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# Foreign Exchange Fixings and Returns Around the Clock


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# Abstract

We document that intraday currency returns display systematic reversals around the major benchmark fixings, characterized by an appreciation of the U.S. dollar pre-fix and a depreciation post-fix. We propose an explanation based on constrained intermediation by foreign exchange dealers. Exploiting data from a major inter-dealer platform, we present evidence of an unconditional demand for U.S. dollars at currency fixings. Dealers hedge this demand pre-fix, driving intraday reversals in both over-the-counter and exchange-traded markets. Furthermore, order imbalances in futures markets are not related to intraday reversal patterns, suggesting that the marginal investors in foreign exchange markets are intermediaries.



*Topics: Financial markets; Exchange Rates; Market structure and pricing*

*JEL codes: F3, F31, G15*

The foreign exchange market trades continuously on a 24-hour decentralized basis across the globe in different time zones, from 5:00 a.m. Sydney time on Monday morning until 5:00 p.m. New York time on Friday afternoon. In this paper, we study high-frequency currency returns around the clock and document a novel intraday return pattern. The U.S. dollar systematically appreciates against all currencies ahead of the three major currency fixes in Tokyo, Frankfurt (the ECB fix) and London, and thereafter reverts. In other words, a portfolio that invests in foreign currencies against the U.S. dollar exhibits $V$-shaped return patterns around the currency fixes that take place at 9:55 a.m. Tokyo time, 2:15 p.m. Frankfurt time and 4:00 p.m. London time.

To establish this fact we construct intraday returns for the G9 currencies for the sample period from January 1999 until December 2019.[1] Consider the dollar portfolio that invests equal weights in the foreign currencies. After trading in New York ceases and in the run up to the Tokyo fix, the dollar portfolio depreciates on average by 5.0%, and appreciates thereafter by 5.3% per annum. That is, during regular Asian trading hours from the end of the day in New York until the opening of the European markets, the dollar portfolio is approximately flat on average but displays a large intraday reversal with a turning point marked by the Tokyo fix. As European markets open, the dollar portfolio again depreciates by 4.2% per annum until the ECB fix, just to reverse its course again and to appreciate by around 4.6% from the London fix until the end of the trading day in New York. As in Asian trading hours, the dollar portfolio remains approximately flat during the European and U.S. trading hours but displays a distinct reversal pattern around the European fixes in Frankfurt and London. All the average movements in the dollar portfolio during the respective windows are highly statistically significant with $t$-statistics ranging between 4.5 and 11.7.

On a daily basis, the intraday reversals imply a roughly 2.5 basis point appreciation of the U.S. dollar before the respective fixes, followed by a depreciation of the same magnitude

[1] The currencies we study against the U.S. dollar are the Australian dollar, the Canadian dollar, the euro, the British pound, the Japanese yen, the New Zealand dollar, the Norwegian krone, the Swedish krona and the Swiss franc. These currency pairs cover approximately 75% of daily spot turnover based on data from BIS (2019).

thereafter. This appears small compared to the volatility in foreign exchange markets but given the size of the spot market alone, this translates into significantly large magnitudes expressed in U.S. dollar terms. Based on daily turnover numbers from the 2019 Triannual BIS survey, we estimate that the patterns we detect imply swings that easily exceed a billion U.S. dollars per day.

The return patterns for the dollar portfolio are robust across individual currency pairs. All currencies display $V$-shaped reversal patterns around Asian and European fixes, respectively, with the Japanese yen being the sole exception to actually depreciate after the London fix. Moreover, we show that our findings are robust over time and are not driven by day of the week or month of the year effects, and they are present throughout the sample period.

Finally, the reversal patterns in the spot market are also present in the over-the-counter forward as well as the exchange-traded futures markets. This is important because the presence of a robust intraday seasonality in spot and derivatives markets implies that the timing of portfolio adjustments should be an important consideration for asset managers, institutional investors and corporate end users of foreign exchange alike. At the same time, this is not very surprising if one assumes that no-arbitrage holds in foreign exchange markets.

We conjecture an explanation for our main empirical finding based on constrained intermediation by foreign exchange dealers who provide immediacy for segmented transaction demand around the clock. Indeed, the structure of the foreign exchange market is such that a huge amount of volume remains intermediated by a small set of firms acting as marginal investors.[2] This implies that a small number of market participants warehouse the majority of foreign exchange inventory risk over the course of the day and across different time zones.

Benchmark microstructure models that study demand for immediacy and inventory risk (see, e.g., Stoll (1978), Grossman and Miller (1988), and Vayanos (1999, 2001)) provide an intuitive framework for our explanation. In these models, dealers are needed because buyers

[2] Data from Euromoney FX Surveys shows that within any given year from 1999 to 2019, between 30% and 60% of total spot volume is concentrated amongst five banks. In 2019 the top five liquidity providers account for 40% of total volume but only three of them are banks (JP Morgan, Deutsche Bank and UBS) while two are non-bank liquidity providers (XTX Markets and HC Tech).

and sellers in financial markets arrive asynchronously, creating transient imbalances between buy and sell volumes. Dealers act as liquidity suppliers, absorbing imbalances by offering immediacy to incoming traders and subsequently transacting with counterparties arriving at later points in the day. A common prediction from these models is that incoming order imbalances due to heterogeneously timed trades generate price reversal patterns around "liquidity events" à la Grossman and Miller (1988). We argue that the key times in the day for these to arise are around the currency fixing times.

Moreover, we draw an analogy between intraday foreign exchange reversals and price patterns in the Treasury market around pre-scheduled auction dates as studied by Lou, Yan, and Zhang (2013), whereby prices of Treasury securities gradually decline in anticipation of the auction date while recovering thereafter. In the Treasury market, dealers face an uncertain positive net supply of bonds and hedge their positions by selling ahead of auction dates. The analogous behavior in currency markets is known as "pre-fix hedging" and happens on a daily basis, i.e., at a much higher frequency. Banks with advanced knowledge of order imbalances are explicit in their intentions to hedge and they openly acknowledge that this practice may have unintended consequences for exchange rates.[3] Unlike the situation in the Treasury market, dealers in the foreign exchange markets can be faced with an excess demand or supply for U.S. dollars on any given day.

Drawing from the stylized facts and using our conjectured explanation, we formulate three testable implications. First, the local peaks in the U.S. dollar imply that there is excess net demand for U.S. dollars around the fixes *on average*. Second, an explanation based on liquidity provision of financially constrained intermediaries implies that we observe *a reversal* in the price of the U.S. dollar after a liquidity event, even though on any given day the net demand for U.S. dollars could be positive or negative. Third, since dealers and intermediaries are ultimately driving the results, we expect order flow from a dealers' market to be *more informative* than order flow from any other market where dealers are not

[3] The intention to engage in pre-fix hedging is usually part of the client agreement laid out in the "FX Disclosure Notice." See, e.g., https://www.db.com/legal-resources/fixed-income-disclosures.

dominant.

Empirically, we study intraday demand for U.S. dollars by exploiting signed trading volume in two markets: (*i*) the Refinitiv FX Matching (RM) inter-dealer platform; and (*ii*) the Chicago Mercantile Exchange (CME) FX futures market. This allows us to consider information from two distinct platforms populated by participants with heterogeneous trading motives. RM is a platform for inter-dealer trading while trading on CME is more diverse and features asset managers, leveraged funds and other participants in addition to dealers and intermediaries.[4] For the sample period from 2006 to 2019, we measure order flow defined as buyer- minus seller-initiated trading volume.

First, we show that for currencies and time periods where liquidity is high on the RM platform, the unconditional dealer order flow is tilted towards an excess demand for U.S. dollars before the fixes and excess demand for foreign currencies thereafter.[5] For example, before the London fix, the Australian dollar and British pound each have a median order imbalance of 20 million U.S. dollars in the direction of dollar demand, thus explaining the unconditional $V$-shaped return pattern around the fix. Second, to test for conditional reversals related to price pressure, we estimate price impact regressions of returns on contemporaneous as well as lagged order flow. Consistent with our proposed explanation, we show that lagged pre-fix dealer order flow has a strong *negative* impact that is highly statistically significant across time zones and currency pairs, i.e., we find strong evidence for reversals around the fixes based on price pressure. Interpreting the economic impact, a one-standard deviation shock to the pre-fix order imbalance results in a post-fix reversal of around 2.5 to 3.5 basis points depending on the currency. This effect is on par with the magnitude of the unconditional average daily swings we document over our full sample period.

We also document evidence that dealer order flow measured using RM data is more informative for price discovery than futures order flow from CME: (*i*) For *contemporaneous* order

[4]According to data from the commodities futures trading commission (CFTC), dealers and intermediaries usually account for 20% to 30% of open positions in foreign exchange futures at any given point in time.

[5]Note that this does not imply an unconditional demand for U.S. dollars when measured over the course of the full day.

flow taken from either RM or CME, we do indeed find positive and statistically significant coefficient estimates when running univariate regressions, as predicted by standard models. However, compared across platforms, the coefficient estimates for the RM order flow are roughly a magnitude larger compared to the estimates for the CME order flow. Moreover, dealer order flow from RM largely subsumes the information contained in the futures order flow once it is added to the CME regressions. (*ii*) Using CME data, we find no evidence of a significant relationship between pre-fix futures order flow and subsequent window returns. At the same time, dealer order flow retains the same sign, and has similar magnitudes and significance when added to the regressions with CME data, i.e., dealer order flow remains informative in the context of futures data. (*iii*) Unconditionally, order flow in the FX futures market displays no discernible pattern over the course of the day. Taken together, the results suggest that the order flow from the dealer platform is informative for prices across different markets. Moreover, the regression results as well as the unconditional patterns in order flow further support the view that information from electronic dealer markets is more informative for price discovery than information from the futures market.[6]

Finally, we study whether the patterns we document can be exploited using various trading strategies. First, ignoring transaction costs, we find that the returns to a strategy that goes long the U.S. dollar before the fix and invests in the foreign currencies thereafter yields significant returns over time. An initial position of 1 U.S. dollar in 1999 grows to 12 (yen), 9 (euro and dollar portfolio) and 5 (pound) U.S. dollars by 2019, respectively, when implementing the trading strategy around the Tokyo fix. Around the European fixes (i.e., going long the U.S. dollar before the ECB fix combined with a long position in the foreign currency after the London fix), the trading portfolio grows to 27 (euro), 14 (pound) and 6 (dollar portfolio) U.S. dollars, respectively, while trading the yen around the European fixes results in a total loss of around 6%. As we argue that the reversals are driven by inventory risk, it is not very surprising that most of the trading profits disappear when transaction costs

[6]See, also, BIS (2018) for evidence on the importance of electronic platforms for price discovery in foreign exchange markets.

are incorporated. Moreover, in line with an explanation based on constrained intermediation, we also show that reversal returns are high in times of high volatility. Similar to the results for equity markets documented in Nagel (2012), we find that returns from liquidity provision are highly predictable using the VIX index.

In addition to the literature cited above, our paper is related to early work on intraday patterns in foreign exchange markets (see, e.g., the discussion in Ranaldo (2009)). Ranaldo (2009) and Breedon and Ranaldo (2013) revisit the early inconclusive evidence and find that foreign currencies depreciate during local trading hours. Moreover, these authors show that returns are correlated with order flow, supporting the view that liquidity effects are important in foreign exchange markets and complementing the transactions hypothesis of Cornett, Schwarz, and Szakmary (1995).[7]

With respect to these papers, our contribution is twofold: First, our granular dissection allows the identification of price reversals around major currency fixes. Indeed, while it is true that the U.S. dollar depreciates during U.S. trading hours, the downward drift only starts after the London fix at 11:00 a.m. ET. Similarly, European currencies depreciate only until the ECB fix at 2:15 p.m. local time, i.e., a couple of hours before the end of the local trading day. Additionally, the yen actually appreciates during Asian trading hours against the U.S. dollar, while the opposite is true during U.S. trading hours. Second, we provide an explanation for the reversal patterns and argue that unconditional dollar demand at the fix coupled with pre-hedging activity by foreign exchange dealers is consistent with the $V$-shaped return patterns around the fixes.

Contributions of Evans and Lyons (2002) and Froot and Ramadorai (2005) show that order flow has powerful explanatory power in exchange rate determination. Complementing these works, our findings highlight that dealer order flow is more important than order flow originating from trading activity of speculators and hedgers in the futures market. Thus, heterogeneity in trading demand matters when linking quantities and prices and it is

[7]The working paper version of Ranaldo (2009) also argues for a liquidity hypothesis based on the Grossman and Miller (1988) framework.

important to understand where the marginal investors trade. Consistent with the idea that dealers are the marginal investors and that they are active on the RM platform, the RM order flow is driving returns across all markets when measured contemporaneously. Moreover, the negative loadings on *lagged* dealer order flow is consistent with the conjecture that their inventory risk is related to the price reversals around the fixes.

As we highlight the importance of the fixes for the return patterns, our paper is also related to a literature in market microstructure studying foreign exchange benchmarks. For the London fix, Evans (2018) assesses price dynamics in tight windows around the fix in the context of collusion as suggested by the fixing scandal, while Evans, O'Neill, Rime, and Saakvitne (2018) show differences in trading behavior across investor types. Unlike these papers, we consider much longer windows around the fixes and highlight the unconditional gradual appreciation and subsequent depreciation of the U.S. dollar. Finally, our paper is also related to Ito and Yamada (2016), who document a structural demand for U.S. dollars at the Tokyo fix. However, unlike them, we show that U.S. dollar demand coupled with pre-fix hedging practices manifests itself in a systematic appreciation and depreciation pattern around both the Tokyo and European fixes tracing out a $W$-shaped return pattern around the clock.

The paper is organized as follows: In Section I we discuss currency fixes before describing the data in Section II. In Section III we present the central empirical contribution, namely the unconditional $V$-shaped return patterns around the fixes along with a series of robustness tests. In Section IV we examine a potential explanation based on trading imbalances and dealer hedging practices. Finally, in Section V we study trading strategies designed to exploit the predictability in intraday reversals and Section VI concludes.

## I. Foreign Exchange Fixes

A foreign exchange fix is a pre-set time of day when bids and offers are aggregated and a reference price is published. Historically, the most popular fixes are the London, ECB and

Tokyo fixes. Figure 1 depicts these fixes visually in Eastern Time (ET, the time in New York) "around the clock." The colored blocks in Figure 1 show the regular trading hours in the futures markets of each location. The figure begins at 5:00 p.m. ET which is the end of the trading day in New York and roughly the beginning of the trading day in Australasia. The first major currency fix that occurs is Tokyo at 9:55 a.m. local time which is 8:55 p.m. ET (or 7:55 p.m. depending on daylight saving time (DST)). The red, green and yellow blocks overlap, meaning that as Japanese trading is closing, European markets are opening. The beginning of the trading day in New York (we assume 8:00 a.m. for currencies) happens close to the "ECB fix" at 8:15 a.m. ET (2:15 p.m. local time) but the timing is clearly not exactly aligned. Moreover, and importantly, the ECB fix is also not aligned with the usual release time of macro announcements at 8:30 a.m. ET. As we argue later, this distinction in timing is important when considering intraday price movements in exchange rates. The final and most important fix of the day is the London fix at 4:00 p.m. local time (or 11:00 a.m. ET).

