-2.36)	(4.04)	(0.58)	(0.94)	(-1.44)	(-0.12)
NOK	-2.23	4.21	-4.76	-2.79	2.87	0.08
	(-2.65)	(7.46)	(-3.18)	(-1.72)	(1.59)	(0.03)
NZD	-8.91	3.54	3.12	-2.25	3.83	1.58
	(-6.88)	(3.36)	(1.81)	(-0.97)	(2.53)	(0.57)
SEK	-2.20	4.40	-7.42	-5.22	5.60	0.38
	(-2.38)	(6.34)	(-5.05)	(-2.95)	(2.78)	(0.16)
dol	-4.29	3.43	-3.08	-3.94	4.28	0.35
	(-7.32)	(8.42)	(-3.39)	(-3.36)	(3.64)	(0.20)
dol	-4.53	3.47	-3.54	-4.60	5.10	0.51
(excl. JPY)	(-7.25)	(7.95)	(-3.63)	(-3.67)	(4.06)	(0.27)

Table II. Forward Premium Puzzle: Intraday vs. Overnight

This table reports results from estimating the following regression with ordinary least squares

$$s_{t+h} - s_t = \alpha + \beta(f_{t,h} - s_t) + \epsilon$$

where $s_{t+h} - s_t$ refers to the monthly close-to-close, intraday, or overnight return in period $t + h$, $f_{t,h}$ denotes the end-of-month log forward rate with maturity h, and s_t is the end-of-month log spot rate. Returns are multiplied by the factor 100, such that all variables are expressed in percent per month. The maturity of the forward rate is 1 month ($h = 1$). The forward discount is calculated using Datastream forward rates and spot rates. The row $\beta = 1$ reports the t-statistic of a simple t-test with the null hypotheses that $\beta = 1$. The sample period is January 1994 to December 2014, comprising 252 monthly observations. ***,**, and * denote statistical significance at the 10%, 5% and 1% level, respectively. Numbers in parentheses display Newey-West standard errors.

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK
Close-to-close									
$\hat{\alpha}$	0.29	-0.04	-0.37	-0.13	0.08	0.01	0.02	-0.18	0.02
s.e($\hat{\alpha}$)	(0.27)	(0.15)	(0.31)	(0.19)	(0.25)	(0.32)	(0.21)	(0.50)	(0.21)
$\hat{\beta}$	-2.01	-2.10	-1.35	-3.55**	-1.23	-0.13	-0.32	0.23	-1.54
s.e($\hat{\beta}$)	(1.47)	(1.66)	(1.54)	(1.47)	(1.89)	(1.13)	(1.37)	(2.27)	(1.15)
$\bar{R}^2$	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
$\beta = 1$	-2.05**	-1.87*	-1.53	-3.10***	-1.18	-1.00	-0.96	-0.34	-2.20**
Intraday									
$\hat{\alpha}$	-0.13	-0.12	-1.02***	-0.71***	-0.53***	-0.03	-0.23	-0.62***	-0.42**
s.e($\hat{\alpha}$)	(0.83)	(0.86)	(4.22)	(5.44)	(3.87)	(0.15)	(1.55)	(2.60)	(2.19)
$\hat{\beta}$	-0.91	-3.58**	-1.96*	-3.14***	-2.41**	-0.84	-0.08	1.3	-1.92
s.e($\hat{\beta}$)	(0.80)	(1.70)	(1.17)	(1.17)	(1.03)	(0.66)	(-0.97)	(-0.99)	(-1.25)
$\bar{R}^2$	0.00	0.03	0.01	0.03	0.01	0.00	0.00	0.00	0.01
$\beta = 1$	-2.39**	-2.70***	-2.54**	-3.55***	-3.30***	-2.78***	-1.12	0.30	-2.34**
Overnight									
$\hat{\alpha}$	0.42*	0.08	0.65***	0.58***	0.61***	0.04	0.25	0.44	0.44***
s.e($\hat{\alpha}$)	(0.24)	(0.13)	(0.21)	(0.13)	(0.19)	(0.23)	(0.16)	(0.51)	(0.16)
$\hat{\beta}$	-1.10	1.48	0.61	-0.42	1.18	0.71	-0.24	-1.07	0.39
s.e($\hat{\beta}$)	(1.12)	(1.61)	(1.01)	(1.26)	(1.55)	(0.81)	(0.81)	(2.14)	(1.13)
$\bar{R}^2$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\beta = 1$	-1.88*	0.30	-0.39	-1.13	0.12	-0.36	-1.53	-0.97	-0.54

Table III. Carry Trade: Intraday vs. Overnight

This table reports the average annualized portfolio returns from a conventional carry trade strategy (Panel A). At the beginning of each month, currencies are sorted according to their forward discount in the previous month. The forward discount is defined as $fp = fw_t - s_t$, where fw_t refers to the log forward rate with one-month maturity and s_t is the log spot rate. Currencies with a low (high) forward discount are assigned to portfolio P1 (P3). Currencies are held for one month and then re-allocated to a new portfolio. The column "P3-P1" refers to a high-minus-low strategy that goes long currencies in P3 and short currencies that are allocated to P1. "dol" refers to the unconditional dollar portfolio that invests equally in all foreign currencies. In Panel B, Intraday-Overnight refers to the return obtain from a strategy that goes long all portfolios during the day, and that shorts portfolios over night. In Panel C, Reversal strategies are based on a strategy that goes long the best (worse) performing portfolio intraday and that sells the worst (best) performing portfolio during overnight periods. Returns are annualized by multiplying log-returns by 12, and then by the factor 100 to express numbers in percent. Further, for intraday and overnight returns, we assume that the forward premium is earned equally during the overnight and intraday period. For these two daily sub-periods, excess returns are constructed as: $(rx_{t+1}^{Over/Intra} = \frac{fw_t - s_t}{2} - \Delta s_{t+1})$. The sample period is January 1994 to December 2014, comprising 252 monthly observations.

