BANK OF ENGLAND

Staff Working Paper No. 964

FX option volume

Robert Czech, Pasquale Della Corte, Shiyang Huang and Tianyu Wang

March 2022

BANK OF ENGLAND

Staff Working Paper No. 964

FX option volume

Robert Czech,[1] Pasquale Della Corte,[2] Shiyang Huang[3] and Tianyu Wang[4]

Abstract

We study the information content of foreign exchange (FX) option volume using a unique dataset on over-the-counter FX options with disclosed counterparty identities and contract characteristics. Our study shows that FX option volume can predict future exchange rate returns, especially when the demand for the US dollar is high. In support of information-based arguments, we also document that the exchange rate predictability is stronger around macro-announcement days or when using options with higher embedded leverage. Finally, we show that hedge funds and real money investors have superior skills in predicting future exchange rates compared to other investor types.

Key words: Currency return, foreign exchange option, Informed trading, dollar demand.

JEL classification: F31, G12, G14, G15.

(1) Bank of England. Email: robert.czech@bankofengland.co.uk
(2) Imperial College London and Centre for Economic Policy Research (CEPR). Email: p.dellacorte@imperial.ac.uk
(3) University of Hong Kong. Email: huangsy@hku.hk
(4) Tsinghua University. Email: wangty6@sem.tsinghua.edu.cn

The authors would like to thank Tim Boobier, Sinem Hacioglu-Hoke, John Lewis, Matt Roberts-Sklar, Misa Tanaka, and seminar participants at the Bank of England for helpful comments. We gratefully acknowledge financial support from the Canadian Derivatives Institute. All remaining errors are our own.

The Bank's working paper series can be found at www.bankofengland.co.uk/working-paper/staff-working-papers

Bank of England, Threadneedle Street, London, EC2R 8AH
Email enquiries@bankofengland.co.uk

ISSN 1749-9135 (on-line)

1 Introduction

Over-the-counter (OTC) derivatives are essential instruments for the functioning of global financial markets. Their bespoke nature makes them attractive to accommodate the risk management needs of various market participants. Also, the lack of a central mechanism that limits leverage expansion makes them ideal for investors that want to profit from price misalignments. These trading incentives may imply that OTC derivatives reflect the underlying fundamentals more accurately than cash instruments, therefore contributing to the process of impounding new information into asset prices. However, OTC derivatives are negotiated privately, making it difficult for academics and policymakers to fully understand whether they are a valuable source of information for price determination.

Among OTC derivatives, foreign exchange (FX) options have experienced an exponential growth that started with the financial crises of the 1990s and continued with the expanding intermediation of international capital flows. By now, the FX option market is one of the largest and most liquid markets of its kind, with an average daily volume that exceeds \$250 billion and an outstanding notional close to \$12 trillion (BIS, 2016a,b). Also, it aggregates information in terms of beliefs, knowledge, and trading motives from a very diverse group of market participants, such as large international banks, asset managers, hedge funds, corporates, and central banks. Despite its importance, there is limited knowledge to date about the role of currency options for price discovery in FX markets since granular data are difficult to gather.

We attempt to fill this important gap in the literature by studying a novel regulatory dataset on contract-level OTC currency options. We observe all transactions where at least one counterpart is a UK legal entity, reported to the Depository Trust & Clearing Corporation (DTCC) Derivatives Repository between November 2014 and December 2016 under the European Market Infrastructure Regulation (EMIR). We have access to counterparty information and contract characteristics for more than one million transactions, amounting to 42% of the global trading activity in terms of average daily volume. Armed with this comprehensive dataset, we examine whether FX option volume predicts future exchange rate returns. Moreover, the granularity of our dataset further allows us to identify which groups of market participants possess superior information for exchange rate predictability.[1]

We begin our analysis by assessing whether aggregate FX option volume can predict future FX returns, similar to the work of Johnson and So (2012) for equity options. We hypothesize that informed trading coupled with investors' persistent demand for dollar assets translates into a negative relationship between aggregate option volume and future exchange rate fluctuations. In other words, higher option volume observed today predicts a foreign currency depreciation (or, equivalently, a US dollar appreciation) tomorrow. To clarify, we conveniently call all non-USD currencies 'foreign' for the remainder of the paper.[2] Intuitively, due to liquidity and safety reasons (e.g., Krishnamurthy and Vissing-Jorgensen, 2012; Maggiori, 2017; Du et al., 2018; Krishnamurthy and Lustig, 2019), investors seek a positive exposure to the dollar, which is unrelated to private information and acts as a short-sale constraint in line with the arguments of Johnson and So (2012).

[1]Section 6.3 presents a robustness analysis that employs data on aggregate FX option volumes from Bloomberg. In these publicly available data, however, we cannot disentangle dealers from clients, which limits the scope for more granular analyses.

[2]We use the traditional approach of defining exchange rates as units of US dollars per unit of foreign currency, such that a negative exchange rate return indicates a foreign currency depreciation or a US dollar appreciation.

More precisely, when informed traders receive a positive signal for the dollar (or, equivalently, a negative signal for the foreign currency), they further increase their exposure to the US dollar. Similarly, informed investors reduce their exposure to the dollar when they obtain a negative signal for the dollar (or, equivalently, a positive signal for the foreign currency), but they avoid to completely offset their initial positive dollar exposure. Put differently, FX option volume reflects more positive than negative signals for the dollar (or more negative than positive signals for the foreign currency). This simple mechanism leads to a negative relationship between FX option volume and future exchange rate returns, and this relationship is stronger when the initial demand for dollars is higher.

Empirically, we evaluate the information content of FX option volume for the cross-sectional predictability of exchange rate returns using conventional portfolio sorting strategies. We find strong evidence that FX option volume negatively predicts future exchange rate returns, especially for major currency pairs, in line with our hypothesis. Specifically, a daily rebalanced strategy that buys major currencies with low option volume and sells major currencies with high option volume delivers an annualized Sharpe ratio of 1.69. In addition to being economically large, this performance is also highly statistically significant. With a larger cross-section of currencies, our low-minus-high volume strategy yields an annualized Sharpe ratio of 0.71. Despite being sizeable in economic terms, it is insignificant from a statistical perspective. These results support our argument that certain investors in the FX option market seem to have superior information on future exchange rate returns. The information advantage could stem from the ability of informed investors to relate publicly available economic fundamentals to the currency market, as well as from unequal access to non-public information (e.g. costly data providers). The trading of informed investors should therefore outperform the trading of less informed investors, as long as learning is imperfect. Moreover, the evidence of stronger return predictability for major currency pairs is consistent with the notion that highly liquid assets attract more informed investors, because high liquidity enables informed traders to better trade on their informational advantage by taking larger positions in the market.[3]

We then conduct several additional tests that corroborate our hypothesis. First, we separate interdealer from dealer-client transactions, and document that the dealer-client volume is a more powerful predictor than interdealer volumes for future exchange rate returns. In this context, we find economically and statistically significant results for all currency pairs as well as for our restricted sample of major currency pairs. Also, the predictive power of the interdealer option volume disappears when combined with dealer-client option volumes, suggesting that any information content of interdealer volumes arises mechanically from dealer-client trading relationships. Second, we show that the excess returns of our strategies are completely obtained by predicting exchange rate returns, as opposed to interest rate differentials. This stands in sharp contrast to the performance of the popular carry strategy, which is primarily driven by interest rate differentials instead of exchange rate changes. Third, we run panel regressions with time and currency fixed effects and show that the return predictability is robust to controlling for currency liquidity and volatility. Finally, we confirm that the return predictability of FX option volume is largely unrelated to existing currency strategies, such as dollar, carry, value, momentum, volatility, and liquidity.

In line with our hypothesis, we therefore document the existence of a negative predictive

[3] We further extend our analysis to currency forward volume but find no evidence of exchange rate predictability. For a detailed description of trade-level currency forwards, see Cenedese et al. (2021).

relationship between FX option volume and exchange rate returns. To reiterate, the negative sign on this link may reflect investors' demand for dollar assets, driven by liquidity and safety concerns. We formally investigate this channel by identifying periods of high and low demand for US dollars. We quantify the demand for dollars using two different proxies. The first one is the US Treasury premium, measured as the yield gap between US government bonds and currency-hedged foreign government bonds, akin to Du et al. (2018) and Jiang et al. (2020, 2021). The second measure is the VXY index, which tracks the aggregate implied volatility of major currency pairs – a sort of a 'VIX equivalent' for FX markets compiled by JP Morgan. As noted in the recent literature, episodes of global financial instability are typically associated with a significant increase in the demand for US Treasuries, a phenomenon known as the 'flight to safety'. In our exercise, periods of high demand for the dollar coincide with periods of high US Treasury premia or periods with high levels of the VXY index. We indeed find that the return predictability arising from FX option volume is largely concentrated around periods of high demand for dollars.

Finally, we run a battery of additional exercises to verify that the return predictability of FX option volume indeed reflects informed trading. First, we show that the return predictability is stronger when using options with higher embedded leverage, i.e. out-of-the-money or short-maturity options, consistent with prior studies (e.g., Black, 1975; Easley et al., 1998; Pan and Poteshman, 2006; Ge et al., 2016). Second, we distinguish between FX option volumes of different client types and find that the return predictability originates from the trading activity of hedge funds and real money investors. This finding corroborates our informed trading hypothesis, since the trading of better informed hedge funds and real money investors (with typically more accurate interpretations of trade-relevant information, see Menkhoff et al., 2016) significantly outperforms the trading of less informed clients such as corporates and non-dealer banks. Third, we examine the return predictability of FX option volume around macro announcements and non-announcement days. Since macro news play an important role for the price discovery process in FX markets (e.g., Andersen et al., 2003), informed investors are more likely to trade on macro announcement days to capitalize on their higher ability to relate economic fundamentals to exchange rate fluctuations. Thus, we expect that the return predictability of FX option volume is stronger around macro announcement days, and we find supporting evidence in our sample. Finally, we use unique data on directional option trading to construct measures of order flow. We confirm that hedge funds and real money investors have superior skills in predicting FX returns relative to other market participants.

The remainder of this paper is organized as follows. Section 2 describes the related literature and the contribution of this paper. Section 3 presents the data and summary statistics. Section 4 verifies the predictive power of FX option volume for exchange rate returns, while Section 5 explores the role of informed trading in the FX option market. Section 6 provides further analyses and refinements of the main results before we conclude in Section 7. A separate Internet Appendix provides additional robustness tests and supporting analyses.

2 Related Literature

Our study contributes to a vast literature on exchange rate predictability that began with the influential contribution of Meese and Rogoff (1983). This literature shows that theoretically motivated macro predictors generally fail to outperform a naïve random model, especially at the short horizon (Mark, 1995; Engel and West, 2005), and this missing link between the state of the economy and exchange rate fluctuations is generally described as the 'exchange rate disconnect puzzle'(e.g., Obstfeld and Rogoff, 2000; Lyons, 2001; Evans, 2010). While the failure of traditional macro-based theories remains puzzling, alternative approaches have been used to predict exchange rate returns. Della Corte et al. (2016), for example, find that currency volatility risk premia can predict exchange rate returns, especially during financial crises and economic recessions. Their finding can be explained with limits to arbitrage and the resulting effects on the interaction between hedgers and speculators. In Londono and Zhou (2017), moreover, the US dollar appreciates when implied variance exceeds realized variance in FX markets because of exposure to global inflation uncertainty. These papers rely on aggregate market prices, and little is known about the underlying mechanism that makes options' implied volatility a powerful predictor of exchange rate returns. To the best of our knowledge, this paper is the first one to assess the information content of FX option volume for exchange rate predictability using highly granular data. In theory, informed investors have an incentive to migrate towards the option market as it provides more leverage or 'bang for the buck'. In this paper, we shed light on this intuitive yet unexplored mechanism in one of the largest and deepest OTC derivative markets.