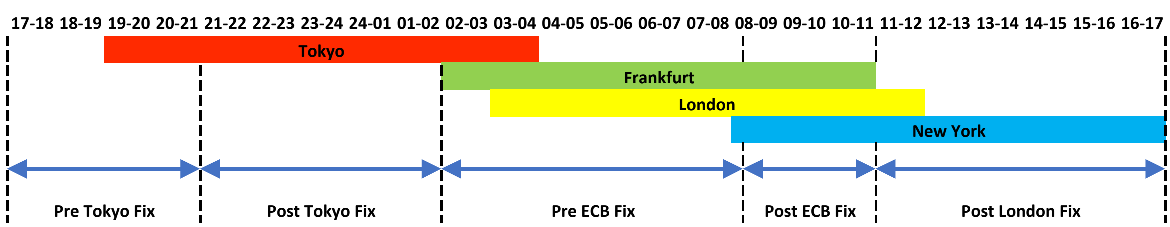



**Figure 1. Currency Fixes across Time Zones**

While all fixes have an impact on foreign exchange markets, they differ from each other with respect to institutional characteristics, publication time of reference rates, and the methodologies to compute fix rates. In what follows, we provide a summary of the institutional characteristics of the three major fixes in currency markets.

First, the Tokyo fix rates are published at 10:00 a.m. local time, whereby each bank determines its own individual fix rate for their customers. This is a major difference compared to the ECB and London fixes, where only one reference rate is published. The rates of the

Tokyo fix are based on transacted prices, which banks sample from their own customer transactions at 9:55 a.m. Further, the fixing rate applies not only to pre-fixing but also to post-fixing customer orders, which are submitted after 10:00 a.m. The Tokyo fixing, therefore, has far-reaching consequences for banks over the remainder of the trading day (see, e.g., Ito and Yamada (2016)).

Second, reference rates from the ECB fix are based on a daily teleconference between eurozone central banks at 2:15 p.m. CET. The reference rates are the average of quoted bid and offer prices against the euro, which means that the ECB reference rate is not based on actual transactions. However, the ECB reference rates are often used by non-financial corporations in the euro-area that use forward contracts for hedging purposes (see, e.g., FSB (2014)). To stress that the euro foreign exchange reference rates are for information purposes *only*, the ECB has moved the publication of the reference rates to 4:00 p.m. CET in July 2016 while keeping the methodology unchanged (ECB (2019)). Subsequently, the Reuters 2:00 p.m. CET fix was introduced to target corporates who had previously valued, hedged and settled cross-border transactions using the ECB fix.

Lastly, the London fix rate is set at 4:00 p.m. London time and published by WM/Reuters. In contrast to the Tokyo fix, the London fix applies to all banks and is calculated from pre-fix orders that arrive before 4:00 p.m. The fix rate is then computed based on trades (and quotes for less-liquid currency pairs) in a window around 4:00 p.m. In a five-minute interval around the fix (3:57:30 p.m. to 4:02:30 p.m.), traded rates are sourced every second from major FX platforms and a median trade based on bid and offer rates is calculated from the pooled sample of trades.[8] The London fix is prominently used by various groups of market participants to value their international portfolio positions (see, e.g., Melvin and Prins (2015)).

[8] Before 15 February 2015, the length of the window to calculate the fix rate was only a one-minute interval from 3:59:30 p.m. to 4:00:30 p.m.

## II. Data

We compile our data from multiple sources including Refinitiv, the CME, Bloomberg and Datastream. In this section we briefly describe the main data, while we discuss additional data sources and further details regarding data pre-processing and cleaning in the Online Appendix. Our full sample starts in January 1999 and ends in December 2019, covering 21 years of high-frequency tick-by-tick data for the G9 currencies, including 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), the Swiss franc (CHF) and the British pound (GBP), all vis-à-vis the U.S. dollar. These currencies are consistently among the most liquid currencies over the sample period, and together they account for close to 75% of the total daily turnover in the foreign exchange market based on calculations using information available from the latest triannual BIS survey (see BIS (2019)).

For the sample period from January 1999 to December 2019, we have high-frequency *indicative* bid and ask quotes from Refinitiv Tick History (RTH) , which essentially acts as an aggregator of quotes from individual banks that are available to market participants to trade "bank-to-client". From the RTH data, we cannot gauge the volume of transactions or the price at which transactions are executed even though most transactions in the foreign exchange market are still executed over-the-counter.

Starting in June 2006 we also have data from the Refinitiv FX Matching (RM) platform that provides real-time data on *traded* prices as well as volumes. Furthermore, the RM data includes information that allows us to calculate various measures of order flow. Together with Electronic Broking Services (EBS), RM is the leading inter-dealer platform for foreign exchange trading with a daily volume for spot transactions exceeding 100 billion U.S. dollars (compared to around 76 billion U.S. dollars traded on EBS).[9] While not all currency pairs

[9]EBS is now part of CME, offering an inter-dealer platform alongside the foreign exchange futures and options traded on the exchange.

are equally liquid on both platforms (RM), e.g., is the leading platform for Commonwealth currencies), Breedon and Vitale (2010) show that returns for a given currency pair are highly correlated. That said, the two primary electronic communication networks account for under 10% of total spot transactions and the proportion of the two venues is further declining. However, BIS (2018) documents that they remain crucial for price discovery in the foreign exchange market, leading, e.g., price changes in futures markets.

In addition, from January 2006 onwards we also have access to futures data from the Chicago Mercantile Exchange (CME), where dealers are not the dominant market participants. In fact, dealers and intermediaries generally account for around 30% of open positions, while the remaining 70% are split between asset managers, leveraged funds and other participants. The additional data allows us to compare intraday dynamics in the spot market that we observe on RM and RTH with developments in the foreign exchange derivatives space in terms of both prices and quantities. Furthermore, we use futures data on the dollar index from the International Continental Exchange (ICE) to have a traded benchmark of average foreign exchange returns; and, finally, we use foreign exchange options data available through Datastream and Bloomberg to calculate option-implied volatility measures.

## III. Currency Returns Around the Clock

In this section, we provide novel evidence on the intraday behavior of currency returns and, in particular, document the following novel stylized fact: *Exchange rate returns display a predictable intraday seasonality such that the U.S. dollar appreciates in the run up to foreign exchange fixes and depreciates thereafter.*

### *A. Dissecting Currency Returns*

Denote by $s_t$ the log of the exchange rate, expressed in units of foreign currency per U.S. dollar and $\Delta s_t$ the change in the log exchange rate between time $t-1$ and $t$. A positive $\Delta s_t$ corresponds to an appreciation of the U.S. dollar relative to the foreign currency. Working in Eastern Time (ET), we define daily close-to-close log spot returns ($\Delta s_t^{CTC}$) as the percent change in the mid-quote from 5:00 p.m. on day $t-1$ to 5:00 p.m. on day $t$, i.e.,

$$\Delta s_t^{CTC} = s_t^{5:00p.m.} - s_{t-1}^{5:00p.m.}.[10] \tag{1}$$

Next, we split the day into different periods guided by the timing of the three main currency fixes across the globe, i.e., ($a$) the Tokyo fix at 9:55 a.m. local time; ($b$) the ECB fix at 2:15 p.m. local time; and ($c$) the London fix at 4:00 p.m. local time. Hence, we calculate returns for the following five intraday windows (all times expressed in ET): ($i$) pre-Tokyo fix ("pre-T", 5:00 p.m. to 8:55 p.m.), ($ii$) post-Tokyo fix ("post-T", 8:55 p.m. to 2:00 a.m.), ($iii$) pre-ECB fix ("pre-E", 2:00 a.m. to 8:15 a.m.), ($iv$) ECB fix to London fix ("E-L", 8:15 a.m. to 11:00 a.m.), and ($v$) post-London fix ("post-L", 11:00 a.m. to 5:00 p.m.).[11] In order to be able to distinguish between the post-Tokyo and the pre-ECB fix periods, we use 8:00 a.m. Frankfurt time (or 2:00 a.m. ET), i.e., the beginning of the FX trading day in Europe. Similarly, we define the start of the FX trading day in New York as 8:00 a.m. ET.

### B. *Currency Returns Around the Clock*

We begin our analysis by plotting the annualized average cumulative five-minute log returns from 5:00 p.m. ET to 5:00 p.m. ET the next day for the sample period 1 January 1999 to 31 December 2019 for the G9 currencies. Figure 2 plots the average annualized returns to the euro, British pound and Japanese yen, while Figure 3 plots cumulative as well as the hour-by-hour returns of the unconditional dollar portfolio (DOL) that goes long all foreign currencies in equal weights.[12]

All currencies show a distinct pattern of depreciation against the U.S. dollar ahead of the

[11] Japan doesn't follow daylight savings time; and, hence, the time difference between Tokyo and New York is either 13 or 14 hours. This means that for part of the year, the windows before and after the Tokyo fix end or start at 7:55 p.m. ET, respectively. In addition, there are a couple of weeks in the year when the time difference between New York and London and the rest of Europe is an hour shorter than usual.

[12] We follow Lustig, Roussanov, and Verdelhan (2011) in constructing the dollar portfolio using the G10 currencies from our sample. To save space remaining individual plots are relegated to the Online Appendix.

Tokyo fix at 8:55 p.m. ET followed by a reversal thereafter. Once European markets open at 2:00 a.m. ET, all currencies depreciate against the U.S. dollar ahead of the ECB fix. This drop is much stronger for the European currencies and more muted for the Australian, New Zealand, and Canadian dollar. The period between the ECB and London fix does not show a clear pattern in the cross-section aside from the euro and yen, which appreciate until one hour before the London fix. After the London fix, all currencies show a strong appreciation versus the U.S. dollar, which continues until the end of the business day in the U.S. at 5:00 p.m. ET. The yen is the sole exception, moving in the opposite direction. Overall, all currencies except the yen appreciate during the U.S. intraday period and depreciate overnight.

[INSERT FIGURES 2 AND 3 HERE]

Aggregating across currencies, we find that the consistent depreciation of foreign currencies before the Tokyo fix and after European markets open combined with the depreciation of the U.S. dollar during the intraday period lead to a distinctive $W$-shaped pattern of the cumulative returns measured over a full day. Overall, there is a significant appreciation of the U.S. dollar during the overnight period of just over 4% per year followed by a reversal during the day of 5%.[13] Given the size of the FX spot market, this translates into very large sums. Using daily turnover numbers from the 2019 Triannual BIS survey, the pattern we detect implies daily swings exceeding a billion U.S. dollars.

[INSERT TABLE I HERE]

Table I summarizes Figures 2 and 3 formally by reporting average FX log returns (i.e., exchange rate changes) along with $t$-statistics for the various intraday sub-periods as defined above.[14]

[13]This means that over the full sample period, the U.S. dollar depreciates against the basket of currencies at a rate of roughly 1% per year.

[14]Note that at this stage we explicitly take daylight savings time into account by calculating pre- and post-Tokyo fix returns using windows that line up around 9:55 a.m. Tokyo time. During the winter months when New York follows EST, this means 7:55 p.m. ET and during the summer months when New York follows EDT this means 8:55 p.m. ET. All figures are plotted using ET only.

As discussed above, all foreign currencies depreciate against the U.S. dollar after trading in New York ceases and in anticipation of the Tokyo fix. The Australian and New Zealand dollar (−7.15% and −8.53%, respectively) show the most negative average returns, while the Swiss franc and the Canadian dollar depreciate the least compared to other currency pairs. It is worth highlighting that irrespective of the magnitude of the returns, average annualized returns of all currency pairs are different from zero at the 1% level of significance. The reversal after the Tokyo fix is equally statistically significant for all currencies in our sample, with the yen and the Norwegian krone exhibiting the highest magnitudes, which are 7.94% and 7.44% per annum, respectively. Not very surprisingly, the dollar portfolio exhibits a very strong and significant reversal pattern as well, dropping around 5% before the Tokyo fix and recouping the losses thereafter.

Leading up to the ECB fix, the European currencies and the yen significantly depreciate against the U.S. dollar. The point estimates are large in both statistical and economic terms. The highest drops are posted by the euro and the Swedish krona, with −8.87% and −7.73% measured on an annual basis, respectively. Between the ECB and the London fixes, currencies do not move as consistently in the cross-section as during other windows, although this may be attributed to the fact that the window contains both a post-(ECB) fix depreciation as well as a pre-(London) fix appreciation of the U.S. dollar, as can be seen in Figures 2 and 3.

After the London fix, the pattern is again quite striking: with the exception of the yen, all currencies appreciate strongly (i.e., between 3.89% for the Canadian dollar and 6.87% for the euro) during the period between the London fix and the close of markets in the U.S., whereas the yen depreciates by 2.92%. Overall, the dollar portfolio appreciates by over 4.5% and movements for all currencies are strongly statistically significant.

The last column in Table I makes clear that the pattern we document is an intraday seasonality (i.e., a predictable component) that does not carry over to close-to-close returns. In fact, with the exception of the Swiss franc, the Australian dollar and the New Zealand dollar (average annual appreciations of 2.43%, 1.20% and 2.33%, respectively) none of the currencies in our sample moves by more than 1% on average over the whole sample period we consider and none of the close-to-close returns are statistically significant. The dollar portfolio for example appreciates on average by just over 1% per year.

### C. *Robustness*

We study the robustness of the reversals around the fixes across two dimensions: (*i*) over time; and (*ii*) across data sets.

First, Table II splits intraday dollar portfolio returns for the respective windows into four subsamples. In each subsample we observe a $W$-shaped return pattern across the 24-hour trading day. The reversal of the dollar portfolio is extremely significant between 1999 and 2014, averaging around 6.5% annualized on either side of the fix. In the 2014 to 2019 sample, the reversal around the Tokyo fix is notably smaller but remains statistically significant. The pre-ECB fix appreciation of the dollar portfolio is large and highly significant between 1999 and 2009 and again between 2014 and 2019, averaging around 5.0% per annum, while the post-London depreciation is large and highly significant between 1999 and 2014, also averaging over to 5.0% per annum.

Thus, pre- and post-fix returns are very robust over time and consistent with the notion of a reversal nets out to zero on average, implying that intraday FX seasonalities do not normally appear in daily data. That said, on a daily basis the movements are on the order of a few basis points, raising the question of whether the pattern is an artefact of using RTH indicative quotes to calculate log spot changes.

[INSERT TABLES II AND III HERE]

We examine this question using three alternative data sets, computing intraday returns for the dollar portfolio from mid quotes of RTH forwards and CME futures as well as from value-weighted average prices (VWAPs) from Refinitiv's Matching (RM) trading platform.