Panel A: Carry Trade

	P1	P2	P3	P3-P1	dol
Close-to-close					
Ann. Avg.	-1.67	0.96	3.37	5.04	0.97
t-stat	(-0.93)	(0.52)	(1.52)	(2.82)	(0.55)
Intraday					
Ann. Avg.	2.43	5.40	5.95	3.52	4.62
t-stat	(1.95)	(4.04)	(4.44)	(3.50)	(3.91)
Overnight					
Ann. Avg.	-4.07	-4.37	-2.52	1.55	-3.60
t-stat	(-3.30)	(-3.61)	(-1.55)	(1.03)	(-3.09)

Panel B: Intraday-Overnight Trading

	P1	P2	P3	P3-P1	dol
Ann. Avg.	6.50	9.77	8.47	1.97	8.22
t-stat	(3.78)	(5.56)	(4.25)	(1.07)	(5.27)

Panel C: Reversal Strategies

	$P3^{Intra} - P1^{Over}$	$P1^{Intra} - P3^{Over}$
Ann. Avg.	10.02	4.95
t-stat	(5.68)	(2.57)

Table IV. Dollar Carry Trade: Intraday vs. Overnight

This table reports the average annualized return of a dollar carry trading strategy, where portfolios are sorted according to the average forward discount $\bar{fw}_t - \bar{s}_t = \frac{1}{N}\sum_{i=1}^{N} fw_t^i - s_t^i$, where $\bar{fw}_t - \bar{s}_t$ is the average monthly forward discount, and fw_t^i and s_t^i are the one-month log forward rate and log spot rate for country i, respectively. The column "AFD $\leq$ 0" refers to the average return from a strategy where investors sell foreign currencies at the beginning of a month (103 months) if the lagged average foreign interest rate in the previous month is below the U.S. interest rate (and no trade is executed otherwise). The column "AFD $>$ 0" refers to a strategy where investors go long foreign currencies (149) at the beginning of the month if the average forward discount in the previous month is positive (and no trade is executed otherwise). "Dollar-Carry" refers to the strategy where investors buy foreign currencies at the beginning of a month, when the average foreign discount in the previous month is positive, and foreign currencies are shorted otherwise. "dol" is the return from an unconditional dollar portfolio where investors go long all foreign currencies if the AFD in the previous month is positive. "AFD $<$ 0 (excl. 0)" and "AFD $>$ 0 (excl. 0)" refer to the average annualized returns if we only consider months, in which a a trade was conducted. In Panel B, Intraday-Overnight refers to the returns obtain from a strategy that going long currencies during the day, and selling currencies overnight. In Panel C, Reversal strategies are based on a strategy that goes long the best (worse) performing portfolio intraday and that sells the worst (best) performing portfolio during overnight periods. The sample period is January 1994 to December 2014, comprising 252 monthly observations.

Panel A: Dollar Carry

	AFD ≤ 0	AFD > 0	Dollar-Carry	dol	AFD ≤ 0 (excl. 0)	AFD > 0 (excl. 0)
Close-to-close						
Ann. Avg.	-1.87	2.85	4.72	0.97	-4.57	4.83
t-stat	(-1.88)	(2.00)	(2.73)	(0.55)	(-1.89)	(2.00)
Obs	252	252	252	252	103	149
Intraday						
Ann. Avg.	0.42	4.20	3.78	4.62	1.03	7.13
t-stat	(0.62)	(4.31)	(3.16)	(3.91)	(0.62)	(4.42)
Overnight						
Ann. Avg.	-2.28	-1.32	0.95	-3.60	-5.55	-2.25
t-stat	(-3.37)	(-1.38)	(0.80)	(-3.09)	(-3.48)	(-1.38)

Panel B: Intraday-Overnight Trading

	AFD ≤ 0	AFD > 0	Dollar-Carry	dol	AFD ≤ 0 (excl. 0)	AFD > 0 (excl. 0)
Ann. Avg.	2.70	5.53	2.83	8.22	6.57	9.37
t-stat	(2.95)	(4.22)	(1.73)	(5.27)	(3.01)	(4.32)

Panel C: Reversal Strategies

	$AFD > 0^{Intra}$ - $AFD \leq 0^{Over}$	$AFD \leq 0^{Intra}$ - $AFD > 0^{Over}$
Ann. Avg.	6.48	1.75
t-stat	(5.62)	(1.49)

Table V. Momentum: Intraday vs. Overnight with different portfolio rankings

This table reports the average annualized return ($\bar{rx}$) of portfolios sorted at the beginning of each month according to close-to-close (rx^{CTC}, left), intraday excess return (rx^{ID}, middle), or overnight excess returns (rx^{ON}, right) in the previous month. In Panel A, P3 refers to the portfolio with currencies with past high excess returns, while P1 is assigned currencies with low excess returns. P3-P1 refers to the conventional high-minus-low portfolio. Intraday-Overnight (Panel B) refers to the average annualized returns obtain from a strategy that is going long currencies during the day, and selling currencies over night ($\bar{rx}^{IN-ON}$). Reversal Strategies (Panel C) are based on a strategy that goes long the best (worse) performing portfolio intraday and that sells the worst (best) performing portfolio during overnight periods ($\bar{rx}^{Reversal}$). The sample period is January 1994 to December 2014, comprising 252 monthly observations. Numbers in parentheses display t-statistics.

Panel A: Momentum												
	Sorted by rx^{CTC}				Sorted by rx^{ID}				Sorted by rx^{ON}			
	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1
$\bar{rx}^{CTC}$	-0.29	1.36	1.48	1.77	-1.53	3.10	1.02	2.55	0.65	1.73	0.17	-0.48
t-stat	(-0.14)	(0.71)	(0.77)	(1.04)	(-0.79)	(1.69)	(0.50)	(1.65)	(0.32)	(0.85)	(0.10)	(-0.28)
$\bar{rx}^{ID}$	3.80	5.74	4.04	0.24	0.72	6.57	6.30	5.58	5.31	6.69	1.58	-3.74
t-stat	(2.65)	(4.24)	(3.22)	(0.21)	(0.54)	(5.20)	(4.60)	(5.19)	(3.75)	(5.02)	(1.28)	(-3.27)
$\bar{rx}^{ON}$	-4.05	-4.34	-2.52	1.53	-2.21	-3.45	-5.25	-3.04	-4.62	-4.94	-1.36	3.27
t-stat	(-2.96)	(-3.16)	(-1.85)	(1.09)	(-1.65)	(-2.68)	(-3.60)	(-2.39)	(-3.38)	(-3.44)	(-1.05)	(2.42)
Panel B: Intraday-Overnight trading												
	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1
$\bar{rx}^{ID-ON}$	7.85	10.08	6.56	-1.28	2.92	10.02	11.55	8.63	9.93	11.63	2.93	-7.00
t-stat	(4.14)	(5.17)	(3.68)	(-0.66)	(1.59)	(5.64)	(5.89)	(4.85)	(5.29)	(6.22)	(1.65)	(-3.77)
Panel C: Reversal Strategies												
	$P3^{ID} - P1^{ON}$		$P1^{ID} - P3^{ON}$		$P3^{ID} - P1^{ON}$		$P1^{ID} - P3^{ON}$		$P3^{ID} - P1^{ON}$		$P1^{ID} - P3^{ON}$	
$\bar{rx}^{Reversal}$	8.09		6.32		8.51		5.97		6.20		6.67	
t-stat	(4.95)		(3.29)		(4.79)		(3.12)		(3.60)		(3.60)	