Our study also speaks to the literature on informed trading in option markets. This strand of the literature mainly focuses on equity options, providing evidence for informed trading activity ahead of corporate news announcements, including the announcement of earnings (Roll et al., 2010), M&As (Cao et al., 2005), leveraged buyouts (Acharya and Johnson, 2010), and the announcements of strategic trades by activist investors (Collin-Dufresne et al., 2021). Some studies, moreover, extract information from options to predict stock returns. The array of proposed predictors includes equity option volume (Easley et al., 1998; Ge et al., 2016), put-call ratios (Pan and Poteshman, 2006), implied volatility (Bali and Hovakimian, 2009; Xing et al., 2010), put-call parity deviations (Cremers and Weinbaum, 2010), option-to-stock volume ratio (Johnson and So, 2012), and hedging activity by option market makers (Hu, 2014). Our contribution to this literature is threefold. First, we show that some of the results documented previously for equity options hold for another important asset class. Second, we show that certain groups of investors have a superior ability to relate macro fundamentals to future FX returns. In the equity market, in which some investors can predict firm-specific news, it remains unclear whether informed traders are also able to accurately forecast macro fundamentals. Third, compared to datasets generally used in the equity literature, our regulatory dataset contains additional features. In particular, we observe investor identities, and we can investigate the return predictability for different groups of investors, e.g., dealer banks, mutual funds, hedge funds, pension funds, non-financial corporates, and non-dealer banks. We can therefore separate informed from uninformed investors, and the heterogeneous trading needs of these investors have distinct implications for asset prices.

3 Data Description and Summary Statistics

We first describe the Trade Repository data on OTC currency options in Section 3.1, and then present preliminary summary statistics in Section 3.2.

3.1 Trade Repository Data

Understanding the nature of OTC derivative markets is generally difficult, as the terms of a transaction are negotiated privately and only observable to the involved counterparties. As a result, regulators and policymakers around the world have often struggled to access key information such as volume, maturity, outstanding transactions, and counterparty identities. Regulatory efforts to enhance the transparency of OTC derivatives markets, however, intensified after the collapse of Lehman Brothers. During the G20 summit in September 2009, it was agreed that OTC derivatives should be reported to trade repositories, thus granting regulators and policymakers access to high-quality and high-frequency data.

In the European Union, the commitment to increase the transparency of OTC derivatives markets has been implemented with the European Market Infrastructure Regulation (EMIR), which makes it mandatory for EU legal entities to report the terms of any derivative transaction to a trade repository authorized by the European Securities and Markets Authority (ESMA) by the next business day.[4] The reporting obligation covers all asset classes and applies to clearinghouses, financial counterparties, and non-financial counterparties that are legal entities under EU jurisdiction.[5] While this reporting obligation was introduced in February 2014, many observations were initially missing or reported incorrectly. In response, ESMA introduced a formal data validation process in November 2014 that substantially improved the quality of the trade reports (for more details, see Abad et al., 2016).[6]

We rely on the EMIR trade repository data to obtain trade-level information on European style OTC options written on exchange rates. Our sample spans the period from November 2014 to December 2016 and we observe all trades submitted to DTCC Derivatives Repository

[4]In the US, a similar reform has been implemented trough the Dodd-Frank Act. Also, according to the Financial Stability Board, most jurisdictions have enforced trade reporting obligations as of 2016.

[5]Since 1 January 2021, following the UK's withdrawal from the EU, derivatives reporting in the UK has been under the UK onshored version of EMIR, applying to all UK legal entities.

[6]As of December 2021, there are four trade repositories authorized under UK EMIR by the Financial Conduct Authority: DTCC Derivatives Reporting Plc; ICE Trade Vault Europe Limited; REGIS-TR UK Limited; and Unavista Limited.

– the largest trade repository in terms of market share at the time – in which at least one of the counterparties is a UK-regulated entity. We begin our analysis by selecting option data on 20 currencies: Australian dollar (AUD), Brazilian real (BRL), Canadian dollar (CAD), Swiss franc (CHF), euro (EUR), British pound (GBP), Hong Kong dollar (HKD), Indian rupee (INR), Japanese yen (JPY), South Korean won (KRW), Mexican peso (MXN), Norwegian krone (NOK), New Zealand dollar (NZD), Russian ruble (RUB), Swedish krona (SEK), Singapore dollar (SGD), Turkish lira (TRY), New Taiwan dollar (TWD), and South African rand (ZAR), relative to the US dollar (USD).[7]

3.2 Data Structure and Classification

We collect our transaction-level data from the "trade activity reports" in the DTCC Trade Repository data. We observe both counterparty information (i.e., legal entity identifier) and contract characteristics (e.g., unique trade identifier, notional amount, strike, maturity date, execution date, execution time), in total more than 100 reportable fields. We then discard duplicates of the same transaction using the unique trade identifier, given that the reporting obligation often applies to both counterparties. For example, a transaction between a UK-regulated bank and a UK-based pension fund would be reported twice, because both counterparties are obliged to report the trade. In contrast, a transaction between between a UK-regulated bank and a Japanese insurance company would only be reported once, as the Japan-based insurer is not obliged to report the trade. In a number of cases, we remove redundant copies of the same trade due to modifications, corrections, and valuation updates.

The currency market consists of an interbank segment where dealers (typically large in-

[7]Options on European currencies like the Polish Zloty, Czech koruna, and Hungarian forint are mostly traded against the euro. These currencies are therefore not included in our sample.

ternational banks) trade among themselves, and a customer segment where financial and non-financial players trade with dealers or among themselves. Using the legal entity identifiers, we first identify dealers and clients, and then group their corresponding transactions. We use a list of 17 dealer banks, which covers the largest banks by market share according to the 2015 and 2016 Euromoney FX survey. Clients, moreover, are conveniently grouped into real money investors (asset managers, pension funds, insurance firms, sovereign institutions, and other financials), hedge funds, non-dealer banks (commercial banks, prime-brokerage firms, and non-bank firms offering trading services), and other clients (corporates, central banks, monetary authorities, and unclassified clients).[8]

3.3 Breakdown by Currency Pair and Counterparty Sector

As we only employ a subset of the entire EMIR trade repository universe, a potential concern is that our dataset may not offer an accurate representation of the trading activity in the OTC currency option market. To shed light on this aspect, we compare the aggregate trading volumes of our dataset with summary statistics reported by publicly available sources such as the Triennial Central Bank Survey (BIS Survey) and the London Foreign Exchange Joint Standing Committee (FXJSC). Figure 1, as of April 2016, shows that the average daily volume for all currency pairs is larger than $254bn across all trading centres, and close to $110bn in London. When restricting the analysis to USD currency pairs, the average daily volume is larger than $218bn on a global scale, and close to $91bn in London. We compare the coverage of our dataset to these publicly available statistics by first adding up the volumes on each trading day, and then calculating the intra-month daily average for April

[8]We allocate investors to an investor group using a best-endeavour sectoral classification, which is naturally subject to uncertainties. The classification follows Menkhoff et al. (2016), who show that real money investors in particular possess superior information processing skills in the FX market.

2016. We find an average daily volume of about \$91bn for selected USD currency pairs in our sample. Although the comparison may be imprecise due to different aggregation criteria, our calculations suggest that our sample captures approximately 42% of the global daily turnover for USD currency pairs, consistent with London's role as the largest trading hub for FX instruments (e.g., BIS, 2016b). The same figure, moreover, also reports the average turnover for the full sample, which amounts to about \$130bn per day. We therefore conclude that our sample covers a substantial amount of the total trading activity in the OTC currency option market. We also present the average daily volume by currency pairs and counterparty sectors. Figure 2 reveals that approximately 69% of the average daily volume (equivalent to \$90bn per day) is concentrated on the EUR (36%), JPY (25.4%), and GBP (7.6%) against the USD. An additional 14.4% (equivalent to \$19bn) of the average daily volume is clustered on other major currency pairs like the AUD (6.1%), CAD (4.5%), CHF (2.4%), and NZD (1.5%) relative to the USD.[9] Finally, the most traded emerging markets currency pairs like the BRL, KRW, MXN, SGD, and TRY account for another 12.1% (equivalent to \$15.8bn) of the average daily volume. The pie charts in Figure 3 show the average daily volume by counterparty sector. We find that 76.5% of trading activity takes place in the interdealer market, 23.4% between dealers and clients, and only a tiny amount of trading is between clients directly. In the dealer-client segment, 38.7% of trading activity can be attributed to hedge funds, 28.7% to real money investors, 19.6% to non-dealer banks, and 13% to other clients. Additional details are reported in Tables A.1–A.2 in the Internet Appendix.

[9] The average turnover on major currency pairs like the NOK and SEK relative to the USD is below \$0.5bn per day, as these pairs are mostly traded against the EUR.

3.4 Breakdown by Option Type and Trading Direction

The decision of a client to buy or sell an option may provide valuable information on her motivation for trading, attitude towards risk, and hedging demand. In November 2015, ESMA has helpfully introduced new reporting guidelines to correctly identify the direction of a transaction. In our dataset, we can therefore determine the trading direction in a slightly shorter sample (from November 2015 to December 2016) using the buy/sell indicator. We re-define our options such that the buyer of a call (put) option has the right to buy (sell) a unit of foreign currency against a given strike price denominated in dollars. Put differently, the buyer of a call option bets on the appreciation of the foreign currency whereas the buyer of a put option expects an appreciation of the dollar. The seller of a call (put) option, moreover, has the obligation to sell (buy) one unit of the foreign currency at a given strike if the option is exercised. Figure 4 describes the call and put option trading volume by currency and by trading direction. We find that the volume of put options is almost twice as high as the one of call options, and this result holds across all currencies in our sample. When zooming in on trading directions, we find that clients are net buyers in both call and put options.

4 FX Option Volume and FX Return Predictability

In this section, we use a portfolio sorting approach (Section 4.1) and panel regressions (Section 4.2) to examine whether FX option volumes predict future FX returns. In Section 4.3, we show that the return predictability of FX option volume remains robust after controlling for other currency risk factors.

4.1 Portfolio Sorting

A main question is whether and how informed trading occurs in the FX option market. The answer to this question would not only shed light on the 'exchange rate disconnect puzzle' (Obstfeld and Rogoff, 2000; Lyons, 2001; Engel and West, 2005; Evans, 2010), but can also contribute to our understanding of how derivatives affect the price discovery in FX markets. To examine this question, we follow Johnson and So (2012) and mainly focus on the return predictability of FX option trading volumes.

Using conventional portfolio sorting strategies, we first evaluate the information content of FX option volume for the cross-sectional predictability of exchange rate returns. In the portfolio sorting exercise, for each currency i on each trading day t, we calculate the given currency's volume across all options and denote this currency's option volume as $V_{i,t}^{adj}$. To account for heteroskedasticity across different currencies and common trends in the time series of volume, the option volume is standardized over a rolling window of 21 trading days prior to the volume signal: $V_{i,t}^{adj} = log(V_{i,t}) - log(\frac{\sum_{s=1}^{M} V_{i,t-s}}{M})$, where $M = 21$.[10]

Admittedly, an intuitive candidate for a FX return predictor would be order flow imbalance, as it can reflect the direction and magnitude of investors' private information. However, only market makers can observe such detailed transaction information, and therefore inferring private information is complex. In our main analyses, we follow the approach of Johnson and So (2012) and address this issue by examining the information content in the option trading volume. That being said, in Section 5.4, we use order flow data and show that our results remain robust.

[10] We also consider alternative measurement windows. Our results remain robust and are reported in section 6.1.

We now examine whether the cross-sectional $V_{i,t}^{adj}$ predicts future FX returns. Specifically, on each day, we sort currencies into four buckets based on FX option trading volume, and then construct equal-weighted portfolios of the currencies within each bucket. The portfolio is rebalanced daily. The portfolio returns are measured relative to the USD. Table 1 reports the results. Panel A focuses on seven main currencies (i.e., "AUD", "CAD", "CHF", "EUR", "GBP", "JPY", and "NZD"), and Panel B shows the results for all currencies (i.e., "AUD", "CAD", "CHF", "EUR", "GBP", "JPY", "NZD", "HKD", "INR", "KRW", "MXN", "NOK", "NZD", "RUB", "SEK", "SGD", "TRY", "TWD", "ZAR").