The dollar portfolio in this exercise comprises the euro, pound and yen, which are the only liquid pairs for all alternative instruments over an extended sample period. In addition, we calculate intraday returns using intercontinental-ICE dollar index (DX) futures. The starting dates for each data set are January 1999 (RTH forwards and ICE futures) and January and June 2006 (CME futures and RM).

Table III shows that the magnitude of the reversals around the fixes computed from forwards is very close to those computed from spot rates, suggesting there is no intraday pattern in implied interest rate differentials. The results from the CME and from the ICE futures are also strongly statistically significant as well as consistent with the main results in Table I, confirming that the patterns also carry over to firm quotes taken from electronic FX derivatives markets. Finally, the patterns are also present in traded prices, sourced from RM, and are thus not absorbed by the effective bid-ask spread.

In summary, the central contribution of this paper, the observation that the U.S. dollar appreciates in the run up to foreign exchange fixings and depreciates thereafter, is robust over time, across data sets, and across different segments of the foreign exchange market. This is important for a number of reasons that go beyond a pure academic interest. Most importantly, the presence of a robust intraday seasonality in foreign exchange spot and derivatives markets implies that the timing of portfolio adjustments should be an important consideration for asset managers, institutional investors and corporates who receive cash flows in U.S. dollars and must convert back to their local currencies, or vice versa.

# IV. FX Intermediation, Dollar Tilting and Pre-Fix Hedging

In this section, we develop and test a set of hypotheses designed to rationalize the findings from the previous section. In motivating these hypotheses, we draw upon the results from the microstructure literature and also consider institutional aspects related to foreign exchange intermediation. Moreover, we study intraday patterns in trading quantities using data from both Refinitiv FX Matching (RM) and from the CME. As discussed in Section II, RM is the leading inter-dealer platform for Commonwealth currencies; and, hence, we focus in this section on the pound and the Australian dollar to ensure a sufficient level of liquidity for our trading data.

### A. *Liquidity Provision and Return Patterns*

In benchmark models of inventory management (Stoll (1978) or Grossman and Miller (1988)), dealers provide liquidity to traders that demand immediacy before they offset their positions later in the day. A key prediction arising in these models is that prices exhibit reversal patterns around liquidity events. We argue that the key times within the day for liquidity events to occur (i.e., for order imbalances to manifest in the foreign exchange market) are at the major fixing times. Moreover, the intraday foreign exchange price patterns around the fixes resemble price patterns in U.S Treasury securities around pre-scheduled auction dates studied in Lou, Yan, and Zhang (2013). They document that prices of Treasury securities gradually decline in anticipation of the auction dates before reversing thereafter. Borrowing from the framework of Vayanos and Wang (2009), Sigaux (2018) formalizes the intuition about the mechanism at play and highlights the importance of uncertain net supply of Treasuries at the auction.

Adapting the insights of these papers to currency markets and combining them with the stylized fact that the price of the U.S. dollar exhibits a local peak at fixing times, we conjecture the existence of an unconditional net demand for U.S. dollars (or, equivalently, a net supply of foreign currency) at each fix. The demand for dollars at the fix could, for example, be driven by the net global demand for U.S. dollar assets coupled with a preference for transacting at the fix. To be clear, however, this does not imply the existence of an unconditional U.S. dollar demand when measured over a full day. Moreover, even with an unconditional demand for U.S. dollars at the fix, there remains considerable uncertainty about the size of the order imbalance at the beginning of the trading day. Thus, dealers should be willing to provide liquidity (or to bear inventory risk) if expected future execution prices (i.e., returns) increase. As a result, dealers face a trade-off between arbitraging the difference of the pre-fix price and the expected price of the U.S. dollar at the fix on the one side, and hedging the uncertainty about the net dollar demand at the fix on the other side. This leads to pre-fix hedging. In fact, banks with advanced knowledge of order imbalances are explicit in their intentions to hedge their positions and this practice may have negative consequences for the rates at which client orders are executed.[15] Given the relevance of the fixes, however, it is reasonable to assume that for most clients the perceived benefits of transacting at the fix using an observable and ex post verifiable benchmark rate outweighs the potential costs in terms of missing out on the best possible exchange rate.

Pre-fix hedging can be seen as analogous to the mechanism described in Sigaux (2018) for the Treasury market, albeit at a much higher frequency. Unlike the situation in the Treasury market, dealers in the foreign exchange market can easily be faced with either an excess demand for or supply of dollars on any given day. Thus, conditional on the daily order imbalance, the reversals we expect to observe should lead to either $V$-shaped or inverse $V$-shaped price patterns around the fixes.

By no arbitrage, returns in different segments of the foreign exchange market are very highly correlated, as for example shown in Table III. At the same time, we expect that contemporaneous order flow is positively correlated with price movements, as implied by standard microstructure models. However, an explanation based on financially constrained intermediaries also implies that the order flow of dealers is most informative for price discovery. Hence, to the extent that we can assign order flow to different market participants, we expect information from dealer transactions to contain more relevant information with respect to the price patterns we observe compared to order flow from other market partici-

[15]The practice is usually described in the "FX Disclosure Notice" that forms part of the client agreement to trade currencies. See, e.g., the notices by Citi Group (www.citigroup.com/citi/spotfxdisclosurenotice.html), Goldman Sachs (www.goldmansachs.com/disclosures/terms-of-dealing.pdf), Banco Santander (www.santander.com/en/landing-pages/foreign-exchange-disclosure-notice), or Nordea (nordeamarkets.com/wp-content/uploads/2018/10/FX-Spot-Disclosure-Notice.pdf). Pre-fix hedging has also attracted attention from policymakers, as can be seen in the press release of the global foreign exchange committee on the relevance of pre-hedging activities for the principles of good practices in the foreign exchange market (https://www.globalfxc.org/press/p210511.htm).

pants.

To summarize, the above arguments lead us to formulate and test the following three hypotheses:

- **Hypothesis 1:** Unconditionally, we expect to observe negative order flow (i.e., a demand for U.S. dollars) ahead of the major currency fixes followed by positive order flow thereafter.
- **Hypothesis 2:** Conditionally, we expect to observe reversals around the fixes. If the order flow before the fix is negative (i.e., there is buying pressure for the U.S. dollar), we should expect the foreign currency to appreciate after the fix and vice versa.
- **Hypothesis 3:** We expect order flow to be positively correlated with prices in the foreign exchange market. At the same time, we expect dealer order flow to be more informative for price discovery and for explaining the reversal patterns than order flow measured using trades from other market participants.

### *B. Intraday Volumes*

We start by comparing trading volumes for the three main currencies studied in Section III plus the Australian dollar on RM and the CME for the sample period from June 2006 to December 2019. Figure 4 displays the intraday volumes measured at a five-minute frequency for the four currencies on both platforms (Panels (a) and (b) for RM, Panels (c) and (d) for the CME). In terms of magnitudes, the discrepancies between the Commonwealth currencies on the one side and the euro and yen on the other side are immediately obvious. While volumes for the pound and the Australian dollar have similar orders of magnitude for futures on the CME as well as for inter-dealer trading on RM, the gap becomes immense for the yen and the euro, where the (notional) volume on the CME is up to a hundred times higher compared to the traded volume on RM. Liquidity for the pound and the Australian dollar is high across both platforms, with daily volumes of 15 and 14 billion U.S. dollars on RM while the notional trading volumes for futures are 8 and 6 billion U.S. dollars, respectively. Daily volumes for the euro and the yen on the other hand are below 1.5 billion U.S. dollars on RM while they reach over 34 and 12 billion U.S. dollars for the euro and yen futures, respectively.

[INSERT FIGURE 4 HERE]

Despite the different orders of magnitude in terms of trading volumes, the intraday volume patterns across currencies and platforms are largely similar. In line with the identified importance of the fixes for returns, volumes generally display spikes in trade at the currency fix times, i.e., we identify the fix times as potential liquidity events in the spirit of Grossman and Miller (1988). For RM, for example, the volume for trading the pound against the U.S. dollar amounts to over 336 million U.S. dollars at the London fix, ten times higher than the daily average. Similarly, traded volume in the euro exceeds 12 million U.S. dollars at the ECB fix (nearly three times the daily average), and the amount of yen traded at the Tokyo fix is twice as large as the daily average (approximately 1.6 million U.S. dollars). Thus, at least when considering inter-dealer trading, the turning points in terms of return reversals are also marked by distinct spikes in trading volumes.

However, the patterns in Figure 4 are not as unambiguous as the return patterns displayed in Figures 2 and 3. In particular, there are other times in the day that display significant spikes in volumes in addition to the three major currency fixes. In fact, some of the highest volumes are recorded at 8:30 a.m. ET and at 10:00 a.m. ET, coinciding with the timing of the most important U.S. macroeconomic data releases and the expiration time for currency options, respectively (see, e.g., Chaboud, Chernenko, and Wright (2007)). In fact, these are the times in the day with the highest volumes for futures, eclipsing even the volume spikes around the London fix. During European and U.S. trading hours, we also observe distinct hourly and half-hourly spikes aligned with intraday fixes from Bloomberg and other data providers. However, high volume does not imply a reversal, as we observe no price trends on either side of these additional volume peaks. In that context, it is important to be reminded that the peak for the U.S. dollar in terms of value is at 8:15 a.m. ET around the ECB fix and not at 8:30 a.m. ET when the macro news are released. That is, while volume data provides interesting and relevant information about intraday trading activity as well as a motivation to specify intraday liquidity events, they do not necessarily help in pinning down the reversal points in terms of returns, further indicating a special role of currency fixes.

### *C. Order Imbalance*

Even though the peaks in daily trading volume are similar for all four currencies and across both platforms, the differences in liquidity dictate that we concentrate on the pound and the Australian dollar for a more detailed analysis of quantities and order imbalances. Moreover, liquidity during European and U.S. trading hours is much higher compared to liquidity during Asian trading hours on RM because the platform is mainly used by European and U.S. banks. Hence, the main focus of the analysis in this section is on the pound and the Australian dollar around the European fixes, although we report all results for the Tokyo fix as well.

[INSERT TABLE IV AND FIGURE 5 HERE]

Hypothesis 1 conjectures the existence of an excess U.S. dollar demand at the fix, while Hypothesis 2 argues for a reversal around the fix conditional on the order flow leading up to the fix. Taken together, the two hypotheses imply the unconditional $V$-shaped price patterns around the fixes. To explore Hypothesis 1, we study the unconditional order flow for U.S. dollars around the fixes. Panel A in Table IV contains pre- and post-fix summary statistics for order flow on RM, defined as buyer- minus seller-initiated trading volume, i.e., negative order flow implies U.S. dollar buying pressure. We report both median and mean values, but our main focus lies on the former because the distribution is skewed and contains significant outliers. For both currencies, the means as well as the medians are negative before the London fix and positive thereafter, lending empirical support for Hypothesis 1.

The medians are strongly statistically significant for the pre- and post-fix windows. For the pre-fix window the median order imbalance is around 20 million U.S. dollars for either currency, which translates to just over 6% of the pound volume traded at the London fix. In contrast, median order imbalances on CME are magnitudes smaller and generally close to zero even though traded volumes on RM for the Australian dollar and pound are only about twice as large as volumes on CME. In the same vein, the fraction of days with negative (positive) order flow is significantly larger than 50% before (after) the London fix for both currencies on RM while there is no significant difference for order flow on CME. Finally, the pre-fix results for RM are qualitatively the same when considering the ECB fix that takes place roughly three hours before the London fix, i.e., the unconditional order imbalance is not simply driven by trading activity that occurs tightly around the London fix.

Figure 5 visualizes the results by displaying the median order flow (in million U.S. dollars) throughout the day for the Australian dollar and the pound at one-hour intervals for both the RM platform (Panels (a) and (b)) and for futures traded on CME (Panels (c) and (d)). The positive (blue) bars represent U.S. dollar selling pressure while the negative (red) bars display U.S. dollar buying pressure. The price patterns we document in Section III largely carry over to patterns in quantities on the RM inter-dealer platform as we observe strong unconditional U.S. dollar buying pressure ahead of the London fix that reverses thereafter. When considering shorter windows, we observe a significant spike in the net demand for U.S. dollars in the five-minute interval at the London fix for both the Australian dollar and the pound.[16] Around the Tokyo fix, the pattern is not obvious because the hourly windows suggest that there is buying pressure for the Australian dollar throughout the Asian trading hours while the buying pressure for the pound is only apparent after the Tokyo fix and in the early hours of European trading. That said, trading patterns during Asian trading hours are likely less informative since the RM platform is used mainly by institutions based in Europe and the U.S. and, thus, volume during Asian hours is significantly smaller (and less

[16]In the Online Appendix, we present the average order flow for five-minute intervals because the median becomes zero for narrow windows away from the fixings times.

representative) than volume during European and U.S. trading hours.

The results suggest that while volume on CME for the Australian dollar and the pound is of a similar order of magnitude compared to RM, the connection between the order flow on the two platforms is weak at best. In fact, order flow correlations for hourly as well as five-minute intervals are usually below 0.2 and never go above 0.3 for any window and currency. At the same time, returns across the two platforms are very close. This may be surprising and seemingly contradictory given the notion that, on aggregate, order flow and returns should be highly correlated in general. However, in the foreign exchange market, the electronic platforms only capture a small fraction of overall activity, as discussed in Section II. The apparent lack of an unconditional pattern in the futures order flow with respect to currency fixes hints at important differences in trading activity in the two segments of the foreign exchange market that we explore further in the next section.

In summary, the unconditional order flow from the inter-dealer platform RM exhibits patterns that are mirroring returns and are in line with the notion that order flow of marginal investors and returns are correlated. Moreover, the unconditional dealer order flow lends support to our Hypothesis 1 that there is unconditional net demand for U.S. dollars at the fixes. On the other hand, futures order flow does not exhibit any clear pattern. This finding is consistent with Hypothesis 3, which is explored in more detail in the next section. Finally, the size of the order imbalances can be economically large, especially when warehoused by a small set of core intermediaries.

### *D. Reversal Regressions*

As highlighted in Section A, our explanation is based on liquidity provision of financially constrained intermediaries. This means that the order flow of these particular market participants should be most informative for price discovery, as expressed in Hypothesis 3. Normally, it is virtually impossible to understand exactly who trades with whom in electronic and anonymous markets. However, we have access to two data sets that contain information on trades and volumes that allow us to calculate high-frequency measures of order flow for different segments of the foreign exchange market. As discussed in Section II, it is reasonable to assume that dealers are dominant on RM while this is not necessarily the case on CME. This allows us to examine Hypothesis 3, which specifies the link between order flow and returns and conjectures that the link is stronger for dealer order flow.

