FX Option Volume*

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Abstract

We study the information content of foreign exchange (FX) option volume by exploiting a unique dataset on over-the-counter FX options with counterparty identities and contract characteristics. We find that FX option volume can predict future exchange rate changes, particularly when the convenience yield of US treasuries is high. These findings are consistent with an asymmetric information model in which informed traders trade either in FX option or spot markets. Supporting information-based arguments, we further document that the exchange rate predictability is stronger when using options with higher embedded leverage and around macro-announcement days. Finally, we document that hedge funds and real money investors have superior skills in predicting future exchange rates compared to less sophisticated market participants.

Keywords: Currency Return, Foreign Exchange Option, Informed Trading, Dollar Demand.

JEL Classification: F31, G12, G14, G15.

1 Introduction

Over-the-counter (OTC) derivatives are essential instruments for the functioning of global financial markets. They play an important role in aggregating information in terms of beliefs and trading motives from a very diverse group of market participants (e.g. asset managers, hedge funds, and non-financial corporates). Among OTC derivatives, foreign exchange (FX) options have experienced exponential growth since the financial crises of the 1990s, not at least due to 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 \$297 billion and an outstanding notional close to \$12 trillion (BIS, 2019a,b).[1] Despite its importance, FX options are negotiated privately, and therefore it is difficult for academics and policymakers to fully understand the role of FX options for price discovery in FX markets. Due to the lack of granular data, there is also limited knowledge to date about how investors trade FX options and how such trading activities affect exchange rates.[2]

We attempt to fill this important gap in the literature by exploiting a comprehensive administrative database on contract-level OTC currency options. This database includes 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 vol-

[1] In the most recent triennial BIS derivative survey BIS (2019b), the daily average OTC volume for FX options is \$297.5 billion. In comparison, the exchange-traded FX option volume is relatively small at around \$15 billion.

[2] The studies in the option literature mainly focus on equity option trading (e.g., Easley, O'Hara and Srinivas, 1998; Pan and Poteshman, 2006; Johnson and So, 2012; Ge, Lin and Pearson, 2016). To the best of our knowledge, there are only a few studies covering FX option trading and its contribution to the price discovery process in FX markets.

ume. Armed with this comprehensive data, we systematically study the information content of FX option trading. We also take advantage of the data granularity to analyze the extent to which any group of investors has an information advantage in FX markets.

To guide the empirical exercise, we start our study by proposing a suggestive model, focusing on the connection between FX option volume and currency returns.[3] Our suggestive model is built on Easley, O'Hara and Srinivas (1998), where informed investors can trade spot and option contracts in FX markets. Different from Easley, O'Hara and Srinivas (1998), we assume that investors derive benefits from holding dollars or dollar assets, and such benefits are unrelated to private information and future exchange rate movements. This assumption is motivated by the special and dominant role of the US dollar in international transactions and global financial markets, as documented in a large strand of the literature.[4]

Our model shows that FX option trading volume can negatively predict future currency returns. The intuition is as follows. The potential benefit of holding US dollars deters informed investors from buying the foreign currency (e.g., via options), even when they receive favorable news about the foreign currency. Importantly, this is not the case when informed investors receive bad news. As a result, FX option volume reflects more negative than positive information about the foreign currency, which can therefore have a negative predictive power for foreign currency returns. Not surprisingly, such return predictability is more pronounced when the benefit of holding dollars is larger. The model also shows that

[3] The most natural return predictor is order flow as it can reflect the direction and magnitude of investors' private information. However, only market makers can observe detailed transaction information, and inferring private information is complex with public data. Meanwhile, our data have a caveat as they only cover signed trading volumes for a short sample period (from November 2015 to December 2016). In our main analyses, therefore, we follow the approach of Johnson and So (2012) and address the issue by examining the information content of unsigned option volume. That being said, we use our short sample of order flow data and confirm the significant information content of FX option trading volume.

[4] There is a growing literature that seeks to understand the special role of the US dollar and dollar assets, for instance, studies on the exorbitant privilege (e.g., Gourinchas and Rey, 2007a; Maggiori, 2017), convenience yield (e.g., Krishnamurthy and Vissing-Jorgensen, 2012; Jiang, Krishnamurthy and Lustig, 2020), and global safe assets (e.g., Caballero, Farhi and Gourinchas, 2008; He, Krishnamurthy and Milbradt, 2019).

the return predictability is stronger among options with high embedded leverage since these options can help informed investors to better exploit their information advantage (Easley et al., 1998).