The results show that FX option volumes are a strong and significant predictor of future FX returns. Importantly, the return predictability is mainly concentrated in the seven main currencies. Specifically, as shown in Panel A, currencies in the portfolio with low option volume significantly outperform those in the portfolio with high option volume. The return spread between the portfolio with low option volume and the portfolio with high option volume (dubbed as Low-Minus-High (LMH) portfolio spread) is 14.63% per year and is statistically highly significant (t = 2.66). In contrast, as shown in Panel B using all currencies, the LMH portfolio return spread is only 5.91% per year and is marginally insignificant (t = 1.11). The comparison of the annualized Sharpe Ratio between the LMH portfolio based on the seven main currencies and the LMH portfolio based on all currencies also confirms this pattern (1.69 vs. 0.71). Given the weak return predictability of FX option volumes using all currencies, our following analyses focus on the seven main currencies if not highlighted otherwise. To understand more about the return predictability of FX option volumes, we conduct several additional empirical tests. First, we separate option volumes into interdealer and dealer-client volumes, and we find similar return predictability patterns.

Second, to address the possibility that the return predictability of FX option volumes is due to the predictability of interest rates, we replace currency returns with returns that are only based on exchange rate changes, and repeat the exercises in Table 1. As shown in Table 2, the magnitude of the return predictability when using FX returns based on exchange rate changes are almost the same as those in Table 1, which underlines that the return predictability of FX option volumes is not driven by interest rates. In summary, the results in Tables 1 and 2 not only uncover that FX option volumes predict future FX returns, but also document the heterogeneous return predictability of FX option volumes across currencies. While the return predictability of FX option volumes suggests that informed trading exists in FX options, it seems to be confined to the seven major currencies. This finding is consistent with the notion that liquidity in options matters for informed investors. Intuitively, informed investors tend to trade liquid options as they can better hide and reap their information advantage in these options, and we therefore observe a more pronounced return predictability of FX option volumes among the most liquid currencies.

4.2 Panel Regressions

Furthermore, we now run additional panel regressions to ensure that the return predictability of FX option volumes is not driven by any particular currency characteristics. Specifically, we run the following regressions:

$$R_{i,t+1} = \alpha + \beta \cdot Option\ Volume_{i,t} + \gamma \cdot X_{i,t} + FE + \epsilon_{i,t+1}, \tag{1}$$

where $R_{i,t+1}$ is currency i's excess return (or return based on the change in the exchange rate) on day $t{+}1$. $Option\ Volume_{i,t}$ is currency i's quartile rank of the standardized option volume on day t with respect to total volume, dealer-dealer volume and dealer-client volume. The vector X includes currency-level characteristics such as the realized volatility of currency returns and the bid-ask spread of the currency. Realized volatility is measured by using intraday hourly returns, and the bid-ask spread is measured by using end-of-day quotes. We also include day and currency fixed effects. We use time-clustered standard errors. We present the results in Table 3. Panel A shows the results for currency excess returns, and Panel B reports the results for exchange rate changes. We make several important observations. First, using only time fixed effects, the total option volume (*Total Volume*), option volume between dealers and clients (*Dealer-Client Volume*), and option volume among dealers (*Dealer-Dealer Volume*) can all significantly and negatively predict currency returns, which confirms the results of the cross-sectional return predictability tests of FX option volume in Tables 1 and 2. Second, as shown in Column 4, the return predictability of *Dealer-Client Volume* remains statistically highly significant, while the return predictability of *Dealer-Dealer Volume* becomes statistically insignificant when including *Dealer-Client Volume* in the regression. This result is not surprising, given that dealers usually do not implement directional currency views, but their positions rather mechanically reflect their clients' trading. Therefore, the return predictability of *Dealer-Dealer Volume* documented in Tables 1 and 2 is likely due to the return predictability of *Dealer-Client Volume*. Third, we find that the return predictability of *Dealer-Client Volume* remains unchanged after controlling for the volatility and liquidity of the given currency (see Column 5), and it also remains robust when we include currency fixed effects. These results confirm that *Dealer-Client Volume* indeed captures information beyond observable and unobservable currency characteristics. Since our main analyses focus on whether FX option volumes can predict next-day currency returns, a potential concern is that such a short-term return predictability is potentially due to price reversals. To address this concern, we construct a LMH portfolio on each day, and then extend the holding period to the next 30 trading days. Figure 5 plots the cumulative returns of the LMH portfolios based on *Dealer-Client Volume*. As shown in Figure 5, the LHM portfolio also earns positive and significant returns over a longer horizon. Importantly, the observed return pattern exhibits no sign of a reversal.

4.3 Time-series Analysis: Correlation with Currency Factors

We conduct an additional test to corroborate that FX option volume captures informed trading beyond any observable factors. Specifically, based on Table 1, we first construct a long-short portfolio (LMH portfolio) that is long the currency portfolio with the lowest option volume and short the currency portfolio with the highest option volume. We then use time-series regressions of the return of this long-short portfolio on other currency return factors. The currency factors include dollar, carry, value, momentum, volatility, liquidity, reversal, and VRP (variance risk premium) factors. As shown in Table 4, the long-short portfolio persistently generates significant alphas after controlling for different currency risk factors. For example, as shown in Column 1, when controlling for the dollar factor, the long-short portfolio still generates an alpha of 6.89bps per day. As shown in Column 4, when controlling all other currency return factors (e.g., dollar, carry, momentum, VRP), the long-short portfolio still generates an alpha of 7.01bps per day. These results confirm that the return predictability of FX option volumes cannot be explained by other well-known currency factors. We therefore conclude that FX option volume indeed captures information that goes beyond these factors.

4.4 Dollar Demand

Having established a robust relation between option volumes and future FX returns, we formally hypothesize in this section that high FX option trading volumes can negatively predict future currency returns (foreign currency depreciation, US dollar appreciation). A key difference between the FX and equity markets is the absence of short-sale constraints in the FX market. We can therefore exclude short-sale constraints as a potential driver of the return predictability.[11]

Our intuition is as follows for the FX market. In a setting with no informed trading, investors have demand for the US dollar and dollar assets due to liquidity and safety reasons (e.g., Krishnamurthy and Vissing-Jorgensen, 2012; Maggiori, 2017; Du et al., 2018; Krishnamurthy and Lustig, 2019; Jiang et al., 2020, 2021), so they would initially have a positive US dollar exposure. In a setting with informed trading, when informed investors obtain a positive signal for the US dollar or a negative signal for the foreign currency, they further increase their exposure to the US dollar relative to their initial positive exposure. Similarly, when informed investors obtain a negative signal for the US dollar or a positive signal for the foreign currency, they decrease their exposure to US dollars, but they avoid to completely offset their initial positive exposure – similar to a short-sale constraint. Following this logic, FX option volumes can better reflect informed investors' positive signals for the US dollar (or negative signals for foreign currencies) than negative signals for the US dollar (or positive

[11] Johnson and So (2012) argue that the negative relation between the Option/Stock volume ratio and future stock returns is mainly driven by short-sale costs in equity markets. Specifically, equity short-sale costs induce informed investors to trade options more frequently for negative signals than for positive ones, leading to a negative relation between the O/S ratio and future stock returns.

signals for foreign currency). Therefore, we would expect a negative relation between FX option volumes and future currency returns, and this relation should be more pronounced when the initial demand for dollars is higher. We formally test this hypothesis by analyzing periods in our sample with high and low dollar demand. We use two proxies for dollar demand: the first one is the US Treasury premium or basis (e.g., Du et al., 2018; Jiang et al., 2020, 2021), which is the yield gap between US government and currency-hedged foreign government bonds; the second one is the VXY index, which is the JP Morgan Index of G7 currency volatility - a sort of a 'VIX equivalent' for currencies. As discussed in the prior literature, investors typically engage in a 'flight to the safety' and purchase large amounts of US Treasury bonds during more volatile periods or episodes of global financial instability. We define high dollar demand periods as periods with high US Treasury premiums or a high VXY index.

The results are reported in Table 5. Panel A reports the results for high dollar demand periods, and Panel B reports the results for low dollar demand periods. Firstly, when using the Treasury Premium, the LMH return spread is 26.49% per year and is statistically highly significant (t = 3.19) during high dollar demand periods. In contrast, as shown in Panel B, the LMH spread is only 2.77% per year and statistically insignificant (t = 0.30) during low dollar demand periods. Furthermore, when we use the VXY index, the annualized LMH spread is 19.09% (t = 2.82) during high VXY periods, while it only 9.82% (t = 1.44) during low VXY periods. Overall, the results confirm the negative currency return predictability of FX option volumes, and show that this relation is more pronounced during periods with high demand for the US dollar.

5 Informed Trading in the Option Market

In this section, we further explore informed trading in the FX option market by analyzing the role of leverage in Section 5.1 and the concentration of informed traders in Section 5.2. In addition to these cross-sectional differences, we also investigate the time-series differences in information intensity by analyzing trading days with and without macroeconomic news in Section 5.3. Last, we extend our analysis by examining the information content of option order flows in our shorter sample, where information on the direction of a trade is available.

5.1 Option Leverage: Moneyness

Similar to the argument in prior studies on equity options (e.g., Black, 1975; Easley et al., 1998; Pan and Poteshman, 2006; Ge et al., 2016), the embedded leverage in FX options enables informed investors to efficiently trade on their information advantage, in particular when compared to FX spot markets. Therefore, we formally hypothesize that the return predictability of FX option trading volumes is more pronounced among options with high leverage.

To study the role of embedded leverage in the return predictability of FX option volumes, we classify put and call options as out-of-the-money (OTM), near-the-money, and in-the-money (ITM) by using the ratio of strike price to spot price. For example, a 5% OTM call option has a strike-to-spot ratio of 1.05, whereas a 5% OTM put option has a strike-to-spot ratio of 0.95. We define near-the-money options as calls and puts with strike-to-spot ratios between 0.98 and 1.02. For ITM and OTM options, we further classify them as deep (above 5%) ITM and OTM options. Table 6 reports the results, and options are sorted by leverage (with high leverage options on top). From the top to the bottom of the table, the LMH portfolio spread is monotonically decreasing in both magnitude and statistical significance. For example, the LMH portfolio based on options with the highest embedded leverage (i.e., options that are larger than 5% OTM) yields an annualized return of 22.95% with a t-statistic of 3.02. The LMH portfolio based on options with intermediate embedded leverage (i.e., options that are between 2% and 5% OTM) yields an annualized return of 11.3% with a t-statistic of 2.13. Other LMH portfolios based on options with even lower embedded leverage generate insignificant returns, and the return is negative for the long-short strategy with deep ITM options. This result is consistent with the notion that informed investors prefer to trade more leveraged options.

We extend our analysis by examining the return predictability of option volumes with different time to expirations. For a given level of moneyness, short-dated options offer considerably higher leverage than long-dated options. To this end, we first classify options based on their time to expiration: within one month, between one month and three months, between three months and six months, and above six months. We then use volumes on options with different time to expirations as the return predictor and repeat the exercise in Table 1. As shown in Appendix Table A.4, the return predictability of option volumes is significantly higher for options with a shorter time to expiration. This result is consistent with the notion that if investors obtain information that is likely to influence exchange rates in the short run, then it would be natural to trade short-dated options.

5.2 Client Sector

In all information-based models it is crucial to be able to identify informed and uninformed traders. In such models, the existence of informed traders is a key variable and has important implications for the informativeness of trading volume (e.g., Easley et al., 1998). We would expect the return predictability to increase with the concentration of informed investors in a given investor group. Traditionally, hedge funds and real money investors are more likely to be informed investors, compared to other investor types (e.g., corporates and non-dealer banks). Therefore, to strengthen our argument that FX option volumes provide information on future FX returns, we allocate all investors in our sample to four groups (i.e., hedge funds, real money investors, non-dealer banks, and others) and examine the return predictability of FX option volumes traded by these different groups. Table 7 reports the results. As shown in the table, the FX option volumes of both hedge funds and real money investors can significantly and negatively predict currency returns. In contrast, we do not find such a significant return predictability of FX option volumes of both non-dealer banks and other clients. Specifically, the LMH portfolio based on FX option volumes of hedge funds yields an annualized return of 14.26% (t = 2.60), and the LMH portfolio based on FX option volumes of real money investors yields an annualized return of 15.06% (t = 2.45). In contrast, the LMH portfolio based on FX option volumes of other clients yields an annualized return of 3.7% (t = 0.58). In fact, these results are not surprising. As can be seen in Figure 3, hedge funds and real money investors account for 39% and 29% of the total dealer-client volume in FX options. In contrast, non-dealer banks and other clients only account for 20% and 8% of the total dealer-client volume.