The regression specification we study is closely related to Campbell, Grossman, and Wang (1993) and Andrade, Chang, and Seasholes (2008), who derive price pressure predictions in equilibrium models. In their models, returns are positively related to contemporaneous order imbalances through an information effect, yet negatively related to lagged order imbalances through an inventory effect.[17]

We start the analysis by regressing post-fix window returns on pre-fix window order flow, both computed from observations from the inter-dealer RM platform:

$$\Delta s_t^{post} = \alpha + \beta_1 OF_t^{pre} + \beta_2 OF_t^{post} + \varepsilon_t, \tag{2}$$

where $\Delta s_t^{post}$ denotes the return measured over the post-fix window on day $t$, while $OF_t^{pre}$ and $OF_t^{post}$ are the order flow before and after the fix, respectively. Returns are expressed in basis points and measured using value-weighted average prices (VWAPs), while order flow is defined as buyer minus seller-initiated volume.[18]

[INSERT TABLES V AND VI HERE]

All coefficients on contemporaneous order flow in Table V are strongly positive and highly significant, in line with the findings of Evans and Lyons (2002) and implying that

[17] Following Kyle (1985) and Glosten and Milgrom (1985), the literature typically interprets price impact due to contemporaneous order flow as an indirect measure of illiquidity in markets where agents trade based on asymmetric information, whereas the lagged price impact of order flow is interpreted as an inventory effect a là Grossman and Miller (1988). For textbook treatments on this subject, see, e.g., Hasbrouck (2007) or Foucault, Pagano, and Röell (2013).

[18] In the Online Appendix we repeat the analysis using normalized order $NOF$ as the independent variable, which is obtained by taking the order flow relative to total traded volume within each trading window. The results remain qualitatively unchanged.

order flow on the RM platform is highly informative about price discovery. According to Hypothesis 2, the coefficient on lagged order flow is expected to be negative, consistent with the idea that banks and dealers engage in pre-hedging activity to provide liquidity at the fix that leads to either a predicted appreciation or predicted depreciation of the U.S. dollar that reverses thereafter. Consistent with the prediction, we find $\beta_1$ to be negative and statistically significant for all fixes, meaning that the lagged order flow robustly predicts a return reversal after the fix. In fact, while the results for the unconditional order flow are weaker around the Tokyo fix, as discussed in Section C, the coefficient estimates for the conditional regressions remain strongly significant and negative. Finally, we find that the relationship between pre-fix order flow and post-fix returns remains statistically and economically strong if we exclude the last three hours leading up to the London fix and measure the order flow only up to the ECB fix. Thus, our results are not driven by trading activity in the last few minutes leading up to the London fix as studied in the previous literature (see, e.g., Evans (2018)).

For the pound, the point estimate of $-4.2$ for the lagged order flow before the London fix implies that an order imbalance of one standard deviation (amounting to approximately 6% of the trading volume during that window) leads to a reversal of around 2.5 basis points, which is larger than the average unconditional effect we document in Section III. For the Australian dollar the results are even stronger, and a one standard deviation shock to lagged order flow implies a reversal of over 3.3 basis points. Before the Tokyo fix, the respective coefficient estimates are $-25.9$ and $-28.1$, implying reversals of 2.4 and 3.7 basis points for a one standard deviation shock for the pound and the Australian dollar, respectively.

We repeat the analysis using quantities measured on the CME in Panel A of Table VI. The results are strikingly different from those presented in Table V. The coefficients on the contemporaneous order flow are much smaller and they are no longer significant for the pound. Similarly, only the lagged order flow before the Tokyo fix is statistically significant for both the pound and the Australian dollar. We add the quantities from the RM platform to the CME regression and estimate a regression model of the form

$$\Delta s_{t,CME}^{post} = \alpha + \gamma_1 OF_{t,CME}^{pre} + \gamma_2 OF_{t,CME}^{post} + \beta_1 OF_{t,RM}^{pre} + \beta_2 OF_{t,RM}^{post} + \varepsilon_t,$$

where $\Delta s_{t,CME}^{post}$ refers to the VWAP-based futures returns from CME, and the subscripts $CME$ and $RM$ indicate the source of the pre- and post-fix order flow measures, respectively. The estimates in Panel B of Table VI show that while trading activity on CME is rather uninformative about price discovery, the RM order flow is highly significant, the coefficients have the same order of magnitude as those in Table V, and the goodness-of-fit increases substantially. More interestingly, even the lagged RM order flow is negative and statistically significant.[19]

The results in Table VI should also be a reminder that the relationship between order flow and returns is not mechanical in the foreign exchange market as it is tremendously fragmented.[20] While it seems intuitive that aggregate U.S. dollar buying pressure leads to an appreciation of the U.S. dollar, this does not need to hold for any platform that captures only a fraction of aggregate trading activity, as discussed earlier.[21] Overall, these results show that trading activity on the RM platform is informative for the aggregate market and, further, provide suggestive evidence that the marginal investors in the foreign exchange markets are foreign exchange dealers and not hedgers or speculators. In fact, in the Online Appendix we also show that qualitative (and quantitative) results remain largely unchanged when using the RTH returns in regression (2) that are based on bank quotes instead of the returns from RM that are based on executed trades.

[19] We show in the Online Appendix that these results also remain robust to using normalized order flow.

[20] See also Ranaldo and Somogyi (2021) for evidence on information content of trades executed by different participants in the spot market.

[21] In fact, running conventional return on order flow regressions across different frequencies (i.e., one-minute, five-minutes, ..., one-day, one-month, etc.) we document in the Online Appendix how regression coefficients and explanatory power of CME order flow is consistently lower compared to order flow obtained from RM (Berger, Chaboud, Chernenko, Howorka, and Wright (2008)).

# V. Reversal Portfolios

In this section, we analyze the reversals around the fixes from a different angle by studying a trading strategy that exploits the sum of the pre- and the post-fix returns for each day $d$ as follows:

$$\Delta s_d^{\text{Tokyo}} = -\Delta s_d^{\text{Pre-T}} + \Delta s_d^{Post-T} \tag{3}$$

$$\Delta s_d^{\text{Europe}} = -\Delta s_d^{Pre-E} + \Delta s_d^{Post-L}, \tag{4}$$

i.e., before the Tokyo and ECB fixes, we take a short position in foreign currencies that is reversed post-Tokyo and reversed post-London fix respectively. Note that we ignore the period between the ECB and the London fixes for this exercise because the results in Table I suggest that there is no clear directional movement between the ECB and the London fix. As seen in Figure 3, on average, the U.S. depreciates after the ECB fix and appreciates again into the London fix.

## A. *Summary Statistics*

We start by reporting summary statistics for all currencies as well as the dollar portfolio in Table VII. First, we ask whether there are significantly more days in which the reversal returns are positive compared to days when they are negative. Overall, returns are significantly more often positive than negative. For the reversals around the Tokyo fix, the differences are always strongly statistically significant for all currencies ranging from 55% positive for the Swiss franc to almost 60% for the dollar portfolio. For the Europe window, the fractions range between 51% for the Pacific and Asian currencies and 55% or 56% for the pound, euro, and the dollar portfolio, for example. The differences for all European currencies are strongly statistically significant; and only for the Japanese yen do we obtain a p-value below 5%. Absent microstructure effects, returns should be unpredictable in efficient markets at high frequencies.[22] And, in fact, when considering daily close-to-close currency returns, only the Australian dollar has more than 51% positive return days. Thus, the results for the reversal returns are rather remarkable when considering the usual benchmarks.

To further put the results in perspective, daily returns to the S&P 500 stock index are positive 54% of the days. Moreover, if the daily results are aggregated to a monthly frequency we find that returns around the Tokyo fix are positive between 70% (for the New Zealand dollar) and 83% (for the dollar portfolio), again with high statistical significance. For the European window, the reversal returns for the European currencies are positive for at least two-thirds of all months, again with the fraction for the monthly S&P 500 returns lagging behind that number (see the Online Appendix for the close-to-close numbers).

[INSERT TABLE VII HERE]

While relatively small, the consistent positive return bias translates into significant average annualized returns over time before taking transaction costs into account. Around the Tokyo fix, the annualized reversal returns range between 6.2% for the Swiss franc and 14.2% for the New Zealand dollar. For the European window, the annualized returns are particularly high for the euro, pound, and Swiss franc, at 15.6%, 12.4% and 12%, respectively. Annualized standard deviations are generally below 8% for all currencies and both reversal windows, or about half the standard deviation of the S&P 500 index over the same time period. Furthermore, almost all reversal return portfolios exhibit positive skewness and fat tails (only the Swiss franc and the Japanese yen returns exhibit negative skewness around the Europe fixes). This is in stark contrast to, for example, daily (or monthly) stock returns that are significantly negatively skewed for the same sample period.

The characteristics for the reversal portfolios are also very different compared to those of the carry portfolios reported in Brunnermeier, Nagel, and Pedersen (2009). While carry trades are profitable but have fat tails and crash risk, our reversal portfolios generate positive returns with fat tails but generally positive skewness. Moreover, there is no clear pattern

[22] At lower frequencies, predictability may arise due to time-varying risk premia.

relating the skewness to the interest rate differential as is the case for close-to-close returns, where for example the Australian and New Zealand dollar exhibit negative skewness while the returns to the Swiss franc and the yen are positively skewed. In summary, the reversal portfolios generate significant returns with favorable characteristics. Next, we further explore the behavior of the reversal portfolio over time.

### B. *Total Return Indices*

Using the daily reversal returns, we construct total return indices that are displayed in Panels (a) and (b) of Figure 6. The reversal portfolios display remarkable persistence over time and for both windows we consider. All portfolios (with the exception of the yen for the Europe window) accrue steadily over the whole period but with a stronger appreciation around the local fixes. An investment of one U.S. dollar in the yen for a trading strategy around the Tokyo fix climbs to over 12.2 U.S. dollars by the end of 2019. The same strategy for the euro, pound and dollar portfolio results in a final portfolio value of 8.9, 5.3 and 8.6 U.S. dollars, respectively. In contrast, the portfolio values for the Europe window are 26.9, 13.5 and 6.4 U.S. dollars for the euro, pound and dollar portfolio, respectively, while the yen portfolio actually loses about 6% of the initial value.

[INSERT FIGURE 6 HERE]

From the total return indices, we construct annual returns to further investigate how the patterns may relate to the state of the economy. In Panels (c) and (d) of Figure 6, we display the year-by-year reversal returns for the dollar portfolio. For both fixes, the returns are particularly high during 2001 when the dot-com bubble burst as well as during the credit crisis, reaching returns of around 20% per year. On the other hand, returns were comparatively lower for the Tokyo fix between 2004 and 2007 and for the Europe fix in 2007. Moreover, returns around the Tokyo fix have been around 5% or below since 2013, and the first year with a negative reversal return was recorded in 2018. For the Europe fix, the average reversal returns have remained around 10% per year after the crisis but dropped to below 5% during the last two years in our sample.

While the reversal returns have remained remarkably robust and consistently positive for most of the sample period, there is a downward trend during the most recent period. First, anecdotal evidence based on conversations with traders suggests that some arbitrage capital is allocated to exploiting the reversal patterns. This would predictably lead to a decline in the potential returns. As we discuss further below, trading the fix can be profitable even when transaction costs are taken into account, but these profits may be even higher if the patterns are exploited by the bigger players in the market. Second, periods with lower returns coincide with periods of low volatility in financial markets. We show in Section D that reversal returns are in fact lower during low volatility periods in line with an explanation based on dealers' risk-bearing capacity.

### *C. Calendar and Information Effects*

We investigate whether reversal returns are related to any known low-frequency return seasonality (or calendar effects) or whether they are driven by monetary policy or macroeconomic announcements. In short, we conclude that neither of these explanations can account for the reversal patterns we document in Table I.

In the Online Appendix, we show that the reversal returns around both the Tokyo and the European fixes are consistently positive in all days of the week, weeks of the month as well as months of the year, generally with very high $t$-statistics. In particular, we can rule out that our results are driven by a Monday or January effect, which have received significant attention in the context of equity markets (Pettengill (2003) or Keamer (1994)). Furthermore, our results are not driven by and end-of-month equity hedging channel as studied by Melvin and Prins (2015) or a third week of the month option hedging channel (Cao, Chordia, and Zhan (2021)). Finally, we also do not find a stronger effect at the end of each quarter that could be due to deviations in covered interest rate parity linking forward and spot FX positions to banks' balance sheets (Du, Tepper, and Verdelhan (2018)).

To test for the effects of monetary policy and macro announcements, we also reproduce Table I in the Online Appendix, splitting up the sample into announcement and non-announcement days. There is virtually no difference between the average window returns measured for all days compared to the window returns measured on non-announcement days only, and we conclude that the average return patterns are not driven by swings on days when monetary policy news is released

In short, as already indicated by the robustness tests in Section III, the return reversal patterns around currency fixes are a pervasive feature of the data that is not concentrated on any particular date or news event.

### *D. Reversal Returns and Volatility*

By inspection, Figure 6 suggests that reversal returns are larger during periods of financial distress, hinting that the fix reversals might be related to dealers' risk-bearing capacity. To investigate this further, we estimate the following panel regression:

$$\Delta s_{i,t}^{j} = \alpha_i + \beta_1 VIX_{t-1} + \beta_2 IRD_{i,t-1} + \beta_3 EQD_{i,t} + \varepsilon_{i,t},$$

where $\Delta s_{i,t}^{TOK}$ and $\Delta s_{i,t}^{EUR}$ refer to portfolio reversal returns for the Tokyo or Europe window, respectively. On the right-hand side, we include the lagged VIX ($VIX_{t-1}$) to proxy for the aggregate level of volatility (or risk) in the market. In addition, we also control for the lagged short-term interest rate differentials between the U.S. and country $i$ ($IRD_{i,t-1}$), as well as the contemporaneous equity return differentials between the U.S. and country $i$ ($EQD_{i,t}$). Portfolio reversal returns are measured in basis points; and $t$-statistics reported in parentheses are computed using a robust covariance estimator. Currency fixed effects are included but omitted from the table to save space. The regression is estimated at the daily frequency and covers the sample period from January 1999 to December 2019.[23]

Table VIII reports both univariate and multivariate specifications for the daily reversal returns for the Tokyo and Europe windows, respectively. First, we find large positive and highly statistically significant coefficient estimates for the lagged VIX. This is in line with the idea that during periods of elevated risk, dealers should demand a higher risk premium for providing immediacy because their constraints are more likely to be binding (Adrian and Xie (2020)) while demand for safe haven assets increases (Jiang, Krishnamurthy, and Lustig (2021)).

[INSERT TABLE VIII]

Interpreting the economic size of the regression estimate, consider a scenario whereby the VIX is at its sample median level of 18%, the factor loading for the Tokyo reversal regression estimates implies a daily return reversal of $\sim$ 4 basis points per day, while the London reversal regression estimates imply a daily return reversal of $\sim$ 2.5 basis points per day. On an annualized basis, these are comparable to the unconditional estimates reported in Table I. Considering the remaining regression specifications, we find that, consistent with standard uncovered interest rate parity logic, the loading on $IRD_{i,t-1}$ is positive and significant; and in line with the uncovered equity parity relationship proposed and studied by Hau and Rey (2006), the contemporaneous loading on the U.S index return is also significant and positive. However, importantly for a global dollar demand explanation in the presence of constrained intermediaries, the final column shows that the positive significant link to volatility is robust to these controls. In line with the special role of the U.S. dollar in global FX markets, we show in the Online Appendix that the distinct intraday pattern cannot be replicated when using other currency base portfolios. Neither the euro, pound, or yen base portfolio shows a distinct reversal in returns around institutional fixes.