Table VI. Time Series Momentum

This table reports average annualized returns ($\bar{rx}$) obtained from a time series momentum strategy, where currencies are bought at the beginning of a month when cumulative close-to-close (rx^{CTC}, Panel A), intraday (rx^{ID}, Panel B), or overnight (rx^{ON}, Panel C) excess returns over the previous 12 months are larger than zero, and currencies are sold if the aggregated excess returns are negative. The column "dol" refers to the dollar portfolio, which goes either long or short all foreign currencies. Numbers in squared parentheses denote the weight the return contributes to the close-to-close returns (% of $\bar{rx}^{CTC}$). ***,**,* indicate significance at the 1%, 5%, or 10% level, respectively. The sample period is January 1994 to December 2014, comprising 252 monthly observations.

Panel A: Sorted by rx^{CTC}

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK	dol
$\bar{rx}^{CTC}$	8.77***	5.43***	8.75***	5.10**	5.05***	10.21***	7.39***	10.15***	7.05***	5.50***
$\bar{rx}^{ID}$	3.49**	3.09**	7.13***	3.13*	3.21**	4.26***	3.11*	3.29**	3.18	1.96
% of $\bar{rx}^{CTC}$	[0.40]	[0.57]	[0.82]	[0.61]	[0.64]	[0.42]	[0.42]	[0.32]	[0.45]	[0.36]
$\bar{rx}^{ON}$	5.27**	2.34*	1.62	1.97	1.84	5.96***	4.28**	6.86***	3.87**	3.53***
% of $\bar{rx}^{CTC}$	[0.60]	[0.43]	[0.18]	[0.39]	[0.36]	[0.58]	[0.58]	[0.68]	[0.55]	[0.64]

Panel B: Sorted by rx^{ID}

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK	dol
$\bar{rx}^{CTC}$	7.45***	3.44*	4.77**	4.97**	3.03*	7.00***	5.42**	4.77*	5.18**	3.74**
$\bar{rx}^{ID}$	6.49***	6.89***	10.69***	8.22***	9.19***	6.21***	6.99***	6.85***	7.11***	6.05***
% of $\bar{rx}^{CTC}$	[0.87]	[2.00]	[2.24]	[1.65]	[3.04]	[0.89]	[1.29]	[1.44]	[1.37]	[1.62]
$\bar{rx}^{ON}$	0.97	-3.45***	-5.92***	-3.25**	-6.16***	0.79	-1.57	-2.08	-1.93	-2.29*
% of $\bar{rx}^{CTC}$	[0.13]	[-1.00]	[-1.24]	[-0.65]	[-2.04]	[0.11]	[-0.29]	[-0.44]	[-0.37]	[-0.61]

Panel C: Sorted by rx^{ON}

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK	dol
$\bar{rx}^{CTC}$	7.17***	1.87	4.80**	2.59	-0.25	9.47***	4.73*	10.32***	3.70	3.50*
$\bar{rx}^{ID}$	0.46	-4.28***	-5.39***	-5.21***	-8.64***	0.60	-2.82	1.80	-4.03**	-2.14*
% of $\bar{rx}^{CTC}$	[0.06]	[-2.29]	[-1.12]	[-2.01]	[34.78]	[0.06]	[-0.60]	[0.17]	[-1.09]	[-0.61]
$\bar{rx}^{ON}$	6.71***	6.15***	10.19***	7.80***	8.39***	8.88***	7.55***	8.52***	7.73***	5.62***
% of $\bar{rx}^{CTC}$	[0.94]	[3.29]	[2.12]	[3.01]	[-33.78]	[0.94]	[1.60]	[0.83]	[2.09]	[1.61]

Table VII. Intraday Returns: Variance Decomposition

This table reports the variance decomposition based on monthly intraday return series. σ^2_{ID} refers to the monthly return variance during main trading hours in New York (8.30 a.m. to 5.00 p.m., EST), while σ^2_{ON} is the monthly return variance over night (5.00 p.m. to 8.30 a.m., EST). $2 \times cov_{(IN,ON)}$ refers to the covariance of these two series, σ^2_{CTC} denotes the monthly return variance of close-to-close returns, sampled at 5.00 p.m. (EST). "dol" refers to the unconditional dollar portfolio that goes long all foreign currencies, and "dol (excl. JPY)" is the unconditional dollar portfolio that invests in all foreign currencies except the Japanese yen. Numbers in parentheses refer to the weight that each intraday return variance contributes to the monthly variance of close-to-close returns. The sum of the intraday variances and the covariance term (first three columns) equals to the monthly variance in the last column (σ^2_{CTC}). The sample period is January 1994 to December 2014, comprising 252 monthly observations.

	σ^2_{ID}	σ^2_{ON}	$2 \times cov_{(IN,ON)}$	σ^2_{CTC}
AUD	3.82	6.88	1.37	12.08
	[0.32]	[0.57]	[0.11]	[1.00]
CAD	3.38	3.03	-1.15	5.26
	[0.64]	[0.58]	[-0.22]	[1.00]
CHF	4.90	4.88	0.38	10.16
	[0.48]	[0.48]	[0.04]	[1.00]
EUR	4.06	3.82	0.78	8.66
	[0.47]	[0.44]	[0.09]	[1.00]
GBP	2.91	3.24	-0.36	5.78
	[0.50]	[0.56]	[-0.06]	[1.00]
JPY	3.40	5.98	0.69	10.06
	[0.34]	[0.59]	[0.07]	[1.00]
NOK	5.67	4.60	-0.73	9.54
	[0.59]	[0.48]	[-0.08]	[1.00]
NZD	3.99	9.38	-0.22	13.16
	[0.30]	[0.71]	[-0.02]	[1.00]
SEK	7.11	5.48	-2.20	10.39
	[0.68]	[0.53]	[-0.21]	[1.00]
dol	2.41	2.41	0.57	5.40
	[0.45]	[0.45]	[0.10]	[1.00]
dol	2.75	2.75	0.67	6.17
(excl. JPY)	[0.45]	[0.45]	[0.11]	[1.00]