With guidance from the suggestive model, we conduct several empirical analyses of the information content of FX option trading volume. We have a range of novel results. First, we document that FX option volume has strong predictive power for currency returns. Precisely, using a simple portfolio approach, a daily rebalanced strategy that buys currencies with low option volume and sells currencies with high option volume (LMH) delivers an annualized Sharpe ratio of 1.69 for major currencies, and is also highly statistically significant. We also document that the dealer-client volume is more powerful than the interdealer volume in predicting future currency returns. The result is slightly weaker but still significant in a broader currency sample, including emerging market currencies. These findings are consistent with the notion that informed investors prefer to trade highly liquid assets, given that high liquidity enables informed traders about exploiting their informational advantage with a low impact on prices.

We further conduct additional tests to examine the robustness of the return predictability of FX option volume. We first confirm that the LMH strategy return is fully obtained by predicting exchange rate changes, addressing the concern that the return predictability of FX option volume may be due to interest rate differentials. In panel regressions, we show that the result barely changes after controlling for various currency characteristics, including FX return volatility, time, and currency fixed effects. We also run horse-race regressions and confirm that the LMH returns based on FX option volume cannot be explained by common currency factors, such as the dollar, carry, value, and momentum. Furthermore, the LMH strategy earns positive and significant returns over a longer horizon without reversal, which helps to rule out the possibility that the return predictability arises from temporary liquidity demand or hedging demand (i.e. price pressure effects).

We then test one key prediction of the model, namely whether the negative return predictability of FX option volume is mainly prevalent in periods when the benefit of holding US dollars or dollar assets is high. We use two empirical proxies for the benefit of holding US dollars. The first measure is the US treasury premium (e.g., Du, Im and Schreger, 2018b) – often referred to as the convenience yield of US treasuries (Jiang, Krishnamurthy and Lustig, 2021) – which is the yield difference between US treasuries and currency-hedged foreign government bonds. As argued by prior studies (e.g., Gourinchas and Rey, 2007a; Caballero, Farhi and Gourinchas, 2008; Krishnamurthy and Vissing-Jorgensen, 2012; Maggiori, 2017; He, Krishnamurthy and Milbradt, 2019; Jiang, Krishnamurthy and Lustig, 2020), the US Treasury premium reflects the special and dominant role of the US dollar in international transactions and global financial markets. Our second measure is based on the VXY index, which is the JP Morgan Index of G7 currency volatility — i.e. a 'VIX equivalent' for currency markets. US treasuries are often viewed as the safest and most liquid financial assets and generally serve as a safe haven in stress periods. As discussed in prior studies (e.g., Jiang, Krishnamurthy and Lustig, 2021), bond investors usually engage in a 'flight to safety' and purchase large amounts of US Treasury bonds during volatile periods or episodes of global financial instability.[5] Following this line of argument, the potential benefit of holding US dollars increases with the VXY index. Using these two proxies, we find evidence that the return predictability of FX option volume is more pronounced during periods with more pronounced benefits of holding US dollars.

The results so far are consistent with the argument that the return predictability of FX option volume is information-driven. To strengthen our argument, we conduct a battery of additional tests. First, we show that the return predictability is stronger when using options

[5]Unsurprisingly, the convenience yield spikes in such periods of market volatility.

with higher embedded leverage, i.e. out-of-the-money or short-maturity options, consistent with prior studies showing that informed investors prefer high-leverage options to trade on their information advantage.[6] Second, we distinguish FX option volumes of different client types and find that hedge funds and real money investors (i.e. informed investors in the conventional view) significantly outperform non-financial corporates and non-dealer banks (i.e. less informed investors).[7] Third, we find that the return predictability is stronger around (informationally intensive) macro-announcement days, which are typically associated with informed trading. Finally, we take advantage of the data granularity and focus on the return predictability of signed FX option volumes (i.e., order flows), albeit our sample with signed volumes is shorter. The return predictability is again highly significant and supports the information-based argument.

Lastly, we conduct additional tests to underline the robustness of our results. We use different volume scaling methods, as well as alternative option data from Bloomberg with a relatively longer sample period to test the external validity of our results. We also extend our study to the FX forward market and show no return predictability of forward volumes (even from hedge funds and asset managers), highlighting the unique return predictability of FX option volumes.

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 short horizons (Mark, 1995; Engel and West, 2005), and this missing link between the state of the economy and exchange rate fluctuations is generally

[6] This phenomenon has been extensively documented in the stock option literature, e.g., Easley, O'Hara and Srinivas (1998); Pan and Poteshman (2006); Ge, Lin and Pearson (2016).

[7] This is in line with the findings in Menkhoff et al. (2016), who use proprietary FX spot order flow data for different investor types. In particular, the authors find that hedge funds' and real money investors' order flows predict future currency returns.