[23] We show in the Online Appendix that these results are robust and qualitatively similar when currency implied volatility is used as a measure of uncertainty.

### *E. Transaction Costs*

The stylized facts regarding the intraday dynamics of currencies around the major fixes presented in Sections III and B are based on indicative high-frequency mid-quotes and, hence, do not account for transaction costs. In this section we examine whether the trading strategies implied by the return patterns are profitable in a practical setting that explicitly takes bid-ask spreads into account. Indeed, the patterns presented in Table I suggest that a trader would have to move aggressively in and out of positions up to four times over the course of a 24-hour period to exploit the systematic exchange rate movements we document. Incorporating transaction costs into the analysis allows us to further explore whether these patterns point towards inefficient markets or whether they are merely consistent with a story related to financial intermediation where dealers set spreads to help offset intraday swings.

Using the quoted high-frequency bid and ask prices from our benchmark RTH data set as a proxy for the effective spread, we calculate reversal returns net of transaction costs. That said, there is evidence that these spreads are considerably larger than the effective spreads based on firm quotes and executed trades, leading to measured net returns that are too conservative compared to what professional traders that move large currency volumes could achieve (see, e.g., Gilmore and Hayashi (2011)). Cespa, Gargano, Riddiough, and Sarno (2021) compare the bid-ask spreads from Datastream with quoted prices from other data providers in the years after the financial crisis, and they suggest decreasing indicative spreads by up to 75% in order to obtain a more realistic proxy of the transaction costs that big traders in the over-the-counter FX market face. When considering the profitability of the trading strategies based on the over-the-counter rates, we take an agnostic approach and report results for different spread levels ranging from zero on the one hand to the full reported bid-ask spreads in our data on the other hand.

We start our analysis by exploring the reversal returns of the three currency pairs euro, pound and yen for the Tokyo and Europe window, respectively. To incorporate transaction costs appropriately, we have to separately consider the pre- as well as the post-fix window as we switch from going long the U.S. dollar before the fix to shorting the U.S. after the fix. For example, suppose within each 24-hour day we fix three periods representing a pre-fix point in time ($\tau = 1$), the time of the fix ($\tau = 2$), and a post fix period ($\tau = 3$). Each day an investor longs the dollar pre-fix, closes this position at the fix, and shorts the dollar post fix. The legs of the trade take into account inter-temporal variation in spreads

$$\Delta s_t^{pre} = -s_1^a + s_2^b$$
$$\Delta s_t^{post} = +s_2^b - s_3^a,$$

where superscript $a$ ($b$) refer to the ask (bid) price in FX spot markets when RTH data is employed. The returns to this strategy are the sum

$$ret_t^{FIX} = \Delta s_t^{pre} + \Delta s_t^{post} = -s_1^a + 2s_2^b - s_3^a$$

and so makes money if bid prices at the fix are larger than the average of ask prices at the beginning and end of the trading session. Put differently, the dollar must rise outside the bid-ask spread across the trading periods

$$ret_t^{FIX} > 0 \rightarrow s_2^b > \frac{1}{2}(s_1^a + s_3^a) \sim s_1^a \sim s_3^a$$

For the Tokyo fix, we take long dollar positions between 5:00 p.m. and 8:55 p.m. and short dollar positions between 8:55 p.m. and 2:00 a.m. For the fixes in Europe, we go long the dollar between 2:00 a.m. and 8:15 a.m. (until the ECB fix) and short the U.S. dollar after the London fix from 11:00 a.m. to 5:00 p.m. The results are summarized in Table IX.

As above for the longer sample period, the annualized returns for trading the three currencies around the fixes are very high as long as transaction costs are ignored. Going long the dollar pre-Tokyo fix and reversing the position post-Tokyo fix yields annualized average returns of 10.44%, 7.94% and 12.0% for the euro, pound and yen, respectively.

Similar gains are obtained for euro and pound around the Europe fixes. Incorporating the full transaction costs adjustment as implied by the indicative quotes, again, reverses the picture, and average returns for most windows turn negative, reflecting the huge turnover that the trading strategy implies. However, reducing the bid-ask spread by 50% now yields positive returns for most windows and all currencies amounting to 2.65%, 0.51% and 2.73% for the euro, pound and yen, respectively. This strategy is even more profitable for European currencies, generating 8.64% and 5.46% returns pre-ECB and post-London fixes. Using T-bill rates we also calculate Sharpe ratios for trading the $W$-shaped intraday patterns. In line with the results for the gross returns, Sharpe ratios are negative using the full transaction costs and positive and very high if transaction costs are ignored. Market participants that are able to trade at better bid-ask spreads $(BA, 50\%)$ may earn Sharpe ratios ranging between 0.12 and 1.03 when exploiting the predictable intraday patterns.

Finally, Figure 7 displays the total return indices presented in Panels (a) and (b) of Figure 6 but accounting for transaction costs as measured by 50% of the reported bid-ask spread. Panel (a) of Figure 7 shows that trading the Tokyo reversal yields negative returns in the early years of the sample, positive but relatively flat returns until around 2007, which subsequently reversed until around 2013 and have since generated negative returns for the EUR and GBP and flat returns for the JPY. To summarize, including costs an investor would have almost doubled an initial one U.S. dollar following our Tokyo fix strategy trading the JPY or EUR and would have come out flat trading GBP. Panel (b) of Figure 7 shows cumulative returns to the London reversal strategy. Consistent with Table IX the returns are large. A one U.S. dollar investment in 1999 would have generated 3.13 U.S. dollars for the pound or 6.08 U.S. dollars for the euro while an investor would have lost significant money entering this trade for the yen, which is obvious given that the yen is the one currency that behaves differently post-London fix (a local currency appreciation in local trading hours for this pair).

[INSERT TABLE IX and FIGURE 7 HERE]

In summary, while there is strong intraday predictability around the fixings, it is not obvious that this can be exploited by the average trader. First, returns from trading in a relatively small window around the fix are usually more than offset by transaction costs. Second, holding the currency positions for a longer window that allows traders to exploit the persistent drift patterns throughout the day may lead to positive excess returns, at least for traders that are able to get reasonably good conditions to trade.

## VI. Conclusion

This paper studies demand shocks for U.S. dollars in high frequency around currency fixings and documents a new empirical fact: the U.S. dollar systematically appreciates ahead of the three major currency fixings and depreciates thereafter. That is, the U.S. dollar reaches an intraday peak at the Tokyo, ECB and London fixes, respectively, implying that on average there is excess demand for U.S. dollars at particular times of the day.

We show that the reversals around the fixes are a pervasive feature of the data, robust over the 21 years of our data span, and are present for all of the G9 currencies, which cover close to 75% of global transaction volumes. The return patterns spill over into over-the-counter forward as well as the exchange-traded futures markets. This is important for institutional investors and corporate hedgers alike because it implies that the intraday timing of their speculative and hedging activities, as well as the timing of currency conversions and portfolio adjustments, affects their balance sheets.

We conjecture an explanation based on constrained intermediation by foreign exchange dealers who provide immediacy for segmented transaction demand around the clock. To test this conjecture we develop a set of hypotheses drawing from insights of the market microstructure literature.

Consistent with our explanation, we present evidence (*i*) of an unconditional demand for U.S. dollars at the currency fixing times; (*ii*) that the order flow from a dealer platform is informative about the intraday price patterns, implying that the "marginal investors" in currency markets are a small set of foreign exchange intermediaries; and (*iii*) that the hedging practices of dealers before the respective fixes are related to the subsequent reversals thereafter. Moreover, we also provide evidence that information on traded quantities from the futures market is not related to the intraday reversal patterns, providing further support that intermediaries are the marginal investors that determine exchange rates.

# VII. Tables

**NOTE 1: Intraday Returns.** Different intraday periods around the Tokyo, ECB and London fixes are defined as follows: The pre-Tokyo fix window starts at 5:00 p.m. ET until the Tokyo fix at 9:55 a.m. local time ("pre-T"), followed by the post-Tokyo window ("post-T") that runs until 2:00 a.m. ET (when European markets open). The pre-ECB fix window ("pre-E") spans the period between European opening hours until the ECB fix at 8:15 a.m. ET. The "interfix" window ("E-L") covers the period between the ECB and the London fix at 11:00 a.m. ET. The final window spans the period after the London fix ("post-L") starting at 11:00 a.m. ET and ending at 5:00 p.m. ET. Thus, the intraday period is the sum of the "E-L" and the "post-L" windows whereas the overnight period covers the "pre-T," "post-T" and "pre-E" windows. All times are measured in Eastern Time, taking into account daylight savings time (DST). Data is daily and covers the sample period from January 1999 to December 2019 (5,264 daily observations). Returns are measured as the average log changes in the mid quote for the respective currency. Positive values imply the foreign currency appreciates versus the U.S. dollar. The dollar portfolio "DOL" is an equal weighted average of all nine currencies in our sample.

**NOTE 2: Reversal Porfolios.** We compute reversal portfolios around the "Tokyo" fix and the "Europe" fixes for each day $d$ as reversal returns as the sum of pre- and post-fix returns as follows:

$$\Delta s_d^{\text{Tokyo}} = -\Delta s_d^{\text{Pre-T}} + \Delta s_d^{Post-T} \tag{5}$$

$$\Delta s_d^{\text{Europe}} = -\Delta s_d^{Pre-E} + \Delta s_d^{Post-L}, \tag{6}$$

i.e., before the Tokyo and ECB fixes we take a short position that is reversed post-Tokyo and post-London fix respectively. For the Tokyo fix the short position is held from 5:00 p.m. ET to the Tokyo fix at 9:55 a.m. local time (taking DST into account), and the long position is held from the Tokyo fix until 2:00 a.m. ET. For the "Europe" window the short position is held from 2:00 a.m. ET until the ECB fix at 2:15 p.m. local time, and the long position is held starting with the London fix at 4:00 p.m. local time until 5:00 p.m. ET. The three-hour period between the two fixes is dropped.

| | pre-T | post-T | pre-E | E-L | post-L | CTC |
|---|---|---|---|---|---|---|
| AUD | -7.15 | 4.66 | -1.03 | -0.13 | 4.86 | 1.20 |
| | (-8.24) | (3.94) | (-0.77) | (-0.10) | (3.75) | (0.44) |
| CAD | -3.83 | 3.78 | -1.91 | -1.04 | 3.89 | 0.90 |
| | (-8.74) | (7.15) | (-1.92) | (-0.89) | (3.81) | (0.47) |
| CHF | -3.12 | 3.15 | -6.43 | 3.18 | 5.65 | 2.43 |
| | (-5.56) | (4.94) | (-4.19) | (2.54) | (5.19) | (1.00) |
| EUR | -4.54 | 5.89 | -8.87 | 1.58 | 6.87 | 0.92 |
| | (-8.83) | (9.29) | (-7.24) | (1.35) | (6.78) | (0.43) |
| GBP | -4.75 | 3.19 | -5.78 | 1.06 | 6.67 | 0.39 |
| | (-9.12) | (5.04) | (-4.62) | (1.04) | (7.44) | (0.20) |
| JPY | -4.06 | 7.94 | -2.61 | 1.56 | -2.92 | -0.08 |
| | (-5.87) | (8.22) | (-2.37) | (1.42) | (-3.03) | (-0.04) |
| NOK | -4.88 | 7.44 | -3.51 | -5.08 | 5.40 | -0.63 |
| | (-7.51) | (9.66) | (-2.19) | (-3.77) | (4.49) | (-0.24) |
| NZD | -8.53 | 5.77 | -0.86 | 1.40 | 4.55 | 2.33 |
| | (-8.41) | (4.99) | (-0.60) | (1.10) | (3.30) | (0.84) |
| SEK | -4.53 | 5.44 | -7.73 | -0.15 | 6.55 | -0.41 |
| | (-6.52) | (7.05) | (-4.93) | (-0.11) | (5.38) | (-0.16) |
| DOL | -5.02 | 5.28 | -4.21 | 0.34 | 4.63 | 1.02 |
| | (-11.69) | (9.19) | (-4.50) | (0.37) | (5.48) | (0.59) |

**Table I. Intraday Returns and the Tokyo, ECB and London Fix**

This table reports annualized average returns for the intraday periods around the Tokyo, ECB and London fixes. *t*-statistics are reported in parentheses. See note 1 for the definitions of the intraday periods. The sample period is January 1999 to December 2019. The data is sourced from Refinitiv's Tick History (RTH) database.

| | pre-T | post-T | pre-E | E-L | post-L | CTC |
|---|---|---|---|---|---|---|
| 99-04 | -4.02 | 6.29 | -8.57 | 3.36 | 7.05 | 4.10 |
| | (-5.01) | (6.68) | (-4.80) | (2.01) | (4.57) | (1.27) |
| 04-09 | -6.01 | 6.96 | -4.68 | -0.88 | 4.54 | -0.07 |
| | (-6.15) | (5.61) | (-2.27) | (-0.39) | (2.48) | (-0.02) |
| 09-14 | -9.05 | 6.50 | -0.92 | 0.93 | 5.20 | 2.66 |
| | (-8.60) | (4.43) | (-0.40) | (0.48) | (2.52) | (0.65) |
| 14-19 | -1.59 | 2.08 | -3.14 | -1.52 | 2.16 | -2.01 |
| | (-2.64) | (2.25) | (-2.28) | (-1.02) | (1.62) | (-0.76) |

**Table II. Intraday Dollar Portfolio Returns Year-by-Year**
This table reports annualized average returns for the intraday periods around the Tokyo, ECB and London fixes for the dollar portfolio for a set of equally spaced sample periods. See note 1 for the definitions of the intraday periods. $t$-statistics are reported in parentheses. The sample period is January 1999 to December 2019. The data is sourced from Refinitiv's Tick History (RTH) database.

| | pre-T | post-T | pre-E | E-L | post-L | CTC |
|---|---|---|---|---|---|---|
| RTH Forwards | -4.58 | 5.78 | -8.57 | 1.55 | 6.69 | 0.88 |
| | (-10.31) | (10.45) | (-7.82) | (1.42) | (7.56) | (0.45) |
| CME Futures | -4.06 | 5.61 | -5.06 | 0.36 | 1.88 | -1.27 |
| | (-8.93) | (10.00) | (-5.81) | (0.38) | (2.60) | (-0.79) |
| ICE Futures | -2.09 | 2.53 | -2.68 | 1.09 | 2.49 | 1.34 |
| | (-3.73) | (5.34) | (-3.27) | (1.59) | (4.58) | (1.02) |
| RM VWAPS | -1.70 | 3.88 | -6.87 | -0.07 | 4.18 | -0.59 |
| | (-3.89) | (6.06) | (-5.12) | (-0.06) | (4.02) | (-0.26) |

**Table III. Intraday Returns for Across Different Data Sets**
This table reports annualized average returns for different intraday periods around the Tokyo, ECB and London fixes for the dollar portfolio using different data sets. $t$-statistics are reported in parentheses. Intraday returns are computed from RTH forwards, CME futures, intercontinental-ICE dollar index (DX) futures and VWAPs from Refinitiv Matching (RM). See note 1 for the definitions of the intraday periods. Dollar portfolio returns from CME futures are computed from the EUR, GBP and JPY, which are the only liquid pairs over an extended sample period. The sample periods are January 1999 to December 2019 for RTH forwards, January 2006 to December 2019 for CME futures, January 1999 to December 2019 for ICE, and June 2006 to December 2019 for RM.