Table VIII. Intraday Jump Risk, Intraday versus Overnight

This table reports the absolute and relative number of jumps for each currency pair for the overnight and intraday period, and for the entire day. Jumps are detected using the Lee and Mykland (2008) jump test statistic, where intraweek periodicity is taken into account following the procedure in Boudt, Croux, and Laurent (2011). The level of significance for the jump statistic is 5%. The test is based on 5-minute return data. $J > 0$ refers to the number of positive jumps (appreciation of foreign currency), $J < 0$ denotes the number of negative jumps (depreciation of foreign currency), and J is the total number of jumps. Numbers in brackets refer to the relative number of jumps in the sub-period, in percent, compared to the total number of jumps. $-\Delta s^{ON}$ refers to the overnight period (5:00 p.m. to 8.30 a.m. EST), $-\Delta s^{ID}$ denotes the intraday period (8:30 a.m. to 5:00 p.m.), and $-\Delta s^{CTC}$ refers to close-to-close, capturing the dynamics of the entire trading day. The sample period is January 1994 to December 2014.

	$-\Delta s^{ON}$			$-\Delta s^{IN}$			$-\Delta s^{CTC}$		
	$J > 0$	$J < 0$	J	$J > 0$	$J < 0$	J	$J > 0$	$J < 0$	J
AUD	5,309	5,735	11,044	2,919	3,223	6,142	8,228	8,958	17,186
	(31)	(33)	(64)	(17)	(19)	(36)	(48)	(52)	(100)
CAD	10,016	9,608	19,624	2,652	2,379	5,031	12,668	11,987	24,655
	(41)	(39)	(80)	(11)	(10)	(20)	(51)	(49)	(100)
CHF	7,226	7,073	14,299	3,125	2,935	6,060	10,351	10,008	20,359
	(35)	(35)	(70)	(15)	(14)	(30)	(51)	(49)	(100)
EUR	4,977	5,147	10,124	2,691	2,697	5,388	7,668	7,844	15,512
	(32)	(33)	(65)	(17)	(17)	(35)	(49)	(51)	(100)
GBP	7,033	7,309	14,342	3,090	2,883	5,973	10,123	10,192	20,315
	(35)	(36)	(71)	(15)	(14)	(29)	(50)	(50)	(100)
JPY	5,074	4,606	9,680	2,968	2,711	5,679	8,042	7,317	15,359
	(33)	(30)	(63)	(19)	(18)	(37)	(52)	(48)	(100)
NOK	11,366	11,389	22,755	3,477	3,374	6,851	14,843	14,763	29,606
	(38)	(38)	(77)	(12)	(11)	(23)	(50)	(50)	(100)
NZD	6,951	7,366	14,317	3,770	3,917	7,687	10,721	11,283	22,004
	(32)	(33)	(65)	(17)	(18)	(35)	(49)	(51)	(100)
SEK	10,713	10,629	21,342	3,582	3,507	7,089	14,295	14,136	28,431
	(38)	(37)	(75)	(13)	(12)	(25)	(50)	(50)	(100)

Table IX. Liquidity Dynamics: Average Bid-Ask Spread

This table reports the average bid-ask spread for close-to-close ($B\bar{A}S^{CTC}$), intraday ($B\bar{A}S^{ID}$, 8.30 a.m. to 5.00 p.m., ET), and overnight ($B\bar{A}S^{ON}$, 5.00 p.m. to 8.30 a.m., ET) periods. Bid-ask spreads are measured in basis points. The bottom part shows t-statistics of a t-test with the null hypothesis $H_0 : B\bar{A}S^i = B\bar{A}S^j$ where $i \neq j$ and $i, j = CTC, ID, ON$. The sample period is January 1994 to December 2014, comprising 252 monthly observations.

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK
$B\bar{A}S^{CTC}$	2.72	2.03	1.98	1.41	1.61	1.84	3.42	4.58	4.20
$B\bar{A}S^{ID}$	2.52	1.68	1.73	1.20	1.37	1.60	2.68	4.00	3.51
$B\bar{A}S^{ON}$	2.49	1.91	1.82	1.28	1.40	1.62	3.03	4.05	3.57
$B\bar{A}S^{CTC} = B\bar{A}S^{ID}$	8.02	29.60	16.48	17.01	18.57	13.89	41.02	17.37	26.27
$B\bar{A}S^{CTC} = B\bar{A}S^{ON}$	9.80	8.81	10.46	9.43	16.06	13.14	18.03	16.30	25.07
$B\bar{A}S^{ON} = B\bar{A}S^{ID}$	9.45	-149.19	-48.18	-52.07	-24.56	-5.99	-137.46	-12.40	-21.95

Table X. Average Annualized Net Returns incl. Transaction Costs

This table reports the average annualized gross ($-\Delta s^i$) and net spot return ($-\Delta s^i_{Net}$), where $i = ON, ID, CTC$ refers to overnight, intraday, and close-to-close, respectively. The superscripts "L" and "S" denote long foreign currency and short foreign currency positions, respectively. Overnight returns are generated between 5:00 p.m. and 8:30 a.m. the following day, while intraday refers to returns generated between 8:30 a.m. and 5:00 p.m. on the same day. Close-to-close returns are sampled at 5:00 p.m. which marks the end of the main trading hours in New York. All times are expressed in Eastern Time. For long positions investors, buy at the asked price and sell at the bid price. For short positions, investors sell at the ask and buy at the bid price. Numbers in parentheses denote t-statistics. The sample period is January 1994 to December 2014, comprising 252 monthly observations.

	Avg. Ann. Return			Avg. Ann. Net Return		
	$-\Delta s^{ON,L}$	$-\Delta s^{ID,L}$	$-\Delta s^{CTC,L}$	$-\Delta s^{ON,S}_{Net}$	$-\Delta s^{ID,L}_{Net}$	$-\Delta s^{CTC,L}_{Net}$
AUD	-2.56	3.41	0.85	-5.15	-3.38	-0.11
	(-1.31)	(2.27)	(0.32)	(-2.69)	(-2.25)	(-0.04)
CAD	-0.92	1.51	0.59	-4.43	-3.55	-0.08
	(-0.69)	(1.07)	(0.33)	(-3.33)	(-2.51)	(-0.05)
CHF	-6.57	8.54	1.97	1.02	3.59	0.71
	(-4.07)	(5.13)	(0.84)	(0.63)	(2.15)	(0.32)
EUR	-7.02	7.41	0.38	3.00	3.89	-0.32
	(-4.80)	(4.88)	(0.18)	(2.07)	(2.56)	(-0.15)
GBP	-8.22	8.48	0.26	3.78	4.46	-0.58
	(-6.10)	(6.65)	(0.14)	(2.85)	(3.51)	(-0.34)
JPY	1.73	-2.01	-0.28	-7.11	-6.61	-0.61
	(0.93)	(-1.46)	(-0.12)	(-3.77)	(-4.78)	(-0.27)
NOK	-2.79	2.87	0.08	-6.46	-5.67	-1.56
	(-1.69)	(1.61)	(0.03)	(-3.84)	(-3.11)	(-0.68)
NZD	-2.25	3.83	1.58	-10.13	-7.58	0.11
	(-0.99)	(2.54)	(0.59)	(-4.53)	(-5.04)	(0.04)
SEK	-5.22	5.60	0.38	-5.99	-4.86	-1.05
	(-2.91)	(2.77)	(0.16)	(-3.32)	(-2.38)	(-0.46)