5.3 Macroeconomic Announcements

To further support our argument that FX option volumes provide information on future FX returns, we now exploit the heterogeneity in information intensity in the time series. More precisely, we classify all trading days as days with or without macroeconomic announcements. Intuitively, since macroeconomic news play an important role in driving currency returns (Tahbaz-Salehi et al., 2017), such announcements provide lucrative opportunities for informed investors, and announcement days are therefore typically associated with high levels of informed trading. For example, prior studies on the equity market (e.g., Krinsky and Lee, 1996; Kim and Verrecchia, 1997; Brennan et al., 2018; Back et al., 2018; Yang et al., 2020) have documented the existence of informed trading prior to earnings announcements.

In the context of options, Roll et al. (2010) find increased option trading volumes prior to earnings announcements, while Cao et al. (2005) document increased option trading prior to takeovers. Both findings are consistent with pronounced informed trading during informationally intensive periods. Similar to the analysis in Section 5.2, we now examine the trading performance of different client types on days with macroeconomic announcements (i.e. FOMC, non-farm payrolls, PMI, PPI, CPI, GDP) compared to days without such announcements. Table 8 reports the results. Compared to non-announcement days, the LMH portfolios based on FX option volumes of different investor groups generate higher returns during announcement periods, evident in both the economic magnitude and statistical significance. This pattern is particularly pronounced for the LMH portfolio based on FX option volumes of hedge funds. These results underline that the return predictability of hedge fund option volumes is stronger on days with macroeconomic announcements, consistent with the notion that informed trading is more pronounced on these days.

5.4 Net Order Flow

Thus far, our results are based on unsigned trading volumes, and we find strong evidence for the existence of informed trading in the FX option market. In this section, we provide additional evidence to strengthen this argument. Specifically, we examine the information content of signed FX option volumes, albeit our sample including signed volumes is somewhat shorter (from November 2015 to December 2016) given that ESMA's new reporting requirements were only introduced in November 2015.

Since signed put and call option volumes entail opposite predictions for FX returns, we first allocate options to different categories. Intuitively, a call option gives investor the right to buy a unit of a foreign currency against the US dollar (call on the foreign currency), and a put option gives investors the right to sell a unit of a foreign currency against the US dollar (put on the foreign currency). For both put and call options, we measure the net buy ratio as the difference between buy and sell volumes, divided by the total volume of the given option type. Therefore, if informed investors trade on their information in put (call) options, then we would expect that the net buy ratio negatively (positively) predicts FX returns. Table 9 reports the results. Similar to the results of the main test, the trades of hedge funds and real money investors have strong predictive power for FX returns. For instance, the LMH portfolio constructed based on hedge fund put (call) option volumes yields a return of 18.01% (-17.12%) with a t-statistic of 2.38 (-2.68). Real money investors' signed put volumes only marginally significantly predict FX returns (with a t-statistic of 1.76), but their signed call volume has no significant predictive power for FX returns. In addition, there is no obvious evidence to support the existence of informed trading by non-dealer banks or other clients for both signed call and put option volumes.

6 Robustness Checks and Alternative Data

In this section, we conduct additional tests to underline the robustness of our results. We first use different volume scaling methods in Section 6.1. In Section 6.2, we extend our study to the FX forward market and show that there is no return predictability of FX forward volumes, highlighting the uniqueness of our findings with regard to the return predictability of FX option volumes. In Section 6.3, we show that our results remain robust when using aggregate option volume data from Bloomberg.

6.1 Different Volume Scaling Methods

In the main portfolio sorting exercise, to account for heteroskedasticity across different currencies and common trends in the time series of volume, we standardize option volume over a rolling window of 21 trading days prior to the volume signal. More precisely, we use the following definition: $V_{i,t}^{adj} = log(V_{i,t}) - log(\frac{\sum_{s=1}^{M} V_{i,t-s}}{M})$, where $M = 21$. For robustness, we consider two alternative windows to standardize option volumes: $M = 5$ and $M = 63$. Furthermore, we also use a volume signal formation period of three days instead of a one day period.

As we can see from Appendix Table A.3, the return predictability of FX option volumes remains robust to different methods of adjusting the volume signal. For instance, when we use a short window (i.e., $M = 5$) to standardize $V_{i,t}^{adj}$ and repeat the exercise in Table 1, the

LMH portfolio yields an annualized return of 15.06% with a t-statistic of 2.61. When we use a long window (i.e., $M = 63$) to standardize $V_{i,t}^{adj}$, the LMH portfolio yields an annualized return of 15.04% with a t-statistic of 2.61. The results also remain robust when we use a three-day signal formation period for FX option volumes. In that case, the LMH portfolio yields an annualized return of 18.75% with a t-statistic of 2.79.

6.2 Forward Volume

In addition to FX option volumes, we also explore the return predictability of trading activity in another FX derivative market: the FX forward market. This empirical exercise is motivated by Cespa et al. (2021) who find that trading volumes in FX forwards/swaps predict next-day currency returns. In this section, we not only examine the return predictability of aggregate volumes in FX forwards (as in Cespa et al., 2021), but also examine the return predictability of trading volumes of different investor types. Table 10 reports the results. We find that FX forward volumes have no significant predictive power for FX returns. For example, when we use the total forward volume as the return predictor, the annualized excess return of the LMH portfolio is 1.62% with a t-value of 0.36, and the return of the LMH portfolio based on exchange rate changes is 2.05% with a t-value of 0.55. The results remain qualitatively unchanged when we analyze FX forward volumes of different investor types. These results suggest that informed FX investors mainly use options rather than forwards to trade on their information. The sharp contrast in the return predictability of FX option volumes compared to FX forward volumes again highlights the novelty of our findings.

6.3 Alternative Data Source

So far, the main analyses are based on regulatory data that are difficult to access. To generalize our results, we use the OTC FX data from Bloomberg in this section, which are public but less granular. The OTC FX option data from Bloomberg are also provided by DTCC, but mainly cover the trading activity in the US market. We only observe aggregate trading activity excluding any investor identities, and the sample period is from March 2013 to December 2020. Table 11 reports the results. We find that the option trading volumes from Bloomberg also significantly and negatively predict FX returns, similar to our main results. For instance, when we analyze the seven major currencies, the annualized excess return is 9.37% with a t-statistic of 3.03; and the annualized return of the LMH portfolio based on exchange rate changes is 9.34% with a t-value of 3.02. When we consider all twenty currencies, the LMH portfolio yields an insignificant return, which is also consistent with our results in Table 1.

In summary, the results in Table 11 not only demonstrate the robustness of our results, but also suggest that our findings can be generalized to other trading venues (e.g., the US market). Moreover, given the availability of Bloomberg data, our study provides robust and transparent return predictors in FX markets, which can help to shed light on the 'exchange rate disconnect puzzle' (Obstfeld and Rogoff, 2000; Lyons, 2001; Engel and West, 2005; Evans, 2010).

7 Conclusion

In this paper, we examine the informational content of FX option volumes for future exchange rate movements. We find strong evidence for informed trading in the FX option market. Moreover, we are able to identify when and in which instruments informed investors are likely to trade on their information advantage. More precisely, we explore the relation between the return predictability and two factors that play a key role in information-based theoretical models: the concentration of informed traders and the embedded leverage of option contracts. Regarding the concentration of informed traders, we find that the trading of the typically more sophisticated client sector is more informative than interdealer volumes. Furthermore, within the client sector, the option volumes of both hedge funds and real money investors strongly predict future FX returns. Using the moneyness and time to expiration of an option as a proxy for leverage, we also find that the return predictability is increasing with the leverage of option contracts. In particular, investors' trading in deep OTM options and short-term options (with time to expiration of less than one month or three months) is associated with stronger predictive power.

This article presents evidence on informed trading in the FX market; a market that closely reflects macroeconomic, market-wide news. This stands in sharp contrast to previous findings in the equity market literature that informed traders tend to possess firm-specific rather than market-wide information. Theoretical work on how informed investors process macroeconomic news in the option market appears to be a particularly promising avenue for future research.

References

Abad, Jorge, Inaki Aldasoro, Christoph Aymanns, Marco D'Errico, Linda Fache Rousova, Peter Hoffmann, Sam Langfield, Martin Neychev, and Tarik Roukny, "Shedding Light on Dark Markets: First Insights from the New EU-wide OTC Derivatives Dataset," Discussion Paper, European Systemic Risk Board 2016.

Acharya, Viral V. and Timothy C. Johnson, "More insiders, more insider trading: Evidence from private-equity buyouts," *Journal of Financial Economics*, 2010, *98*, 500–523.

Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Clara Vega, "Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange," *American Economic Review*, 2003, *93*, 38–62.

Back, Kerry, Kevin Crotty, and Tao Li, "Identifying Information Asymmetry in Securities Markets," *Review of Financial Studies*, 2018, *31*, 2277–2325.

Bali, Turan G. and Armen Hovakimian, "Volatility Spreads and Expected Stock Returns," *Management Science*, 2009, *55*, 1797–1812.

BIS, *OTC Derivatives Statistics at end-June 2016*, Basel: Bank for International Settlements, 2016.

— , *Triennial Central Bank Survey of Foreign Exchange and OTC Derivatives Markets Activity in 2016*, Basel: Bank for International Settlements, 2016.

Black, Fischer, "Fact and Fantasy in the USE of Options," *Financial Analysts Journal*, 1975, *31*, 36–41.

Brennan, Michale J, Sahn-Wook Huh, and Avanidhar Subrahmanyam, "High-Frequency Measures of Informed Trading and Corporate Announcements," *Review of Financial Studies*, 2018, *31*, 2326–2376.

Cao, Charles, Zhiwu Chen, and John Griffin, "Informational Content of Option Volume Prior to Takeovers," *The Journal of Business*, 2005, *78* (3), 1073–1109.

Cenedese, Gino, Pasquale Della Corte, and Tianyu Wang, "Currency Mispricing and Dealer Balance Sheets," *Journal of Finance*, 2021, *76*, 2763–2803.

Cespa, Giovanni, Antonio Gargano, J Steven Riddiough, and Lucio Sarno, "Foreign Exchange Volume," *Review of Financial Studies*, 2021, *forthcoming.*

Collin-Dufresne, Pierre, Vyacheslav Fos, and Dmitry Muravyev, "Informed Trading in the Stock Market and Option-Price Discovery," *Journal of Financial and Quantitative Analysis*, 2021, *56* (6), 1945–1984.

Cremers, Martijn and David Weinbaum, "Deviations from Put-Call Parity and Stock

Return Predictability," *Journal of Financial and Quantitative Analysis*, 2010, *45*, 335–367.

Della Corte, Pasquale, Tarun Ramadorai, and Lucio Sarno, "Volatility Risk Premia and Exchange Rate Predictability," *Journal of Financial Economics,*, 2016, *120*, 21–40.

Du, Wenxin, Joanne Im, and Jesse Schreger, "US Treasury Premium," *Journal of International Economics*, 2018, *112*, 167–181.

Easley, David, Maureen O'Hara, and P. S. Srinivas, "Option Volume and Stock Prices: Evidence on Where Informed Traders Trade," *Journal of Finance*, 1998, *53*, 431–465.

Engel, Charles and Kenneth D. West, "Exchange Rates and Fundamentals," *Journal of Political Economy*, 2005, *113*, 485–517.

Evans, Martin D., "Order Flows and the Exchange Rate Disconnect Puzzle," *Journal of International Economics*, 2010, *80*, 58–71.

Ge, Li, Tse-Chun Lin, and Neil D. Pearson, "Why does the Option to Stock Volume Ratio Predict Stock Returns?," *Journal of Financial Economics*, 2016, *120*, 601–622.

Hu, Jianfeng, "Does Option Trading Convey Stock Price Information?," *Journal of Financial Economics*, 2014, *111*, 625–645.

Jiang, Zhengyang, Arvind Krishnamurthy, and Hanno Lustig, "Dollar Safety and the Global Financial Cycle," *NBER Working Paper No. 27682*, 2020.