**Panel A: RM**

| | AUD | | | | | GBP | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | pre-T | post-T | pre-E | pre-L | post-L | pre-T | post-T | pre-E | pre-L | post-L |
| Fraction positive | 0.55 | 0.57 | 0.48 | 0.47 | 0.52 | 0.51 | 0.55 | 0.48 | 0.48 | 0.54 |
| Probability | 0.00 | 0.00 | 0.01 | 0.00 | 0.01 | 0.10 | 0.00 | 0.03 | 0.04 | 0.00 |
| Mean | 8.34 | 24.26 | -7.92 | -26.42 | 2.53 | 1.47 | 14.45 | 2.36 | -3.44 | 22.51 |
| $t$-stat | (3.78) | (6.60) | (-1.86) | (-4.25) | (0.71) | (0.92) | (6.05) | (0.31) | (-0.34) | (5.03) |
| Median | 9.33 | 20.81 | -10.22 | -19.44 | 6.55 | 1.57 | 8.06 | -12.98 | -20.61 | 18.63 |
| $z$-score | (5.70) | (7.90) | (-2.75) | (-3.40) | (2.51) | (1.66) | (6.33) | (-2.24) | (-2.04) | (4.81) |
| Std. Dev. | 129.21 | 214.78 | 248.64 | 363.52 | 208.60 | 93.48 | 139.73 | 450.65 | 592.66 | 261.49 |
| Skewness | -0.05 | -0.35 | -0.21 | -0.23 | -0.46 | -0.19 | 0.55 | 0.61 | 0.36 | 0.18 |
| Kurtosis | 7.63 | 7.96 | 6.34 | 5.34 | 9.41 | 18.63 | 12.84 | 10.52 | 7.54 | 8.02 |

**Panel B: CME**

| | AUD | | | | | GBP | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | pre-T | post-T | pre-E | pre-L | post-L | pre-T | post-T | pre-E | pre-L | post-L |
| Fraction positive | 0.46 | 0.50 | 0.49 | 0.48 | 0.50 | 0.48 | 0.50 | 0.49 | 0.49 | 0.50 |
| Probability | 0.00 | 0.60 | 0.40 | 0.07 | 0.88 | 0.04 | 0.95 | 0.28 | 0.10 | 0.80 |
| Mean | -3.14 | 0.55 | 0.35 | -2.15 | -0.16 | -1.85 | -0.35 | -3.31 | -7.27 | -1.46 |
| $t$-stat | -4.39 | 0.49 | 0.19 | -0.64 | -0.07 | -2.51 | -0.44 | -1.13 | -1.44 | -0.31 |
| Median | -1.97 | 0.18 | -0.97 | -4.69 | -0.15 | -0.73 | 0.00 | -2.07 | -5.93 | 0.60 |
| $z$-stat | -4.34 | 0.53 | -0.84 | -1.83 | -0.15 | -2.06 | -0.07 | -1.08 | -1.62 | 0.26 |
| Std. Dev. | 41.78 | 65.88 | 109.64 | 196.05 | 129.82 | 43.12 | 46.75 | 170.79 | 294.41 | 272.16 |
| Skewness | -1.45 | -0.27 | 0.09 | -2.33 | -2.96 | -21.56 | -2.73 | -0.89 | -0.54 | 1.12 |
| Kurtosis | 34.30 | 10.32 | 32.48 | 81.32 | 70.94 | 866.87 | 68.23 | 28.71 | 37.19 | 153.96 |

**Table IV. Summary Statistics: Order Flow**

At the daily frequency, each panel reports the fraction of order flow observations that are positive, the p-value from a two-sided test of observing order flow in one direction under the null hypothesis of a random walk, as well as mean, median, z-score, standard deviation, skewness, and kurtosis. The z-score refers to a non-parametric test assessing if the median is different from zero. Order flow is defined as buyer- minus seller-initiated volume measured in million U.S. dollars. See note 1 for the definitions of the intraday periods. The sample period is June 2006 to December 2019. Data in Panel A is sourced from Refinitiv's Matching (RM) trading platform, while results in Panel B are based on data from CME.

| | AUD | | | GBP | | |
|---|---|---|---|---|---|---|
| | Tokyo | Europe | | Tokyo | Europe | |
| $\text{OF}^{preTOK}$ | -28.13 | | | -25.86 | | |
| | (-7.09) | | | (-3.57) | | |
| $\text{OF}^{preECB}$ | | -7.22 | | | -3.54 | |
| | | (-2.79) | | | (-3.77) | |
| $\text{OF}^{preLON}$ | | | -9.28 | | | -4.16 |
| | | | (-5.88) | | | (-5.67) |
| $\text{OF}^{post}$ | 104.39 | 106.26 | 108.75 | 61.01 | 46.86 | 47.66 |
| | (27.45) | (24.40) | (24.95) | (11.78) | (18.09) | (18.43) |
| adj-R2 | 0.38 | 0.30 | 0.30 | 0.16 | 0.21 | 0.22 |
| Obs | 3,406 | 3,406 | 3,406 | 3,406 | 3,406 | 3,406 |

**Table V. Return Reversal Regressions**

This table reports results referring to the regression model

$$\Delta s_t^{post} = \alpha + \beta_1 OF_t^{pre} + \beta_2 OF_t^{post} + \varepsilon_t,$$

where $\Delta s_t^{post}$ refers to log spot returns, based on volume-weighted average prices (VWAP), during the post-fix hours for the Australian dollar ($AUD$) or the British pound ($GBP$) on day $t$, and $OF_t^{preTOK}$, $OF_t^{preECB}$, and $OF_t^{preLON}$ measure the order flow in the pre-fix hours of the Tokyo and European fixes, respectively. $OF_t^{post}$ is order flow during the post-fix hours. Returns are measured in basis points. Order flow is defined as buyer- minus seller-initiated volume and is measured in billion U.S. dollar. See note 1 for the definitions of the intraday periods. The sample period is June 2006 to December 2019. The intercept is omitted to preserve space. Parentheses report $t$-statistics based on Newey-West adjusted standard errors. All data is sourced from Refinitiv's Matching (RM) trading platform.

| | Panel A: CME Order Flow | | | | | | Panel B: CME & RM Order Flow | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | AUD | | | GBP | | | AUD | | | GBP | | |
| | Tokyo | Europe | | Tokyo | Europe | | Tokyo | Europe | | Tokyo | Europe | |
| $\text{OF}_{CME}^{preTOK}$ | -49.08 | | | -22.35 | | | -39.81 | | | -15.06 | | |
| | (-5.11) | | | (-2.20) | | | (-4.70) | | | (-1.86) | | |
| $\text{OF}_{RM}^{preTOK}$ | | | | | | | -13.73 | | | -13.29 | | |
| | | | | | | | (-5.08) | | | (-6.50) | | |
| $\text{OF}_{CME}^{preECB}$ | | -1.55 | | | 0.16 | | | -2.88 | | | -0.09 | |
| | | (-0.38) | | | (0.09) | | | (-0.81) | | | (-0.05) | |
| $\text{OF}_{RM}^{preECB}$ | | | | | | | | -4.89 | | | -1.89 | |
| | | | | | | | | (-2.73) | | | (-2.75) | |
| $\text{OF}_{CME}^{preLON}$ | | | -3.82 | | | -0.62 | | | -3.26 | | | -1.04 |
| | | | (-1.50) | | | (-0.54) | | | (-1.59) | | | (-0.89) |
| $\text{OF}_{RM}^{preLON}$ | | | | | | | | | -6.74 | | | -2.94 |
| | | | | | | | | | (-5.81) | | | (-5.55) |
| $\text{OF}_{CME}^{post}$ | 116.23 | 19.90 | 21.79 | 90.41 | -0.13 | 0.16 | 68.98 | 19.44 | 18.66 | 63.13 | 1.11 | 1.15 |
| | (12.97) | (3.48) | (3.69) | (8.92) | (-0.09) | (0.11) | (9.32) | (4.31) | (4.25) | (9.98) | (0.93) | (0.91) |
| $\text{OF}_{RM}^{post}$ | | | | | | | 63.39 | 76.34 | 78.17 | 36.08 | 33.69 | 34.32 |
| | | | | | | | (28.97) | (27.49) | (27.95) | (19.81) | (22.41) | (22.97) |
| adj-R2 | 0.10 | 0.01 | 0.01 | 0.13 | -0.00 | -0.00 | 0.41 | 0.33 | 0.33 | 0.29 | 0.20 | 0.20 |
| Obs | 3,408 | 3,408 | 3,408 | 3,408 | 3,408 | 3,408 | 3,406 | 3,406 | 3,406 | 3,406 | 3,406 | 3,406 |

**Table VI. Return Reversal Regressions: CME Futures**

This table reports results referring to the regression model

$$\Delta s_{t,CME}^{post} = \alpha + \gamma_1 OF_{t,CME}^{pre} + \gamma_2 OF_{t,CME}^{post} + \beta_1 OF_{t,RM}^{pre} + \beta_2 OF_{t,RM}^{post} + \varepsilon_t,$$

where $\Delta s_{t,CME}^{post}$ refers to log futures returns, based on volume-weighted average prices (VWAP), during the post-fix hours of the Australian dollar ($AUD$) or the British pound ($GBP$) on day $t$; and $OF_{t,j}^{preTOK}$, $OF_{t,j}^{preECB}$ and $OF_{t,j}^{preLON}$ measure the order flow in the pre-fix hours of the Tokyo fix and London fix, respectively. $OF_{t,j}^{post}$ is order flow during the post-fix hours. The subscript $j$, where $j \in \{CME, RM\}$, indicates the source of the order flow measures. Returns are measured in basis points. Order flow is defined as buyer- minus seller-initiated volume measured in billion U.S. dollars. See note 1 for the definitions of the intraday periods. The sample period is June 2006 to December 2019. For regressions in the left panel (Panel A), the coefficients $\beta_1$ and $\beta_2$ are restricted to zero. The intercept coefficient is omitted to preserve space. Parentheses report $t$-statistics based on Newey-West adjusted standard errors. Data is sourced from Refinitiv's Matching (RM) and CME's trading platform.

| | AUD | CAD | CHF | EUR | GBP | JPY | NOK | NZD | SEK | DOL |
|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Tokyo** | | | | | | | | | | |
| Fraction positive | 0.56 | 0.57 | 0.55 | 0.57 | 0.56 | 0.57 | 0.58 | 0.56 | 0.56 | 0.59 |
| Probability | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Mean | 11.82 | 7.61 | 6.27 | 10.44 | 7.94 | 12.00 | 12.33 | 14.31 | 9.98 | 10.30 |
| $t$-stat | (8.03) | (10.68) | (7.19) | (12.60) | (9.87) | (10.12) | (11.93) | (9.29) | (9.56) | (14.46) |
| Median | 13.36 | 6.67 | 4.21 | 8.22 | 6.53 | 10.50 | 9.94 | 12.74 | 7.33 | 9.04 |
| $z$-score | (8.47) | (10.47) | (6.93) | (9.85) | (9.21) | (10.49) | (11.27) | (8.63) | (8.96) | (13.32) |
| Std. Dev. | 6.72 | 3.26 | 3.98 | 3.79 | 3.68 | 5.42 | 4.72 | 7.04 | 4.77 | 3.25 |
| Skewness | -0.33 | 0.77 | 0.80 | 0.25 | -0.24 | -0.05 | 0.47 | 0.02 | 2.30 | 0.02 |
| Kurtosis | 10.48 | 16.67 | 34.22 | 8.67 | 38.30 | 15.35 | 17.70 | 7.40 | 55.60 | 8.46 |
| **Panel B: Europe** | | | | | | | | | | |
| | AUD | CAD | CHF | EUR | GBP | JPY | NOK | NZD | SEK | DOL |
| Fraction positive | 0.51 | 0.52 | 0.54 | 0.56 | 0.55 | 0.51 | 0.52 | 0.51 | 0.55 | 0.55 |
| Probability | 0.04 | 0.00 | 0.00 | 0.00 | 0.00 | 0.35 | 0.00 | 0.04 | 0.00 | 0.00 |
| Mean | 5.91 | 5.82 | 12.08 | 15.76 | 12.48 | -0.31 | 8.92 | 5.43 | 14.31 | 8.85 |
| $t$-stat | (3.20) | (4.01) | (6.81) | (9.95) | (7.96) | (-0.21) | (4.51) | (2.70) | (7.25) | (7.03) |
| Median | 4.03 | 4.35 | 10.73 | 13.64 | 11.43 | 1.12 | 6.21 | 4.50 | 14.13 | 9.16 |
| $z$-score | (2.04) | (3.45) | (6.23) | (8.55) | (7.01) | (0.94) | (2.92) | (2.07) | (6.77) | (7.01) |
| Std. Dev. | 8.43 | 6.63 | 8.11 | 7.24 | 7.17 | 6.77 | 9.04 | 9.20 | 9.02 | 5.75 |
| Skewness | 0.14 | 0.36 | -0.63 | 0.01 | 0.30 | -0.18 | 0.03 | 0.08 | -0.08 | 0.01 |
| Kurtosis | 10.41 | 7.39 | 36.26 | 6.87 | 6.94 | 6.79 | 6.01 | 8.23 | 6.25 | 6.61 |

**Table VII. Statistical Properties of Return Reversals**

At the daily frequency, each panel reports the fraction of return observations that are positive, the p-value from a two-sided test of observing returns in one direction under the null hypothesis of a random walk, as well as mean (annualized), median (annualized), z-score, standard deviation (annualized), skewness, and kurtosis. The z-score refers to a non-parametric test assessing if the median is different from zero. Panels A and B report summary statistics for the Tokyo and Europe fix reversal portfolios, respectively. See note 2 for the definitions of the reversal portfolios. The sample period is January 1999 to December 2019. The data is sourced from Refinitiv's Tick History (RTH) database.