VIII. Appendix: Figures

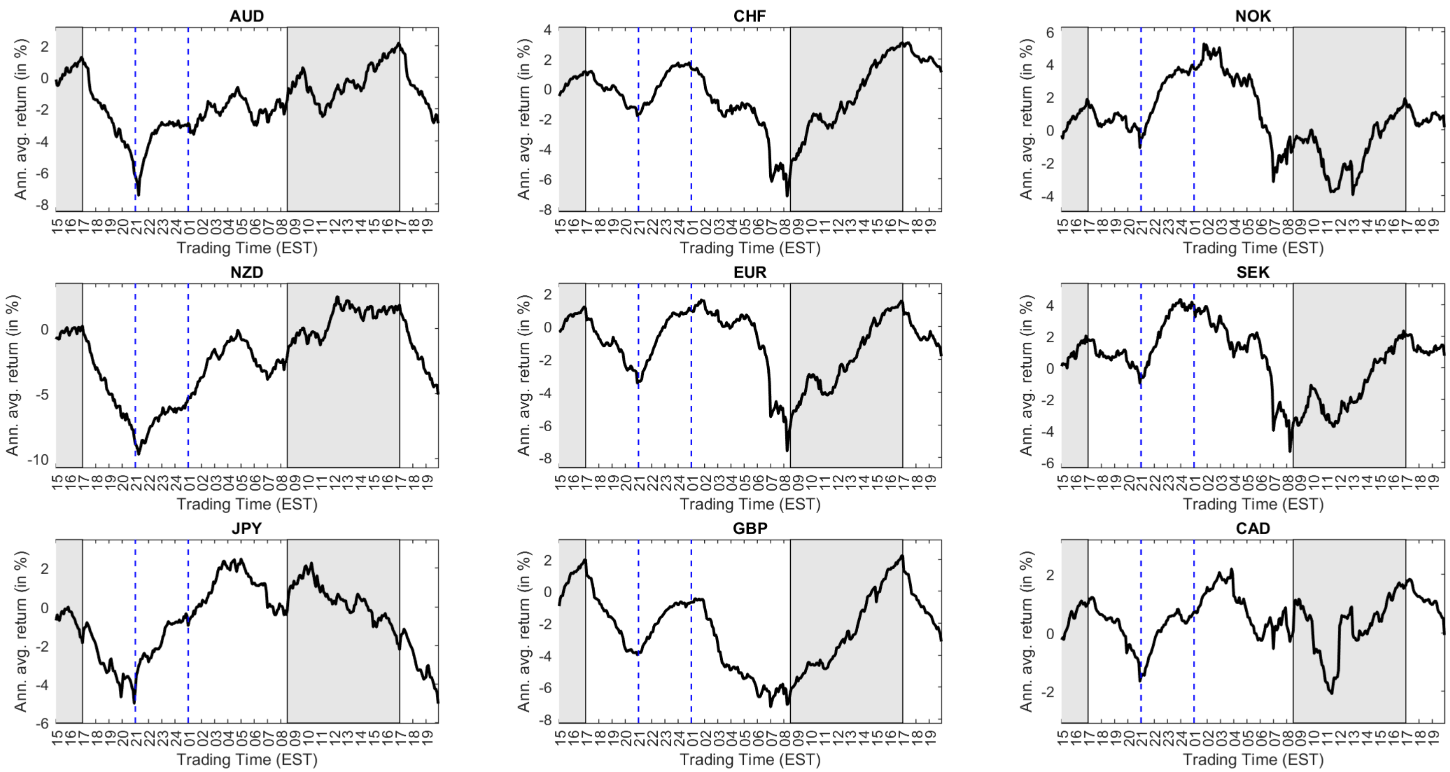

Figure 1. Cumulative 5-min returns

This figure displays the cumulative average annualized 5-min returns ($-\Delta s$). The grey shaded area marks main trading hours in New York (8:30 a.m. to 5:00 p.m.). Blue dashed lines indicate opening hours of main Southeast Asian trading venues in Singapore and Hong Kong, and beginning of European trading. Hours (x-axis) refer to Eastern Standard Time. The sample period comprises all months between January 1994 to December 2014.