_ , _ , and _ , "Foreign Safe Asset Demand and the Dollar Exchange Rate," *The Journal of Finance*, 2021, *76* (3), 1049–1089.

Johnson, Travis L. and Eric C. So, "The Option to Stock Volume Ratio and Future Returns," *Journal of Financial Economics*, 2012, *106*, 262–286.

Kim, Oliver and Robert E Verrecchia, "Pre-Announcement and Event-Period Private Information," *Journal of Accounting and Economics*, 1997, *24*, 395–419.

Krinsky, Itzhak and Jason Lee, "Earnings Announcements and the Components of the Bid-Ask Spread," *Journal of Finance*, 1996, *51*, 1523–1535.

Krishnamurthy, Arvind and Annette Vissing-Jorgensen, "The Aggregate Demand for Treasury Debt," *Journal of Political Economy*, 2012, *120*, 233–267.

_ and Hanno Lustig, "Mind the Gap in Sovereign Debt Markets: The U.S. Treasury Basis and the Dollar Risk Factor," *Working Paper*, 2019.

Londono, Juan M. and Hao Zhou, "Variance risk premiums and the forward premium puzzle," *Journal of Financial Economics*, 2017, *124*, 415–440.

Lyons, Richard K., *The Microstructure Approach to Exchange Rates*, Cambridge: MIT Press, 2001.

Maggiori, Matteo, "Financial Intermediation, International Risk Sharing, and Reserve

Currencies," *American Economic Review*, 2017, *107*, 3038–3071.

Mark, Nelson C., "Exchange Rates and Fundamentals: Evidence on Long-Horizon Predictability," *American Economic Review*, 1995, *85*, 201–218.

Meese, Richard A. and Kenneth Rogoff, "Empirical Exchange Rate Models of the Seventies: Do They Fit Out of Sample?," *Journal of International Economics*, 1983, *14*, 3–24.

Menkhoff, Lukas, Lucio Sarno, Maik Schmeling, and Andreas Schrimpf, "Information Flows in Foreign Exchange Markets: Dissecting Customer Currency Trades," *The Journal of Finance*, 2016, *71* (2), 601–634.

Obstfeld, Maurice and Kenneth Rogoff, "The Six Major Puzzles in International Macroeconomics: Is There a Common Cause?," *NBER Macroeconomics Annual*, 2000, *15*, 339–412.

Pan, Jun and Allen Poteshman, "The Information in Option Volume for Future Stock Prices," *Review of Financial Studies*, 2006, *19*, 871–908.

Roll, Richard, Eduardo Schwartz, and Avanidhar Subrahmanyam, "O/S: The Relative Trading Activity in Options and Stock," *Journal of Financial Economics*, 2010, *96*, 1–17.

Tahbaz-Salehi, Alireza, Philippe Mueller, and Andrea Vedolin, "Exchange Rates and Monetary Policy Uncertainty," *Journal of Finance*, 2017, *72*, 1213–1252.

Xing, Yuhang, Xiaoyan Zhang, and Rui Zhao, "What Does the Individual Option Volatility Smirk Tell Us About Future Equity Returns?," *Journal of Financial and Quantitative Analysis*, 2010, *45*, 641–662.

Yang, Yung Chiang, Bohui Zhang, and Chu Zhang, "Is Information Risk Priced? Evidence from Abnormal Idiosyncratic Volatility," *Journal of Financial Economics*, 2020, *135*, 528–554.

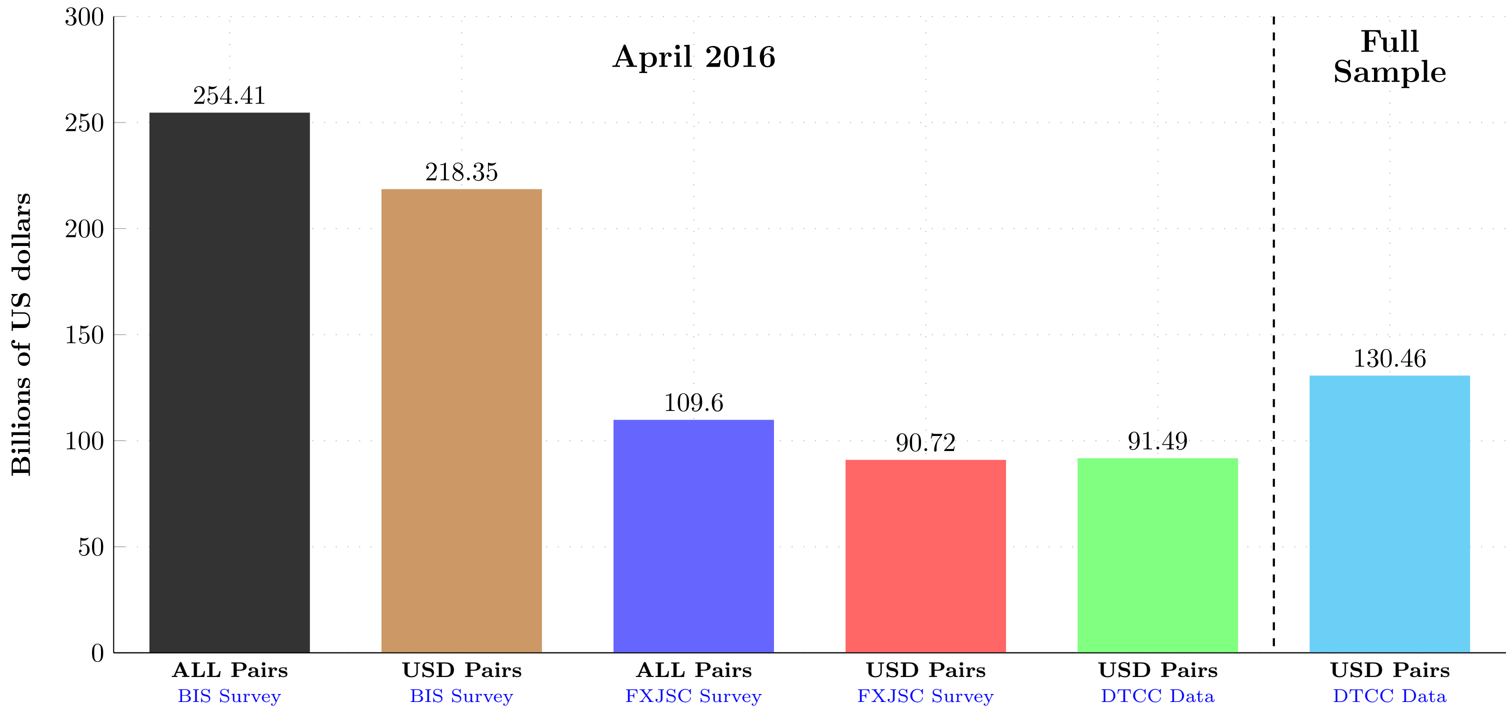

Figure 1. FX Option Volume

This figure displays the average daily volume of foreign exchange (FX) options traded over-the-counter. In our data, we observe all trades submitted to the DTCC Derivatives Repository in which at least one of the counterparties is a UK-regulated entity. Our sample covers the period between November 2014 and December 2016. For comparison, we compute the daily average turnover in April 2016 for our sample and compare it to publicly-available aggregated statistics from the 2016 Triennial Central Bank Survey (BIS Survey) and from the London Foreign Exchange Joint Standing Committee (FXJSC).

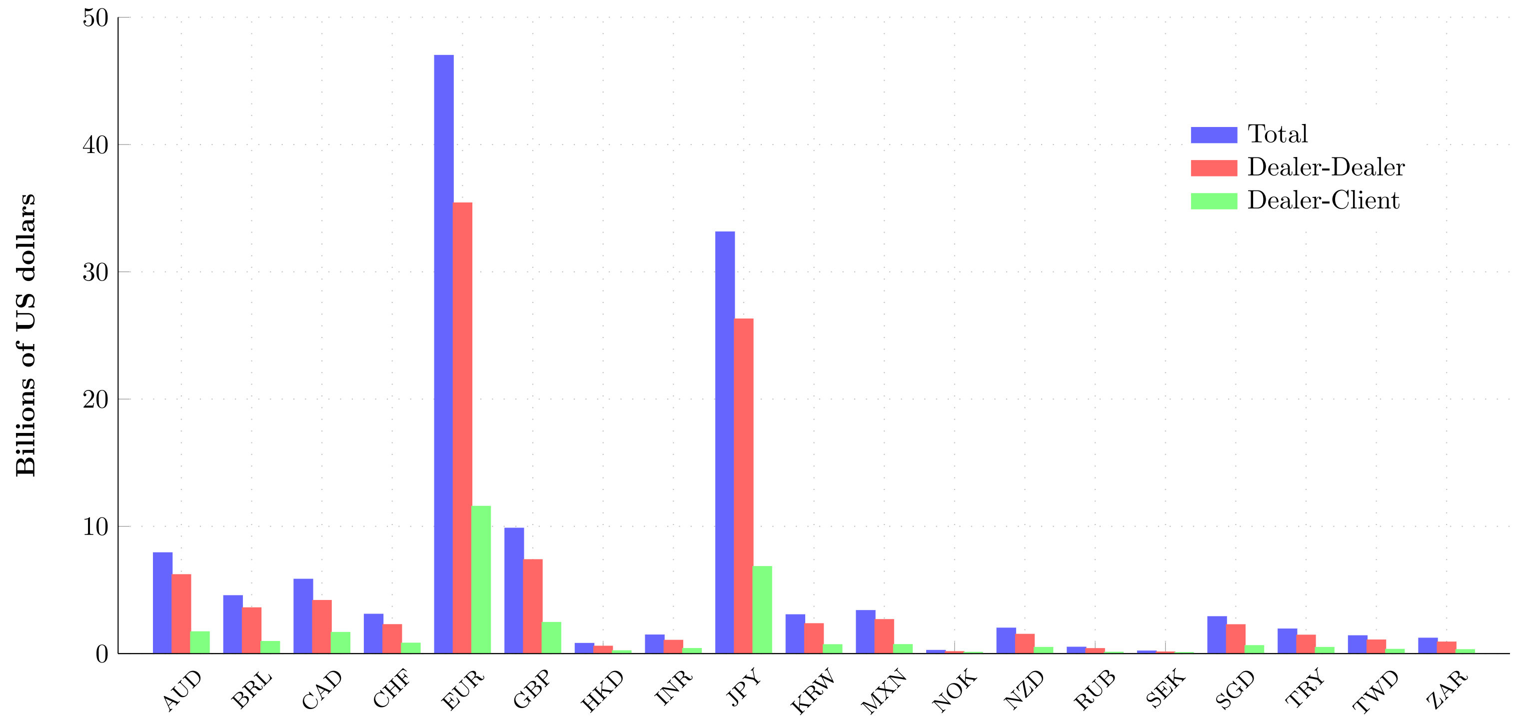

Figure 2. FX Option Volume: Currency Pairs

This figure displays the average daily volume of foreign exchange (FX) options traded over-the-counter by currency pairs. We observe all trades submitted to the DTCC Derivatives Repository in which at least one of the counterparties is a UK-regulated entity. Our sample covers the period between November 2014 and December 2016. ‘Dealer-Dealer’ and ‘Dealer-Client’ denotes the interdealer and customer segments, respectively, of the currency option market.