| | Tokyo | Europe | Tokyo | Europe | Tokyo | Europe | Tokyo | Europe | Tokyo | Europe |
|---|---|---|---|---|---|---|---|---|---|---|
| $\text{VIX}_{t-1}$ | 0.24 | 0.14 | | | | | | | 0.23 | 0.10 |
| | (9.54) | (3.39) | | | | | | | (8.63) | (2.62) |
| $\text{IRD}_{i,t-1}$ | | | 7.91 | 3.08 | | | | | 5.69 | 2.36 |
| | | | (6.71) | (2.31) | | | | | (4.80) | (1.65) |
| $\text{EQD}_{i,t}$ | | | | | 0.26 | 2.20 | | | | |
| | | | | | (0.74) | (1.54) | | | | |
| $\text{EQ}_t^{US}$ | | | | | | | 0.85 | 2.84 | 0.98 | 2.03 |
| | | | | | | | (3.67) | (1.96) | (4.95) | (2.22) |
| $\text{EQ}_{i,t}$ | | | | | | | 0.27 | -1.63 | | |
| | | | | | | | (0.54) | (-1.14) | | |
| adj-R2 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 |
| Obs | 47,358 | 47,358 | 45,081 | 45,081 | 45,081 | 45,081 | 42,192 | 42,192 | 42,183 | 42,183 |

**Table VIII. Reversal Portfolios and Economic Factors**

This table reports results to the following fixed-effects panel regression model:

$$\Delta s_{i,t}^{j} = \alpha_i + \beta_1 VIX_{t-1} + \beta_2 IRD_{i,t-1} + \beta_3 EQ_{i,t} + \varepsilon_{i,t},$$

where $\Delta s_{i,t}^{j}$ refers to portfolio reversal returns around the Tokyo ($j = TOK$) or European fixes ($j = EUR$), and the right-hand side variables include the lagged VIX volatility index ($VIX_{t-1}$), lagged short-term interest rate differentials between the U.S. and country $i$ ($\text{IRD}_{i,t-1}$), and an equity factor ($EQ_{i,t}$), that refers to either the contemporaneous equity return differentials between the U.S. and country $i$ ($EQ_{i,t}$), or equity returns in country $i$ ($EQ_{i,t}$) or equity returns in the U.S. ($EQ_t^{US}$). Portfolio reversal returns are measured in basis points. $t$-statistics are in parentheses based on robust standard errors. See note 2 for the definitions of the reversal portfolios. Coefficients of currency fixed effects are omitted to save space. Data is daily and covers the sample period from January 1999 to December 2019.

| Panel A: Tokyo | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | EUR | | | GBP | | | JPY | | |
| | pre | post | pre+post | pre | post | pre+post | pre | post | pre+post |
| $\text{Avg}^{BA,100\%}$ | -3.51 | -1.63 | -5.14 | 0.29 | -0.58 | -6.92 | -5.52 | -1.02 | -6.54 |
| $\text{Avg}^{BA,50\%}$ | 0.52 | 2.13 | 2.65 | 4.18 | 2.96 | 0.51 | -0.73 | 3.46 | 2.73 |
| $\text{Avg}^{BA,0\%}$ | 4.55 | 5.89 | 10.44 | 4.75 | 3.18 | 7.94 | 4.06 | 7.93 | 12.00 |
| $\text{SR}^{BA,100\%}$ | -1.98 | -0.97 | -1.66 | -0.06 | -0.11 | -2.19 | -2.12 | -0.50 | -1.42 |
| $\text{SR}^{BA,50\%}$ | -0.28 | 0.33 | 0.39 | 0.20 | 0.12 | -0.18 | -0.60 | 0.52 | 0.29 |
| $\text{SR}^{BA,0\%}$ | 1.43 | 1.63 | 2.45 | 1.50 | 0.69 | 1.84 | 0.91 | 1.53 | 1.99 |
| Panel B: Europe | | | | | | | | | |
| | EUR | | | GBP | | | JPY | | |
| | pre | post | pre+post | pre | post | pre+post | pre | post | pre+post |
| $\text{Avg}^{BA,100\%}$ | 2.02 | -0.50 | 1.52 | -0.86 | -0.66 | -1.51 | -6.04 | -12.19 | -18.23 |
| $\text{Avg}^{BA,50\%}$ | 5.45 | 3.19 | 8.64 | 2.46 | 3.00 | 5.47 | -1.71 | -7.56 | -9.27 |
| $\text{Avg}^{BA,0\%}$ | 8.88 | 6.88 | 15.75 | 5.79 | 6.66 | 12.45 | 2.61 | -2.92 | -0.31 |
| $\text{SR}^{BA,100\%}$ | 0.15 | -0.36 | 0.05 | -0.36 | -0.45 | -0.38 | -1.43 | -3.03 | -2.86 |
| $\text{SR}^{BA,50\%}$ | 0.76 | 0.43 | 1.03 | 0.23 | 0.44 | 0.60 | -0.57 | -1.98 | -1.54 |
| $\text{SR}^{BA,0\%}$ | 1.37 | 1.23 | 2.01 | 0.81 | 1.34 | 1.57 | 0.29 | -0.93 | -0.22 |

**Table IX. Trading Around the Fixes Including Transaction Costs**

This table reports annualized average returns ($Avg$) and Sharpe ratios ($SR$) for different intraday periods around the Tokyo and Europe fixes for the euro, pound and yen, taking transaction costs into account. This means that foreign currencies are bought at the bid and sold at the ask. We report results for the pre-fix and post-fix periods, and for the combination of the two. See note 1 for the definitions of the intraday periods. We consider different degrees of reported transaction costs of indicative quotes, accounting for 100%, 50% and 0% of the bid-ask spread ($BA$). Data is daily and the sample period is January 1999 to December 2019.

# VIII. Figures

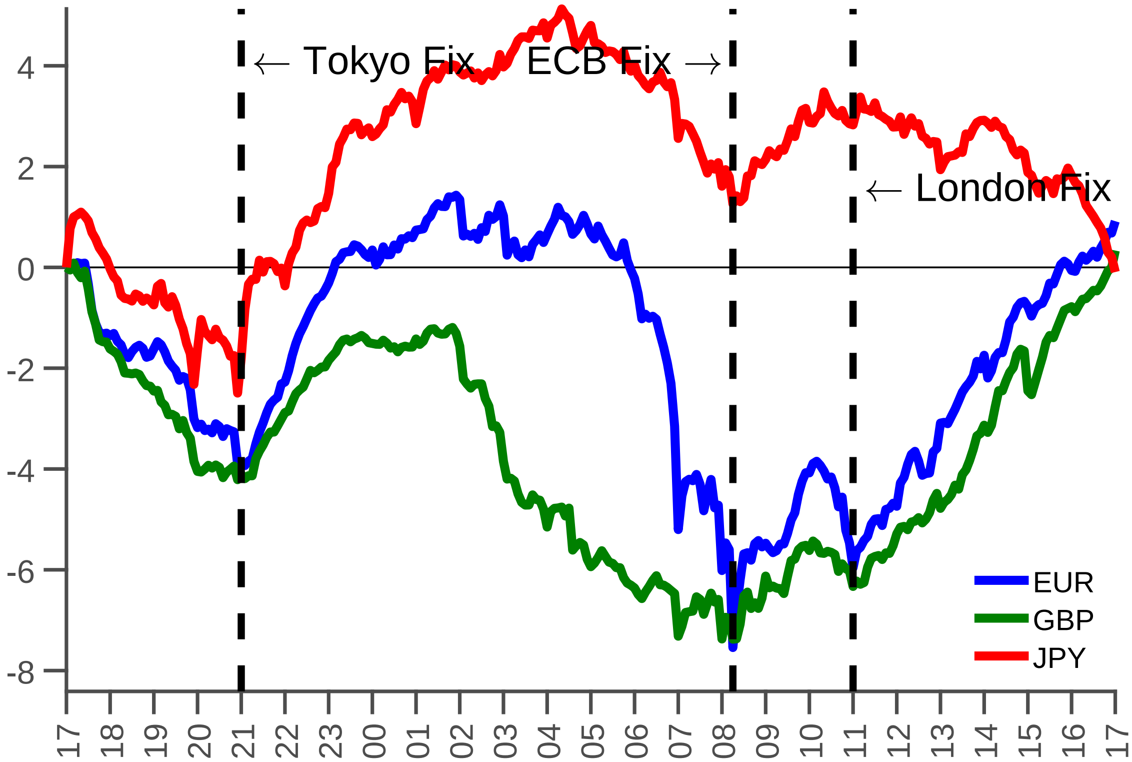



**Figure 2. Cumulative 5-min Returns for EUR, GBP, and JPY**

This figure displays cumulative average annualized 5-min returns ($-\Delta s$) over the course of a trading day for the EUR (blue), GBP (green), and JPY (red). An increase means the foreign currency appreciates against the U.S. dollar. The three black dashed lines at 8:55 p.m., 8:15 a.m., and 11:00 a.m. refer to the Tokyo fix, the ECB fix and the London fix, respectively. All returns are annualized and expressed in percent. The time is measured in Eastern Time (ET). The sample period is January 1999 to December 2019.

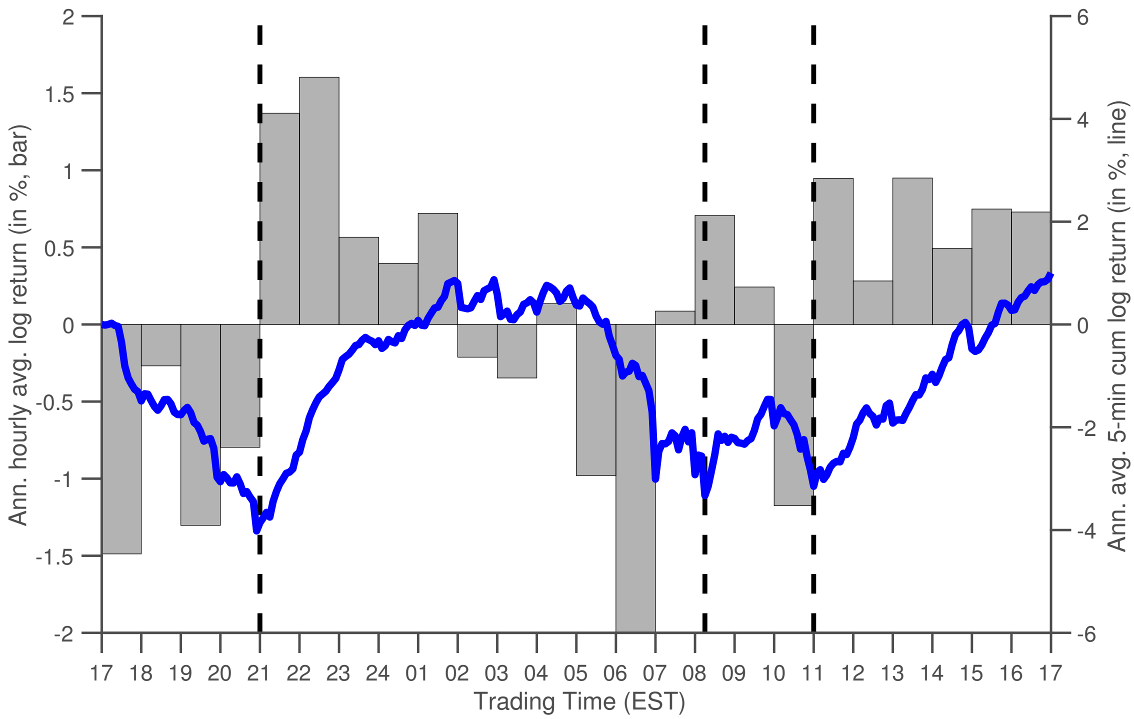
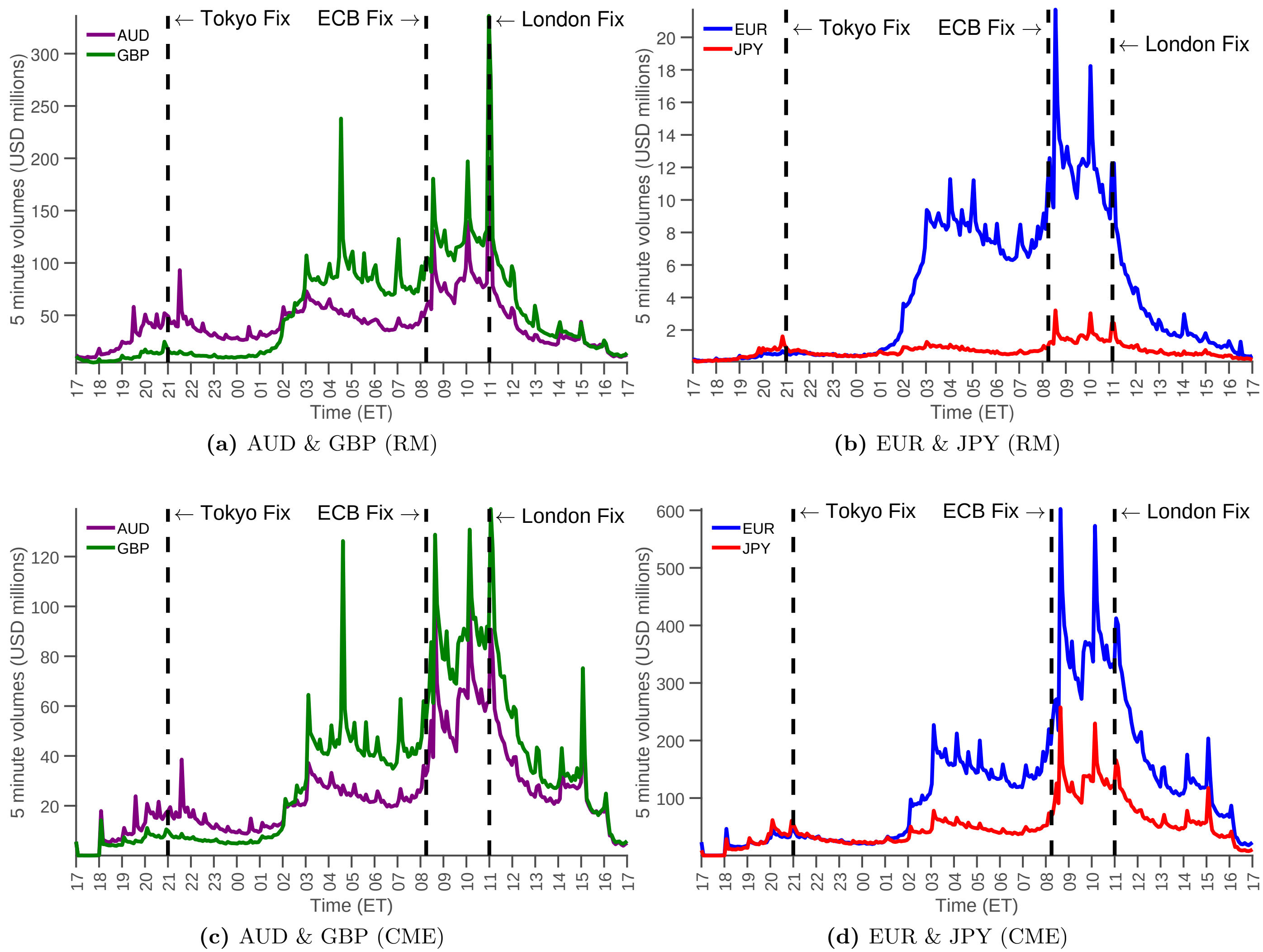



**Figure 3. Intraday Returns Dynamics: Dollar Portfolio**

This figure displays cumulative average annualized 5-min returns ($-\Delta s$) for the dollar portfolio over the course of a trading day. An increase means the basket of foreign currencies appreciates against the U.S. dollar. The three black dashed lines at 8:55 p.m., 8:15 a.m., and 11:00 a.m. refer to the Tokyo fix, the ECB fix and the London fix, respectively. All returns are annualized and expressed in percent. The time is measured in Eastern Time (ET). The sample period is January 1999 to December 2019.