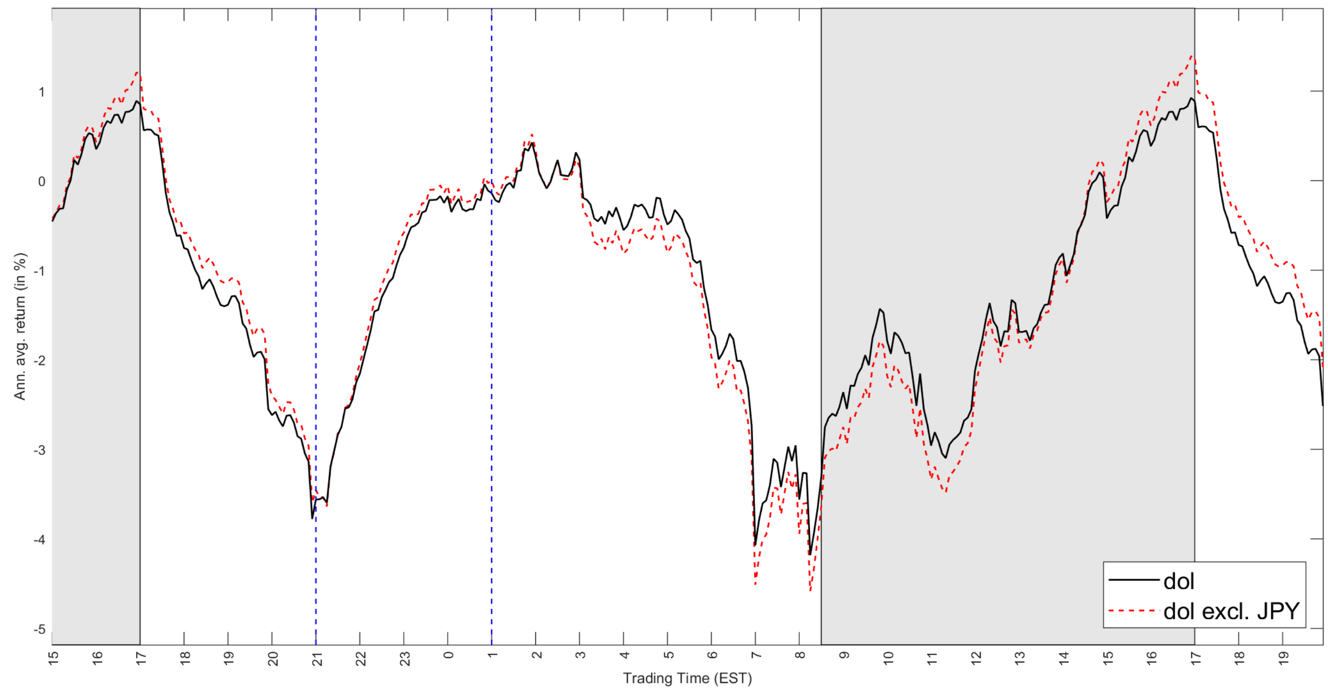

Figure 2. Unconditional Dollar Portfolio: Cumulative 5-min returns
This figure displays the cumulative average annualized 5-min returns ($-\Delta s$) of the unconditional dollar portfolio that goes long all foreign currencies ("dol") and all currencies except the japanese yen ("dol excl. JPY"). The grey shaded area marks main trading hours in New York (8:30 a.m. to 5:00 p.m.). Blue dashed lines indicate opening hours of main Southeast Asian trading venues in Singapore and Hong Kong, and beginning of European trading. An increase of the dollar portfolio implies that foreign currencies appreciate against the U.S. dollar. Hours (x-axis) refer to Eastern Standard Time. The sample period comprises all months between January 1994 to December 2014.

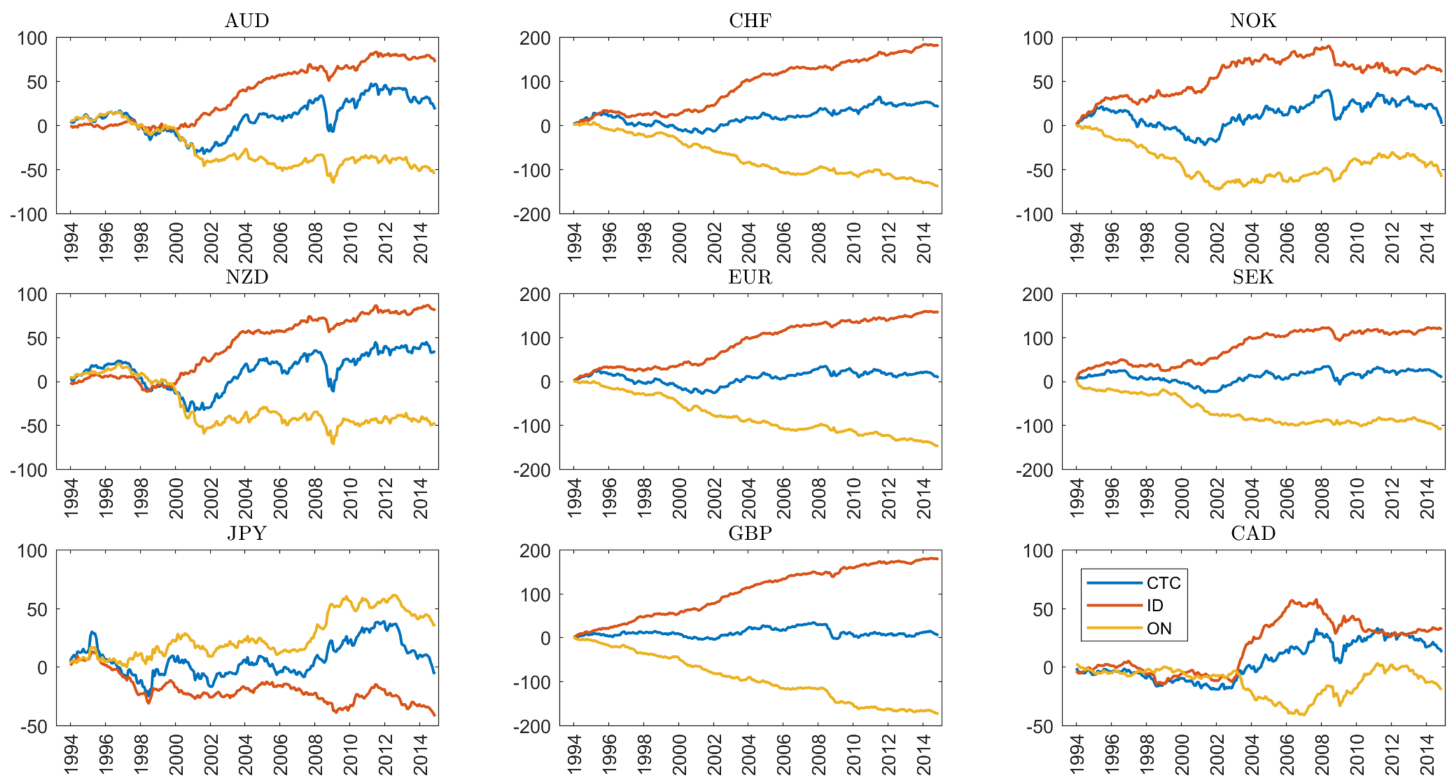

Figure 3. Cumulative returns

This figure displays cumulative monthly log returns for close-to-close ($-\Delta s^{CTC}$), intraday ($-\Delta s^{intra}$), and overnight ($-\Delta s^{over}$) time series. The sample period is January 1994 to December 2014.