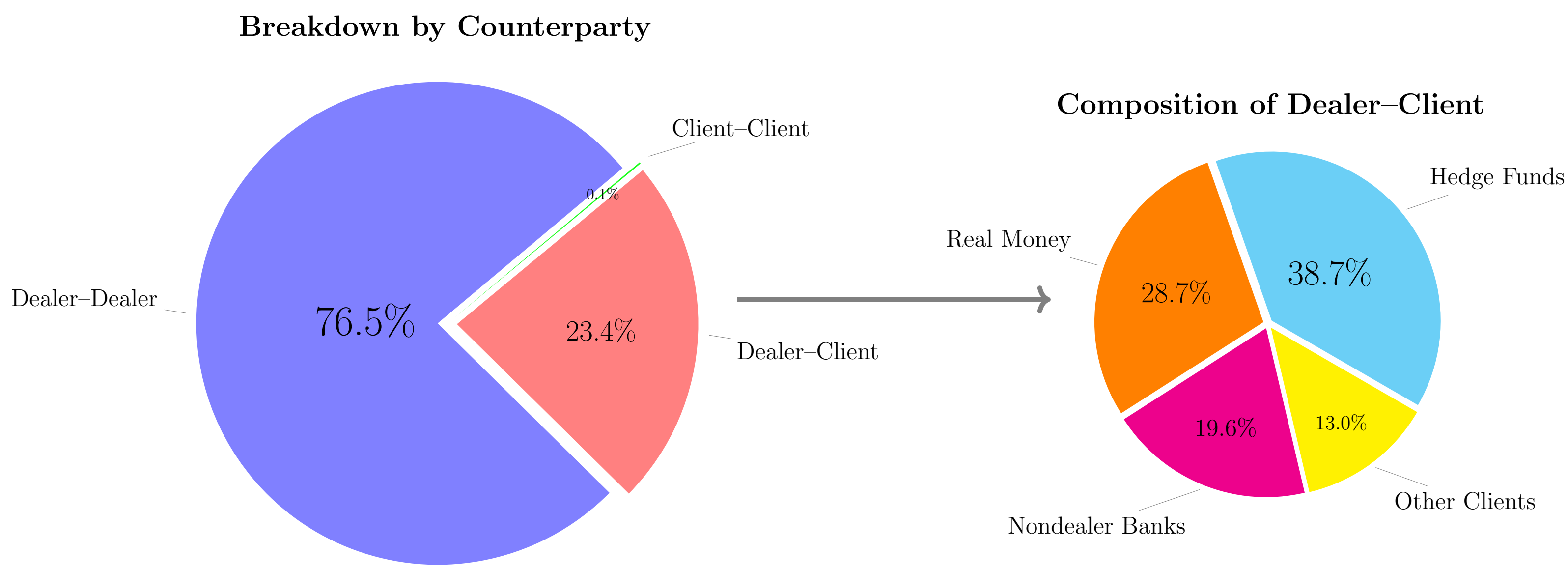

Figure 3. FX Option Volume: Counterparty Sectors

This figure displays, in percentages, the average daily volume of foreign exchange (FX) options traded over-the-counter by counterparty sectors. We observe all trades submitted to the DTCC Derivatives Repository in which at least one of the counterparties is a UK-regulated entity. Our sample covers the period between November 2014 and December 2016. 'Dealer-Dealer' refers to the interdealer segment, while 'Dealer-Client' denotes the dealer-client segment of the currency option market. The latter segment is comprised of real money investors (asset managers, pension funds, insurance firms, sovereign institutions, and other financials), hedge funds, non-dealer banks (commercial banks, prime brokerage firms, and non-bank firms offering trading services), and other clients (corporates, central banks, monetary authorities, and unclassified clients).

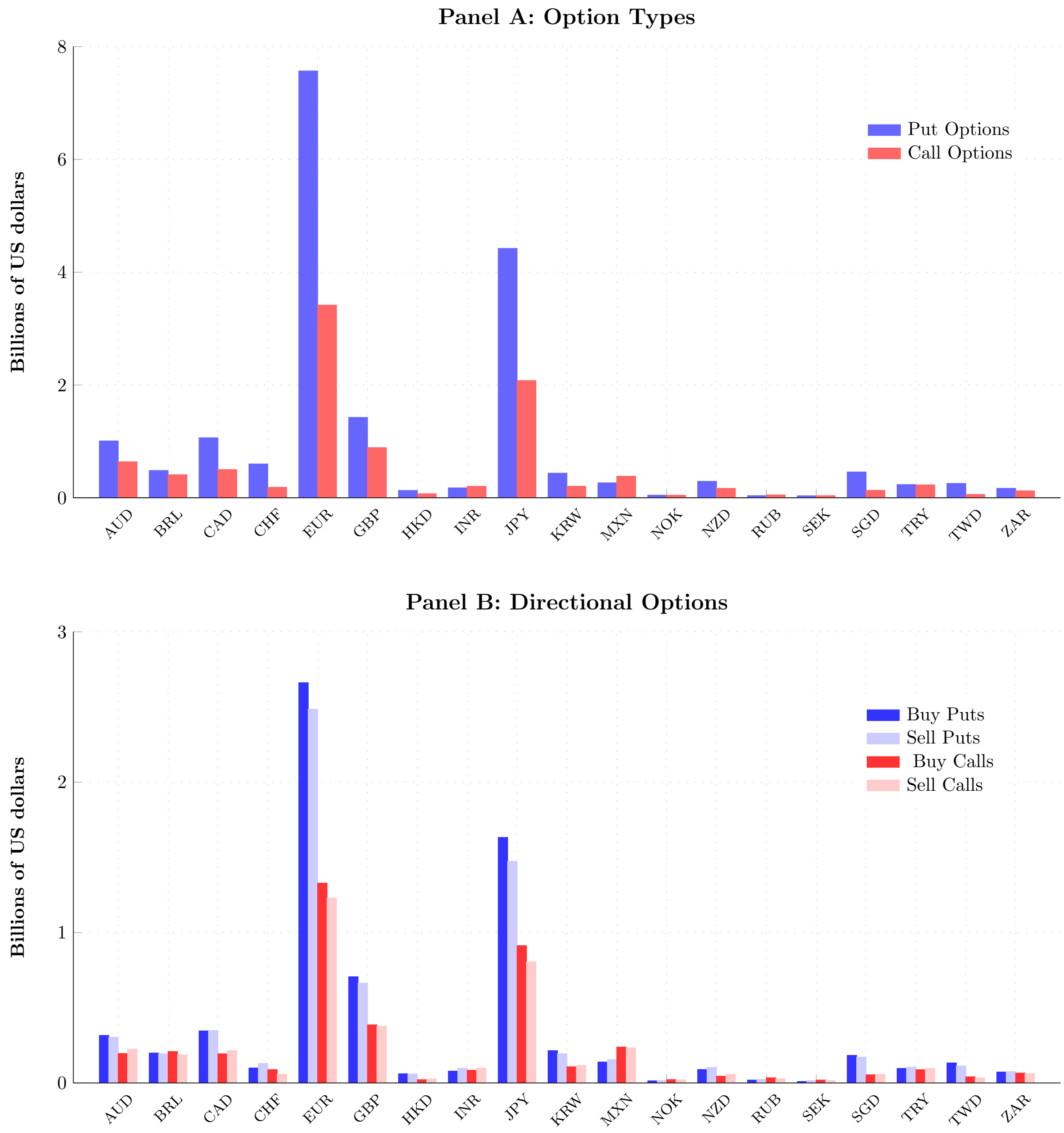

Figure 4. FX Option Volume: Trading Direction

This figure displays the average daily volume of foreign exchange (FX) options traded over-the-counter by option types across both all market segments (Panel A) and trading direction for the customer segment (Panel B). We observe all trades submitted to DTCC Derivatives Repository in which at least one of the counterparties is a UK-regulated entity. The sample ranges between November 2015 and December 2016 (see Section 3 for more details).

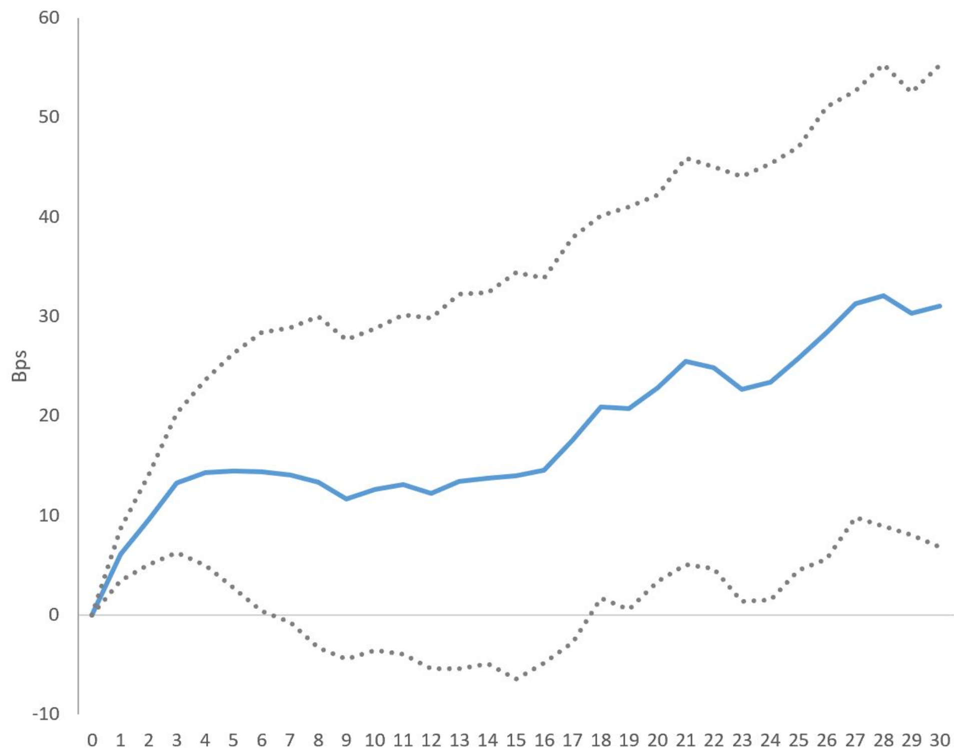

Figure 5. Post-Formation Excess Returns

This figure shows event-time returns of the long-short portfolio sorted by total client volume up to thirty trading days. On each day, we sort all currencies into four groups based on clients' option volumes and construct a long-short portfolio that goes long the bottom group and short the top group. The 90% confidence intervals (dashed lines) are based on block-bootstrapped standard errors.

Table 1. Portfolios sorted by FX Option Volume: Excess Returns

This table reports average annualized portfolio excess returns for currency portfolios sorted by lagged FX option volumes. The sorting variable includes total volumes as well as volumes disaggregated by inter-dealer and dealer-client groups. Volume is standardized over a rolling window of 21 trading days prior to the volume signal, as outlined in the text. The frequency is daily and the sample is from December 2014 to December 2016. Column "LMH" (Low minus High) reports average returns for long-short portfolios in currencies with the lowest versus highest volume. Returns and standard deviations are annualized and shown in percentages. SR is annualized Sharpe Ratio. Numbers in brackets are t-statistics based on Newey-West standard errors.

		P_1 (Low)	P_2	P_3	P_4 (High)	LMH	P_1 (Low)	P_2	P_3	P_4 (High)	LMH
		Panel A: Major Currencies					*Panel B: All Currencies*				
Total	mean	2.42	−2.67	−6.89	−12.21	14.63	−3.42	1.45	−8.97	−9.33	5.91
	t-stat	[0.42]	[−0.45]	[−1.22]	[−2.34]	[2.66]	[−0.54]	[0.28]	[−1.66]	[−1.63]	[1.11]
	std	9.06	8.76	10.67	9.85	8.64	9.13	8.51	8.65	9.17	8.37
	SR	0.27	−0.30	−0.65	−1.24	1.69	−0.37	0.17	−1.04	−1.02	0.71
Dealer-Dealer	mean	−0.08	−0.79	−5.69	−12.06	11.98	−2.53	1.09	−9.66	−9.15	6.62
	t-stat	[−0.01]	[−0.14]	[−0.95]	[−2.31]	[1.97]	[−0.37]	[0.22]	[−2.06]	[−1.54]	[1.11]
	std	8.93	8.74	10.88	9.97	8.74	9.22	8.45	8.73	9.23	8.51
	SR	−0.01	−0.09	−0.52	−1.21	1.37	−0.27	0.13	−1.11	−0.99	0.78
Dealer-Client	mean	3.51	−1.12	−8.90	−13.28	16.80	3.37	−1.34	−13.66	−7.40	10.76
	t-stat	[0.59]	[−0.22]	[−1.40]	[−2.31]	[2.71]	[0.57]	[−0.22]	[−2.29]	[−1.39]	[1.99]
	std	9.50	8.49	10.93	9.65	9.04	9.05	8.63	8.95	8.90	7.88
	SR	0.37	−0.13	−0.81	−1.38	1.86	0.37	−0.16	−1.53	−0.83	1.37

Table 2. Portfolios sorted by FX Option Volume: Exchange Rate Returns

This table reports average annualized portfolio exchange rate returns for currency portfolios sorted by lagged FX option volumes. The sorting variable includes total volumes as well as volumes disaggregated by inter-dealer and dealer-client groups. Volume is standardized over a rolling window of 21 trading days prior to the volume signal, as outlined in the text. The frequency is daily and the sample is from December 2014 to December 2016. Column "LMH" (Low minus High) reports average returns for long-short portfolios in currencies with the lowest versus highest volume. Returns and standard deviations are annualized and shown in percentages. SR is annualized Sharpe Ratio. Numbers in brackets are t-statistics based on Newey-West standard errors.