**(a)** AUD & GBP (RM)

**(b)** EUR & JPY (RM)

**(c)** AUD & GBP (CME)

**(d)** EUR & JPY (CME)

**Figure 4. Intraday Volumes**

The figures show the average volume dynamics in each 5-minute interval over the course of the trading day for the Australian dollar and the British pound or the euro and Japanese yen on Refinitiv's Matching (Panels (a) and (b)) and CME's (Panels (c) and (d)) trading platform. Average volume is measured in million U.S. dollars. The sample period is June 2006 to December 2019. Data is from Refinitiv's Matching (RM) and CME's trading platforms.

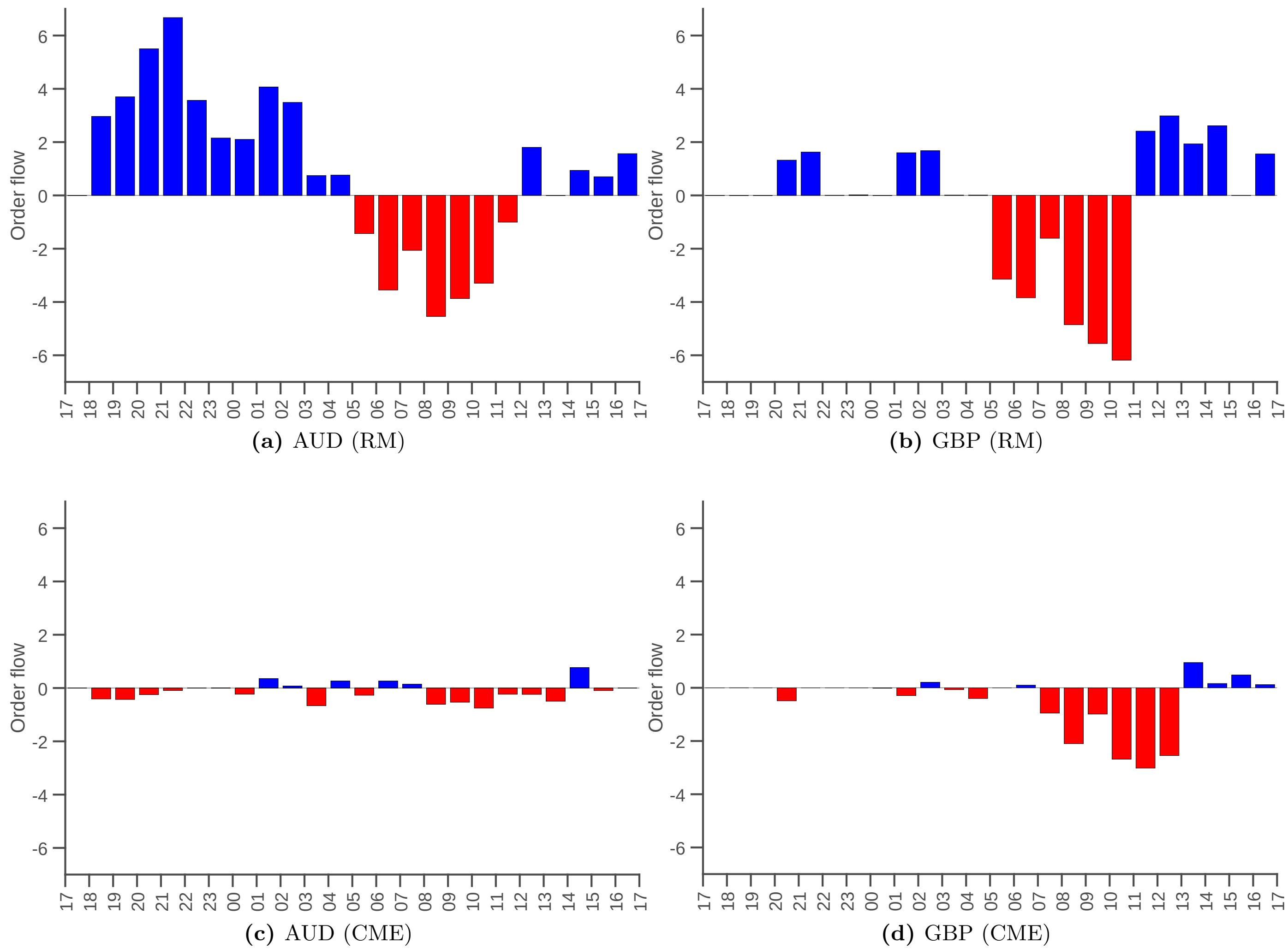
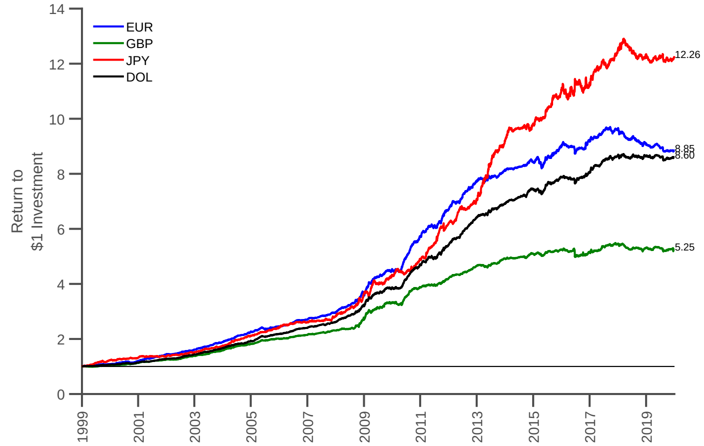
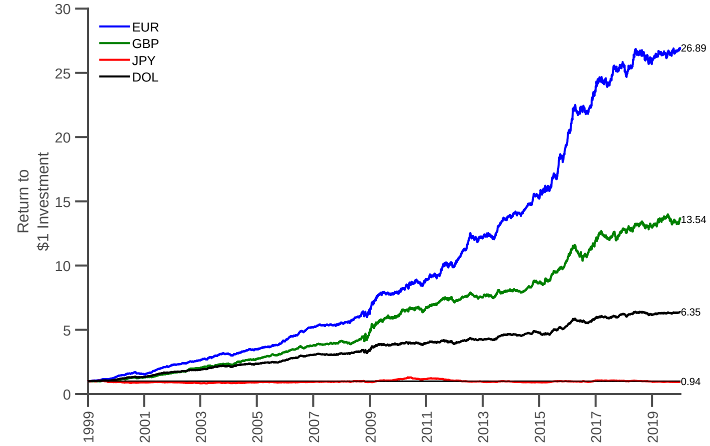



**Figure 5. Order Flow Dynamics**

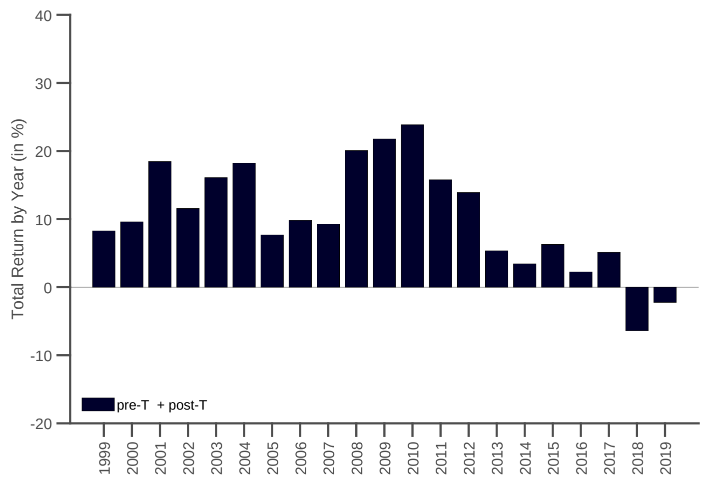
The figures show the median order flow dynamics in every hourly interval over the course of the trading day for the Australian dollar and the British pound on Refinitiv's Matching (Panels (a) and (b)) and CME's (Panels (c) and (d)) trading platform. Order flow is defined as buyer- minus seller-initiated traded volume, measured in million U.S. dollar. The sample period is June 2006 to December 2019. Data is from Refinitiv's Matching (RM) and CME's trading platforms.



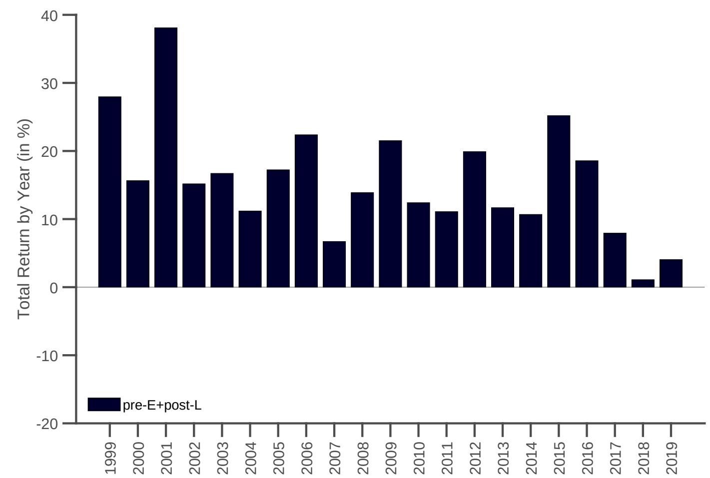

**(a)** Total Return Index: Tokyo Fix




**(b)** Total Return Index: Europe Fix



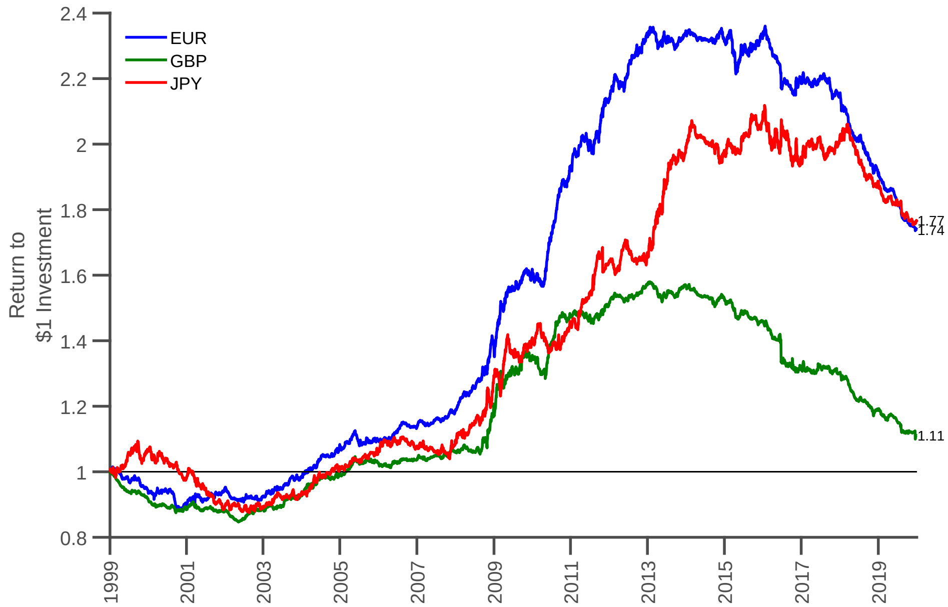

**(c)** DOL around Tokyo Fix



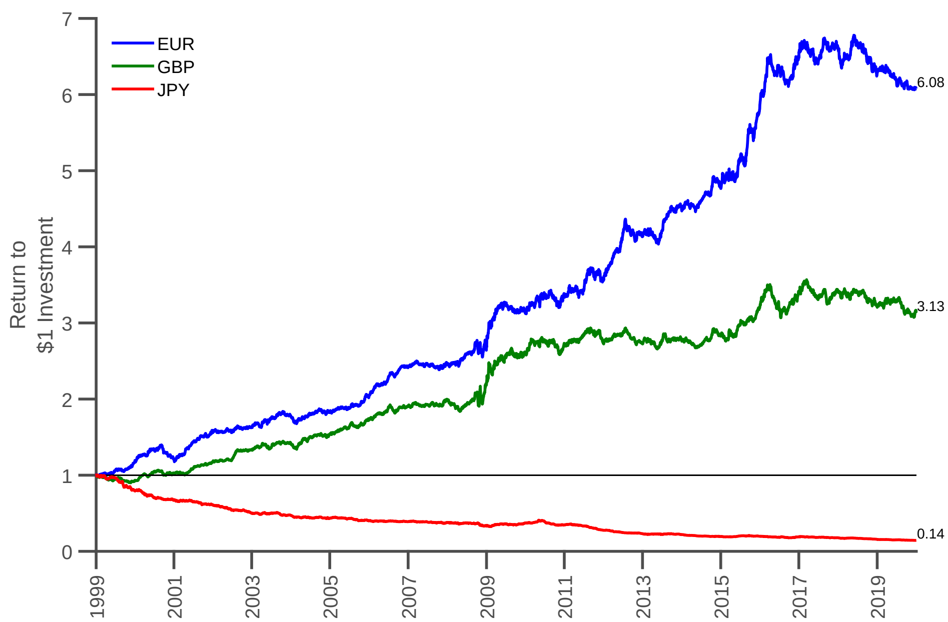

**(d)** DOL around Europe Fix

**Figure 6. Total Return Indices and Year-By-Year Performance: Trading the *W***

The figures show the performance of a trading strategy around the Tokyo and ECB/London fixes, where an investor takes a short position during the pre-fix and a long position during the post-fix, respectively. Panels (a) and (b) show the total return indices for the three major currencies (EUR, GBP, JPY) and the dollar portfolio (DOL) with an initial investment of one U.S. dollar. Panels (c) and (d) show the total returns split year by year for the dollar portfolio. The sample period is January 1999 to December 2019.




**(a)** Total Return Index: Tokyo Fix




**(b)** Total Return Index: Europe Fix

**Figure 7. Total Return Indices: Trading the *W* with Transaction Costs**
The figures show the performance of a trading strategy around the Tokyo and ECB/London fixes, where an investor takes a short position during the pre-fix and a long position during the post-fix, respectively. Panel (a) shows the total return indices for the three major currencies (EUR, GBP, JPY) with an initial investment of one U.S. dollar around the Tokyo fix. Panel (b) shows the total return indices for the three major currencies (EUR, GBP, JPY) with an initial investment of one U.S. dollar around the Europe fixes. We use 50% of the reported bid-ask spread on RTH as a proxy of transaction costs. The sample period is January 1999 to December 2019.

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