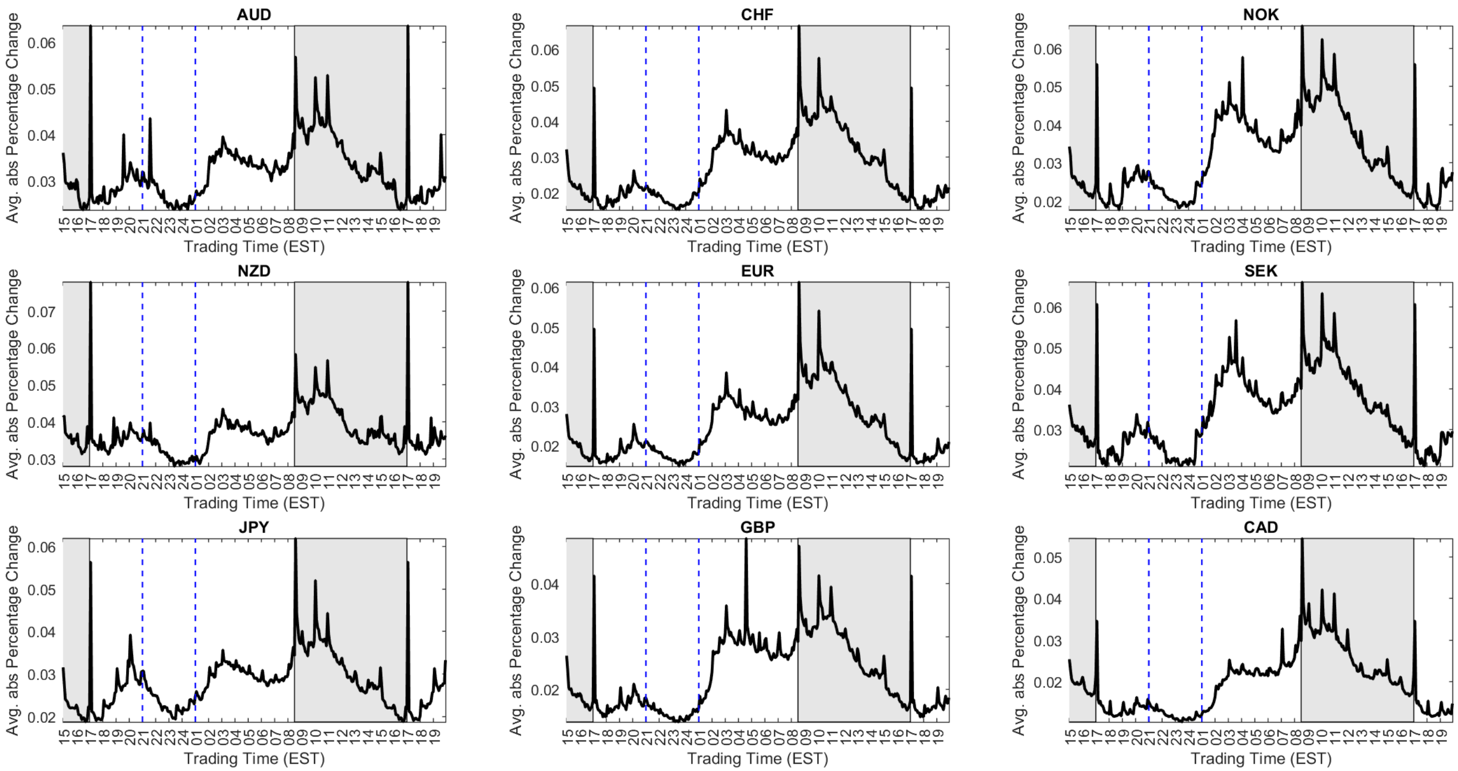

Figure 4. Intraday Volatility: Average Absolute Percentage Change

This figure displays the average absolute percentage change $|\Delta \bar{s}_i| = 1/T \sum_{i=1}^{T} |\Delta s_i|$ as a measure of intraday volatility, where Δs_i refers to the 5-min return at time i, and T refers to the total number of days in the sample. The grey-shaded area marks main trading hours in New York (8:30 a.m. to 5:00 p.m.). Blue dashed lines indicate opening hours of the main Southeast Asian trading venues in Singapore and Hong Kong, and beginning of European trading. Hours (x-axis) refer to Eastern Standard Time. The sample period comprises all months between January 1994 to December 2014.