		P_1 (Low)	P_2	P_3	P_4 (High)	LMH	P_1 (Low)	P_2	P_3	P_4 (High)	LMH
		Panel A: Major Currencies					*Panel B: All Currencies*				
Total	mean	2.26	−2.77	−7.07	−12.37	14.63	−5.42	−0.29	−10.69	−11.30	5.88
	t-stat	[0.39]	[−0.46]	[−1.25]	[−2.38]	[2.67]	[−0.86]	[−0.06]	[−1.98]	[−1.98]	[1.10]
	std	9.06	8.76	10.66	9.85	8.64	9.14	8.50	8.66	9.17	8.37
	SR	0.25	−0.32	−0.66	−1.26	1.69	−0.59	−0.03	−1.23	−1.23	0.70
Dealer-Dealer	mean	−0.24	−0.89	−5.82	−12.24	12.00	−4.65	−0.53	−11.39	−11.17	6.53
	t-stat	[−0.04]	[−0.15]	[−0.98]	[−2.35]	[1.98]	[−0.69]	[−0.11]	[−2.43]	[−1.87]	[1.09]
	std	8.93	8.74	10.88	9.97	8.73	9.21	8.45	8.73	9.23	8.50
	SR	−0.03	−0.10	−0.54	−1.23	1.37	−0.50	−0.06	−1.30	−1.21	0.77
Dealer-Client	mean	3.38	−1.25	−9.06	−13.45	16.83	1.45	−3.19	−15.54	−9.32	10.76
	t-stat	[0.56]	[−0.24]	[−1.42]	[−2.35]	[2.72]	[0.24]	[−0.52]	[−2.60]	[−1.75]	[1.99]
	std	9.49	8.50	10.93	9.65	9.03	9.05	8.63	8.95	8.90	7.89
	SR	0.36	−0.15	−0.83	−1.39	1.86	0.16	−0.37	−1.74	−1.05	1.36

Table 3. Return Predictability of FX Option Volume

This table reports the results of panel regressions of currency returns on lagged FX option volumes. Volume is standardized over a rolling window of 21 trading days prior to the volume signal, as outlined in the text. The key independent variable used in the regressions is the quartile rank of standardized volume. The sample is from December 2014 to December 2016. Panel A and B report results for excess returns and exchange rate returns, respectively. Other control variables include the realized volatility and FX bid-ask spread, as well as time and currency fixed effects. Numbers in parentheses are standard errors clustered at the time dimension. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Excess Returns					
Total Volume	−1.968**					
	(0.796)					
Dealer-Client Volume		−2.396***		−2.057**	−2.088**	−2.119**
		(0.823)		(0.861)	(0.859)	(1.002)
Dealer-Dealer Volume			−1.677**	−0.753	−0.778	−0.776
			(0.813)	(0.848)	(0.849)	(0.950)
Realized Volatility					0.103	0.049
					(0.295)	(0.214)
Bid-Ask Spread					−0.597	−0.470
					(0.818)	(0.732)
AdjR^2 (%)	42.3	42.3	42.3	42.3	42.3	42.3
# Obs	3,552	3,552	3,552	3,552	3,552	3,552
	Panel B: Exchange Rate Returns					
Total Volume	−1.971**					
	(0.796)					
Dealer-Client Volume		−2.402***		−2.062**	−2.089**	−2.119**
		(0.823)		(0.860)	(0.859)	(1.001)
Dealer-Dealer Volume			−1.682**	−0.755	−0.777	−0.779
			(0.812)	(0.847)	(0.849)	(0.949)
Realized Volatility					0.065	0.049
					(0.295)	(0.215)
Bid-Ask Spread					−0.660	−0.471
					(0.818)	(0.732)
AdjR^2 (%)	42.3	42.3	42.3	42.3	42.3	42.3
# Observations	3,552	3,552	3,552	3,552	3,552	3,552
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Currency FE	No	No	No	No	No	Yes

Table 4. Factor Exposures: Time Series Analysis

This table reports the results of time-series regressions of returns of the long-short FX option volume (LMH) strategy on other currency factors. Currency factors include the dollar, carry, value, momentum, volatility, liquidity, reversal, and VRP factors. Numbers in parentheses are Newey-West standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
Alpha	6.888**	6.646**	7.025**	7.006***
	(2.846)	(2.651)	(2.688)	(2.561)
DOL	0.022	0.041	0.048	0.042
	(0.075)	(0.067)	(0.063)	(0.064)
CAR		0.004	0.017	0.049
		(0.054)	(0.053)	(0.061)
VAL		0.064	0.088	0.082
		(0.061)	(0.060)	(0.063)
MOM		0.036	0.046	0.043
		(0.065)	(0.067)	(0.066)
VOL			-0.028	-0.004
			(0.071)	(0.072)
LIQ			-0.094**	-0.060
			(0.043)	(0.045)
R25				-0.062
				(0.065)
VRP				0.127*
				(0.069)
$AdjR^2$ (%)	-0.2	0.1	1.0	2.5
# Observations	512	512	512	512

Table 5. Portfolios sorted by FX Option Volume: Dollar Demand

This table reports average annualized portfolio exchange rate returns for currency portfolios sorted by lagged FX option volumes in two subsamples: high versus low dollar demand periods. We use the total option volumes of major currencies. Volume is standardized over a rolling window of 21 trading days prior to the volume signal as outlined in the text. The frequency is daily and the sample is from December 2014 to December 2016. Column "LMH" (Low minus High) reports average returns for long-short portfolios in currencies with the lowest versus highest volume. Returns and standard deviations are annualized and shown in percentages. SR is annualized Sharpe Ratio. Numbers in brackets are t-statistics based on Newey-West standard errors.

		P_1 (Low)	P_2	P_3	P_4 (High)	LMH	P_1 (Low)	P_2	P_3	P_4 (High)	LMH
		Panel A: High Dollar Demand					*Panel B: Low Dollar Demand*				
Proxied by Treasury Premium	mean	10.32	−5.48	−4.14	−16.17	26.49	−5.80	−0.05	−10.00	−8.56	2.77
	t-stat	[1.20]	[−0.71]	[−0.45]	[−1.61]	[3.19]	[−0.67]	[−0.01]	[−0.95]	[−0.92]	[0.30]
	std	8.60	7.83	9.67	9.59	7.83	9.49	9.61	11.59	10.12	9.34
	SR	1.20	−0.70	−0.43	−1.69	3.38	−0.61	−0.01	−0.86	−0.85	0.30
Proxied by VXY Index	mean	15.79	7.52	0.35	−3.29	19.09	−11.89	−13.02	−14.35	−21.71	9.82
	t-stat	[1.85]	[0.91]	[0.05]	[−0.44]	[2.82]	[−1.83]	[−1.48]	[−1.44]	[−3.00]	[1.44]
	std	9.27	8.42	11.48	9.72	8.54	8.76	9.03	9.72	9.93	8.73
	SR	1.70	0.89	0.03	−0.34	2.23	−1.36	−1.44	−1.48	−2.19	1.12

Table 6. Portfolios sorted by FX Option Volume: Moneyness

This table reports average annualized portfolio exchange rate returns for currency portfolios sorted by lagged FX option volumes based on option moneyness. We sort option moneyness into five groups: above 5% out-of-the money (OTM), 2%-5% OTM, near-the-money, 2%-5% in-the-money (ITM), above 5% ITM. We use the entire dealer-client option volumes in major currencies. Volume is standardized over a rolling window of 21 trading days prior to the volume signal, as outlined in the text. The frequency is daily and the sample is from December 2014 to December 2016. Column "LMH" (Low minus High) reports average returns for long-short portfolios in currencies with the lowest versus highest volume. Returns and standard deviations are annualized and shown in percentages. SR is annualized Sharpe Ratio. Numbers in brackets are t-statistics based on Newey-West standard errors.

		P_1 (Low)	P_2	P_3	P_4 (High)	LMH
Above 5% OTM	mean	7.09	−6.90	−14.48	−15.86	22.95
	t-stat	[1.29]	[−1.01]	[−2.34]	[−2.62]	[3.02]
	std	9.70	11.42	10.72	10.28	10.18
	SR	0.73	−0.60	−1.35	−1.54	2.25
2%-5% OTM	mean	2.78	−3.44	−4.70	−8.52	11.30
	t-stat	[0.46]	[−0.55]	[−0.91]	[−1.44]	[2.13]
	std	9.33	11.09	10.62	10.02	7.93
	SR	0.30	−0.31	−0.44	−0.85	1.42
Near-the-money	mean	−1.40	−1.02	−11.48	−7.95	6.55
	t-stat	[−0.26]	[−0.15]	[−1.77]	[−1.36]	[1.13]
	std	8.93	9.36	10.19	9.88	8.49
	SR	−0.16	−0.11	−1.13	−0.80	0.77
2%-5% ITM	mean	0.93	−10.06	−2.45	−5.58	6.52
	t-stat	[0.15]	[−1.63]	[−0.37]	[−0.90]	[1.05]
	std	9.29	10.66	10.21	8.98	8.79
	SR	0.10	−0.94	−0.24	−0.62	0.74
Above 5% ITM	mean	−2.59	−9.79	−3.71	−2.39	−0.20
	t-stat	[−0.41]	[−1.40]	[−0.61]	[−0.39]	[−0.03]
	std	9.39	11.33	10.09	10.27	9.77
	SR	−0.28	−0.86	−0.37	−0.23	−0.02

Table 7. Portfolios sorted by FX Option Volume: Client Sectors

This table reports average annualized portfolio excess returns and exchange rate returns for currency portfolios sorted by lagged FX option volumes. The sorting variables include volumes disaggregated by client sectors: hedge funds, real money investors, non-dealer banks, and others. Volume is standardized over a rolling window of 21 trading days prior to the volume signal, as outlined in the text. The frequency is daily and the sample is from December 2014 to December 2016. Column "LMH" (Low minus High) reports average returns for long-short portfolios in currencies with the lowest versus highest volume. Returns and standard deviations are annualized and shown in percentages. SR is annualized Sharpe Ratio. Numbers in brackets are t-statistics based on Newey-West standard errors.

		P_1 (Low)	P_2	P_3	P_4 (High)	LMH
Hedge Funds	mean	0.50	−1.86	1.21	−13.76	14.26
	t-stat	[0.08]	[−0.28]	[0.17]	[−2.09]	[2.60]
	std	9.01	9.61	11.32	9.43	8.30
	SR	0.06	−0.19	0.11	−1.46	1.72
Real Money	mean	2.27	−5.48	−9.35	−12.79	15.06
	t-stat	[0.38]	[−0.79]	[−1.27]	[−1.92]	[2.45]
	std	9.13	10.12	10.30	9.62	8.83
	SR	0.25	−0.54	−0.91	−1.33	1.71
Non-dealer Banks	mean	2.95	−12.03	−7.34	−5.47	8.42
	t-stat	[0.45]	[−2.02]	[−1.05]	[−0.83]	[1.43]
	std	9.09	8.68	10.79	9.53	8.17
	SR	0.32	−1.39	−0.68	−0.57	1.03
Other Clients	mean	−3.63	−5.57	−1.21	−7.33	3.70
	t-stat	[−0.56]	[−0.89]	[−0.17]	[−1.12]	[0.58]
	std	9.51	9.90	10.17	9.55	8.70
	SR	−0.38	−0.56	−0.12	−0.77	0.43

Table 8. Portfolios sorted by FX Option Volume: Macroeconomic Announcements

This table reports average annualized portfolio exchange rate returns for currency portfolios sorted by lagged FX option volumes. Trading days are sorted into days with or without macroeconomic announcements. The sorting variables include volumes disaggregated by client sectors: hedge funds, real money investors, non-dealer banks, and others. Volume is standardized over a rolling window of 21 trading days prior to the volume signal, as outlined in the text. The frequency is daily and the sample is from December 2014 to December 2016. Column "LMH" (Low minus High) reports average returns for long-short portfolios in currencies with the lowest versus highest volume. Returns and standard deviations are annualized and shown in percentages. SR is annualized Sharpe Ratio. Numbers in brackets are t-statistics based on Newey-West standard errors.

		P_1 (Low)	P_2	P_3	P_4 (High)	LMH	P_1 (Low)	P_2	P_3	P_4 (High)	LMH
		Panel A: Announcement Days					*Panel B: Non-Announcement Days*				
Hedge Funds	mean	4.29	10.29	−22.12	−25.79	30.09	1.66	−1.78	7.72	−11.25	12.91
	t-stat	[0.33]	[0.62]	[−1.44]	[−2.01]	[4.17]	[0.24]	[−0.26]	[0.97]	[−1.68]	[1.75]
	std	10.91	13.88	11.24	9.84	8.46	8.63	9.56	11.33	9.29	8.53
	SR	0.39	0.74	−1.97	−2.62	3.56	0.19	−0.19	0.68	−1.21	1.51
Real Money	mean	−0.92	−14.77	−10.52	−19.79	18.87	4.55	−3.11	−9.03	−10.71	15.27
	t-stat	[−0.05]	[−1.63]	[−0.97]	[−1.69]	[1.94]	[0.71]	[−0.43]	[−1.21]	[−1.57]	[1.79]
	std	10.37	10.45	10.42	9.70	9.48	9.06	10.00	10.26	9.57	9.09
	SR	−0.09	−1.41	−1.01	−2.04	1.99	0.50	−0.31	−0.88	−1.12	1.68
Non-dealer Banks	mean	−0.12	−21.97	−17.43	−15.30	15.17	6.52	−7.99	−6.17	−3.55	10.07
	t-stat	[−0.01]	[−2.04]	[−1.14]	[−0.96]	[1.36]	[1.05]	[−1.39]	[−0.90]	[−0.52]	[1.35]
	std	9.36	9.41	10.53	10.35	7.79	9.00	8.47	10.70	9.38	8.21
	SR	−0.01	−2.33	−1.66	−1.48	1.95	0.72	−0.94	−0.58	−0.38	1.23
Other Clients	mean	−8.42	−20.97	−30.34	−19.54	11.12	1.90	−10.62	−1.86	−2.68	4.57
	t-stat	[−0.54]	[−1.55]	[−1.86]	[−1.66]	[0.73]	[0.32]	[−1.39]	[−0.25]	[−0.41]	[0.60]
	std	9.90	9.92	9.84	9.73	8.59	8.80	10.61	10.11	9.60	9.95
	SR	−0.85	−2.11	−3.08	−2.01	1.29	0.22	−1.00	−0.18	−0.28	0.46

Table 9. Portfolios sorted by FX Option Volume: Buy-Sell

This table reports average annualized portfolio exchange rate returns for currency portfolios sorted by lagged FX option net volumes. Net volume is the difference between buy and sell volumes, scaled by the sum of buy and sell volumes. The frequency is daily and the sample is from November 2015 to December 2016. Column "LMH" (Low minus High) reports average returns for long-short portfolios in currencies with the lowest versus highest net volume. Returns and standard deviations are annualized and shown in percentages. SR is annualized Sharpe Ratio. Numbers in brackets are t-statistics based on Newey-West standard errors.

		P_1 (Low)	P_2	P_3	P_4 (High)	LMH	P_1 (Low)	P_2	P_3	P_4 (High)	LMH
		Panel A: Put Option Net Buy					*Panel B: Call Option Net Buy*				
All Client Sectors	mean	14.01	2.69	−10.50	−9.32	23.33	−9.35	6.77	5.05	3.75	−13.11
	t-stat	[1.84]	[0.36]	[−1.07]	[−1.32]	[2.98]	[−1.51]	[0.97]	[0.43]	[0.63]	[−2.14]
	std	9.37	8.51	12.62	9.23	8.01	9.57	8.89	10.94	9.54	8.76
	SR	1.49	0.32	−0.83	−1.01	2.91	−0.98	0.76	0.46	0.39	−1.50
Hedge Funds	mean	11.16	−1.28	−3.19	−6.85	18.01	−5.66	3.46	−6.40	11.46	−17.12
	t-stat	[1.29]	[−0.15]	[−0.42]	[−0.96]	[2.38]	[−0.76]	[0.43]	[−0.62]	[1.63]	[−2.68]
	std	10.55	10.11	9.75	9.55	8.95	9.68	10.25	12.40	9.46	8.93
	SR	1.06	−0.13	−0.33	−0.72	2.01	−0.58	0.34	−0.52	1.21	−1.92
Real Money	mean	10.59	0.85	−18.76	−6.90	17.49	−1.97	7.14	1.21	13.92	−15.89
	t-stat	[1.61]	[0.09]	[−2.52]	[−0.74]	[1.76]	[−0.27]	[0.58]	[0.12]	[1.36]	[−1.28]
	std	9.10	11.25	9.38	9.69	9.16	10.10	10.89	10.64	9.67	11.28
	SR	1.16	0.08	−2.00	−0.71	1.91	−0.20	0.66	0.11	1.44	−1.41
Non-dealer Banks	mean	1.61	4.05	−1.52	−3.99	5.60	−1.81	9.99	0.23	−1.54	−0.27
	t-stat	[0.23]	[0.51]	[−0.16]	[−0.56]	[0.86]	[−0.29]	[1.40]	[0.02]	[−0.28]	[−0.04]
	std	9.29	8.69	10.49	9.81	8.66	8.99	9.03	10.50	9.46	8.06
	SR	0.17	0.47	−0.14	−0.41	0.65	−0.20	1.11	0.02	−0.16	−0.03
Other Clients	mean	3.22	−1.26	−0.69	0.57	2.64	0.20	−9.12	−2.86	10.60	−10.40
	t-stat	[0.39]	[−0.19]	[−0.08]	[0.06]	[0.26]	[0.03]	[−1.05]	[−0.31]	[1.43]	[−1.49]
	std	9.76	9.50	10.03	10.79	9.65	9.80	10.13	10.27	9.01	9.00
	SR	0.33	−0.13	−0.07	0.05	0.27	0.02	−0.90	−0.28	1.18	−1.16

Table 10. Portfolios sorted by FX Forward Volume

This table reports average annualized portfolio exchange rate returns for currency portfolios sorted by lagged FX forwards volumes. The sorting variable includes the total client volume as well as volumes grouped by client sectors: hedge funds, real money investors, non-dealer banks, and others. Volume is standardized over a rolling window of 21 trading days prior to the volume signal, as outlined in the text. The frequency is daily and the sample is from December 2014 to December 2016. Column "LMH" (Low minus High) reports average returns for long-short portfolios in currencies with the lowest versus highest volume. Returns and standard deviations are annualized and shown in percentages. SR is annualized Sharpe Ratio. Numbers in brackets are t-statistics based on Newey-West standard errors.

		Panel A: Major Currencies P_1 (Low)	P_2	P_3	P_4 (High)	LMH	Panel B: All Currencies P_1 (Low)	P_2	P_3	P_4 (High)	LMH
All Client Sectors	mean	−0.17	−5.29	0.71	−1.79	1.62	0.69	−6.01	−6.51	−1.35	2.05
	t-stat	[−0.04]	[−1.23]	[0.13]	[−0.38]	[0.36]	[0.17]	[−1.42]	[−1.50]	[−0.31]	[0.55]
	std	7.69	7.72	9.59	7.61	7.00	7.34	7.25	7.55	7.36	6.12
	SR	−0.02	−0.69	0.07	−0.23	0.23	0.09	−0.83	−0.86	−0.18	0.33
Hedge Funds	mean	−0.56	1.31	−6.37	−4.58	4.01	−1.95	−2.85	−3.92	−3.38	1.43
	t-stat	[−0.12]	[0.31]	[−1.17]	[−1.05]	[0.95]	[−0.41]	[−0.74]	[−0.88]	[−0.91]	[0.43]
	std	7.83	7.56	9.65	7.37	6.90	7.84	6.95	7.30	7.16	6.03
	SR	−0.07	0.17	−0.66	−0.62	0.58	−0.25	−0.41	−0.54	−0.47	0.24
Real Money	mean	−1.95	−1.85	−2.13	−1.22	−0.73	−1.19	−2.75	−6.94	−1.03	−0.16
	t-stat	[−0.43]	[−0.39]	[−0.41]	[−0.26]	[−0.16]	[−0.27]	[−0.64]	[−1.38]	[−0.24]	[−0.04]
	std	7.69	7.67	8.87	7.88	7.14	7.24	7.03	7.67	7.44	6.01
	SR	−0.25	−0.24	−0.24	−0.16	−0.10	−0.16	−0.39	−0.90	−0.14	−0.03
Non-dealer Banks	mean	−2.12	−4.65	1.25	−0.46	−1.66	−2.80	−3.05	−2.36	−3.24	0.44
	t-stat	[−0.52]	[−1.11]	[0.20]	[−0.11]	[−0.40]	[−0.68]	[−0.79]	[−0.63]	[−0.70]	[0.13]
	std	7.50	7.40	9.33	8.22	7.12	7.05	7.25	7.14	7.75	6.08
	SR	−0.28	−0.63	0.13	−0.06	−0.23	−0.40	−0.42	−0.33	−0.42	0.07
Other Clients	mean	−0.43	−1.81	−6.63	−2.00	1.57	−5.99	−0.40	−3.00	−3.51	−2.48
	t-stat	[−0.11]	[−0.37]	[−1.20]	[−0.40]	[0.40]	[−1.34]	[−0.10]	[−0.60]	[−0.88]	[−0.76]
	std	7.49	7.98	9.02	7.70	6.76	7.18	7.42	7.48	7.25	5.93
	SR	−0.06	−0.23	−0.74	−0.26	0.23	−0.83	−0.05	−0.40	−0.48	−0.42

Table 11. Portfolios sorted by FX Option Volume: Bloomberg Data

This table reports average annualized portfolio excess returns and exchange rate returns for currency portfolios sorted by lagged FX option volumes using alternative Bloomberg data. Volume is standardized over a rolling window of 21 trading days prior to the volume signal, as outlined in the text. The frequency is daily and the sample is from March 2013 to December 2020. Column "LMH" (Low minus High) reports average returns for long-short portfolios in currencies with the lowest versus highest volume. Returns and standard deviations are annualized and shown in percentages. SR is annualized Sharpe Ratio. Numbers in brackets are t-statistics based on Newey-West standard errors.

		P_1 (Low)	P_2	P_3	P_4 (High)	LMH	P_1 (Low)	P_2	P_3	P_4 (High)	LMH
		Panel A: Excess Returns					*Panel B: Exchange Rate Returns*				
Major Currencies	mean	4.57	−1.45	−1.46	−4.79	9.37	4.82	−1.21	−1.16	−4.53	9.34
	t-stat	[1.49]	[−0.54]	[−0.54]	[−1.54]	[3.03]	[1.57]	[−0.46]	[−0.43]	[−1.45]	[3.02]
	std	8.62	7.37	7.42	8.28	8.55	8.62	7.37	7.42	8.28	8.55
	SR	0.53	−0.20	−0.20	−0.58	1.10	0.56	−0.16	−0.16	−0.55	1.09
All Currencies	mean	−1.89	−0.07	−3.20	−3.30	1.41	−3.29	−1.37	−4.47	−4.75	1.46
	t-stat	[−0.72]	[−0.03]	[−1.19]	[−1.25]	[0.63]	[−1.26]	[−0.51]	[−1.65]	[−1.79]	[0.65]
	std	7.09	7.20	7.02	7.20	6.07	7.08	7.20	7.02	7.20	6.08
	SR	−0.27	−0.01	−0.46	−0.46	0.23	−0.46	−0.19	−0.64	−0.66	0.24