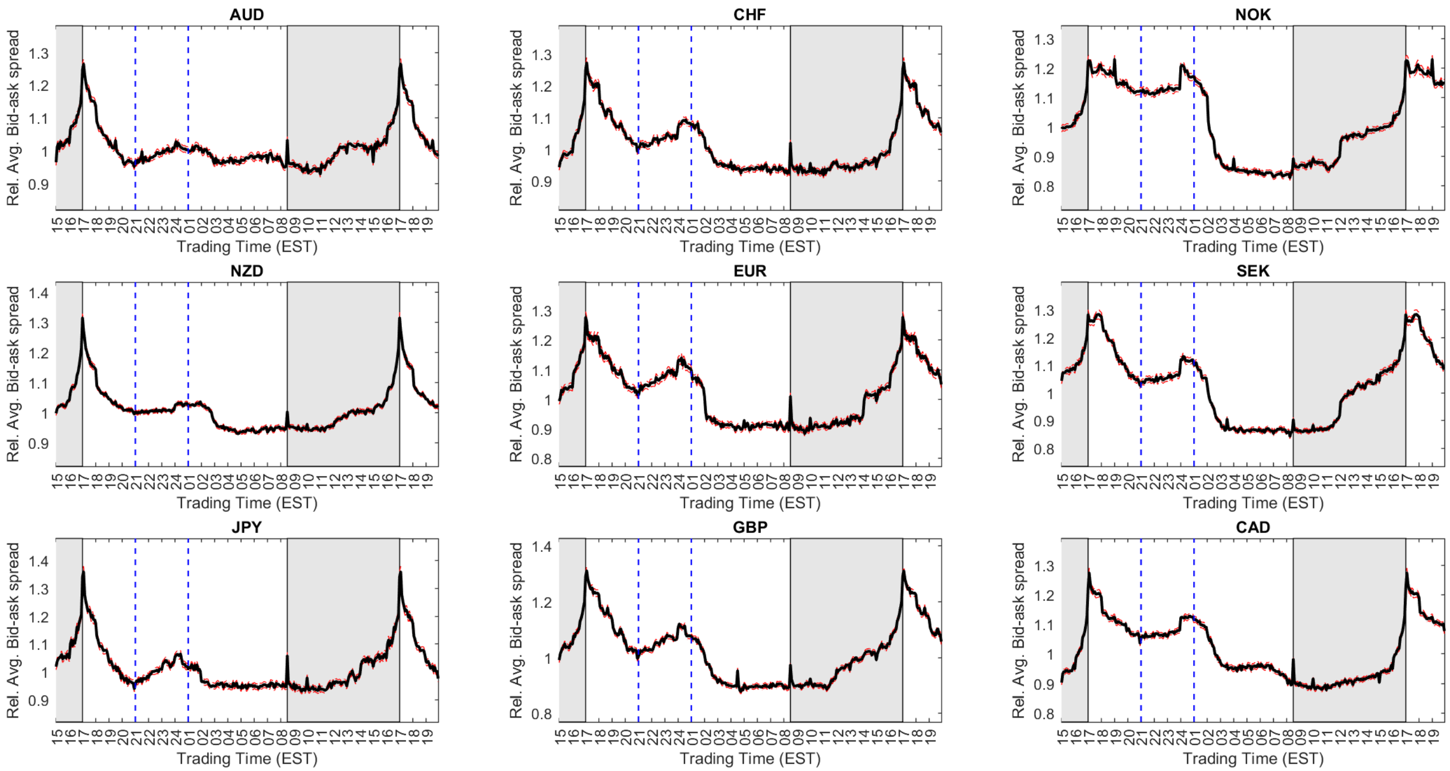

Figure 5. Average Bid-Ask Spread

This figure displays the relative average bid-ask spread at the 5-min frequency. The bid-ask spread is constructed as $(ask_t - bid_t)/mid_t$, where ask_t, bid_t, and mid_t refer to the ask, bid, and mid price, respectively. Each bid-ask spread is normalized by the average bid-ask spread during the associated day. Values above (below) 1 indicate a bid-ask spread higher (lower) than the daily average. The grey shaded area marks main trading hours in New York (8:30 a.m. to 5:00 p.m.). Blue dashed lines indicate opening hours of the main Southeast Asian trading venues in Singapore and Hong Kong, and beginning of European trading. Hours (x-axis) refer to Eastern Standard Time. The sample period comprises all months between January 1994 to December 2014.

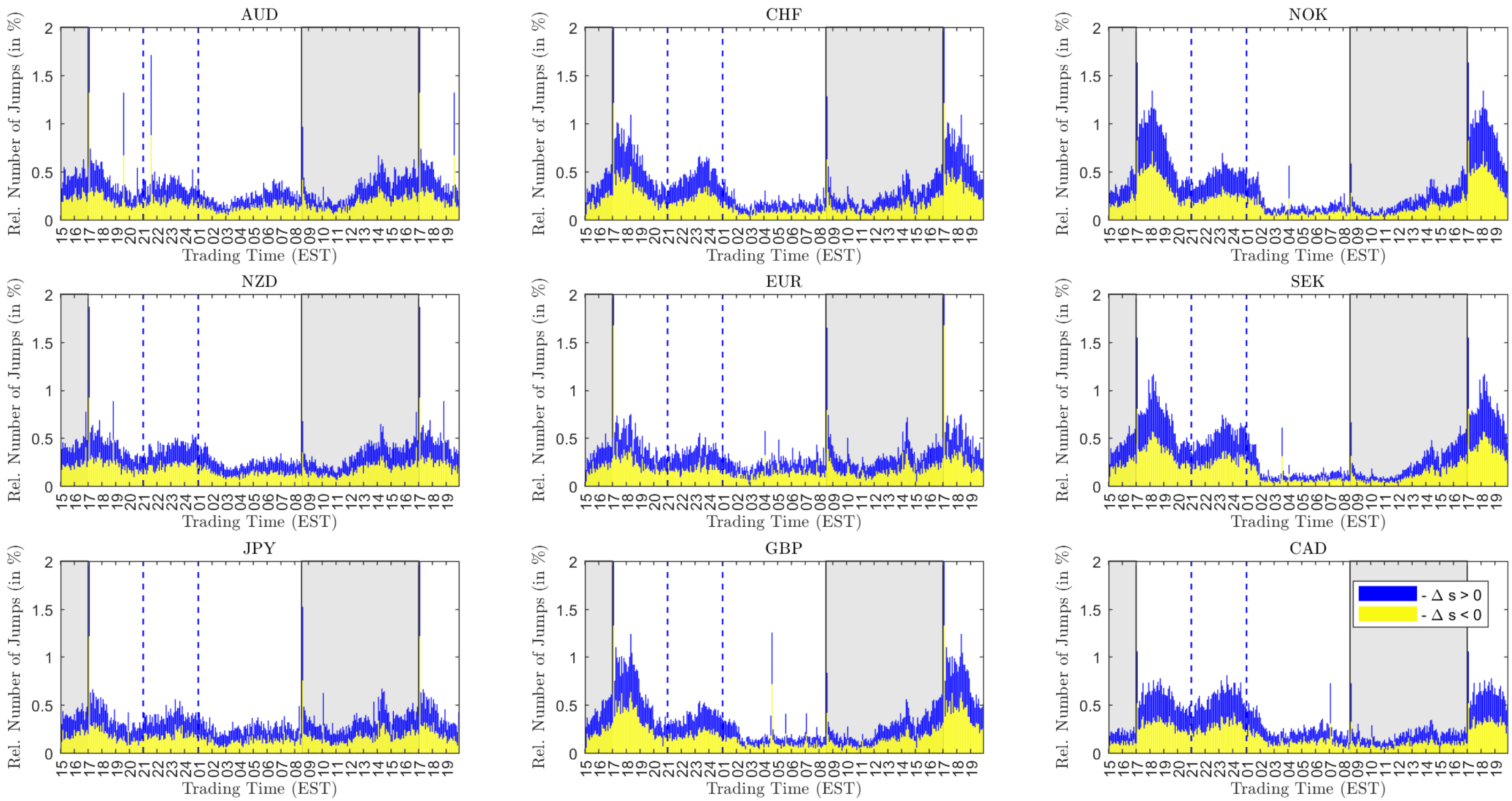

Figure 6. Intraday Crash Risk

This figure displays the relative number of jumps that occur during each 5-minute interval across the entire trading day. Jumps are detected using the Lee and Mykland (2008) jump test statistic, where intraweek periodicity is taken into account following the procedure in Boudt, Croux, and Laurent (2011). The level of significance for the jump statistic is 5%. The blue bars ($-\Delta s_t > 0$) denote positive jumps (appreciation of the foreign currency), while the yellow bars ($-\Delta s_t < 0$) refer to negative jumps (depreciation of the foreign currency). The x-axis refers to daily trading hours, measured in Eastern Standard Time (EST). They y-axis measures the relative number of jumps (in %) during each 5-minute interval.

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