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 the 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. Cespa et al. (2021) find that trading volumes in FX forwards/swaps are associated with short-term currency return reversals but provide no significant predictive power for currency returns. To the best of our knowledge, our 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 the incentive to migrate towards the option market as it provides more leverage or 'bang for the buck'. We shed light on this intuitive yet unexplored mechanism in one of the largest and deepest OTC derivative markets.

Our paper is also related to the recent literature on the role of the US dollar in global financial markets. The US dollar and dollar-denominated assets play a central role in the international financial system. In particular, the role of safe assets has shaped the dynamics of the dollar exchange rate (e.g., Gourinchas and Rey, 2007b; Caballero, Farhi and Gourinchas, 2008; Maggiori, 2017; He, Krishnamurthy and Milbradt, 2019). Gourinchas and Rey (2007a) and Maggiori (2017) focus on the 'exorbitant privilege' of the dollar that drives low rates of return on dollar assets while providing valuable insurance to global investors. Besides, much empirical evidence shows that non-US borrowers tilt the denomination of their debt to the US dollar (see, e.g., Maggiori, Neiman and Schreger (2020) on corporate bond borrowing).

Several studies show that there is a sizable convenience yield concerning owning dollars and dollar assets (e.g., Krishnamurthy and Vissing-Jorgensen, 2012). Jiang, Krishnamurthy and Lustig (2020) show that this convenience yield can be inferred from the Treasury basis, which is the yield difference between US treasuries and currency-hedged foreign government bonds.

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 the 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 previously documented results for equity options hold for another important class of options. Second, we show that certain groups of investors have superior abilities to relate macroeconomic fundamentals to future currency returns. In the stock market, some investors are able to predict firm-specific news, but it remains unclear whether informed traders are also able to forecast macroeconomic information accurately. Third, compared to the data generally used in the stock market literature, our regulatory dataset contains additional important features. In particular, we observe investor identities, allowing us to investigate the return predictability for different groups of investors, e.g. hedge funds, real money investors, non-financial corporates, and non-dealer banks. We can therefore separate informed from uninformed investors and pin down a particular price discovery mechanism in the FX market.

The remainder of this paper is organized as follows. Section 2 presents a simple model to show the relationship between FX option volume and currency returns. Section 3 presents the data and summary statistics. Section 4 verifies the predictive power of FX option volume for currency 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 other supporting analyses.

2 On the Co-Existence of Spot and Option Markets

This section builds on Easley, O'Hara and Srinivas (1998) and develops a simple model in which investors can trade spot and option contracts in FX markets. In this setting, informed investors derive private benefits from holding US dollars (or dollar-denominated assets), an assumption that is motivated by dollar dominance in financial markets and documented by a growing literature on the exorbitant privilege (e.g., Gourinchas and Rey, 2007a; Maggiori, 2017), convenience yield (e.g., Krishnamurthy and Vissing-Jorgensen, 2012; Jiang, Krishnamurthy and Lustig, 2020), and global safe assets (e.g., Caballero, Farhi and Gourinchas, 2008; He, Krishnamurthy and Milbradt, 2019). Ultimately, we show that FX option volume is negatively correlated with future exchange rate returns (or, equivalently, high option volume today predicts a US dollar appreciation tomorrow) in particular when both options' embedded leverage and private benefits from holding US dollars are high.

2.1 Model Setup

We consider a static model with time periods indexed with $t = \{0, 1\}$. There is a risky asset – a unit of foreign currency – that trades against the US dollar in the spot market. The exchange rate at time t is denoted as e_t and indicates the amount of US dollars that is required to purchase a unit of foreign currency, such that an increase (decrease) means foreign currency appreciation (depreciation). The asset is traded at time $t = 0$ and its liquidating value is realized in the future at time $t = 1$. When the asset is traded, all market participants observe the current exchange rate e_0, but some of them are uncertain about the future exchange rate e_1, which can take on the high liquidating value of $e_0 + \overline{V}$ when a positive information event occurs or the low liquidating value of $e_0 - \overline{V}$ when a negative information event happens; both events are equally likely and $\overline{V} > 0$. Interest rates are set equal to zero to simplify the notation, implying that exchange rate returns and currency excess returns are identical.[8]

In addition to the spot market, there is also an option market that allows investors to trade a call and a put option on a risky asset. These options can only be exercised at maturity since FX options are primarily European-style options. With a call option trading on the inception date $t = 0$, the holder acquires the right to buy a unit of the foreign currency at K_c units of US dollars on the expiry date $t = 1$. The payoff of a call option at maturity is equal to $\max\{e_1 - K_c, 0\}$, where the strike price K_c is such that $e_0 - \overline{V} \leq K_c < e_0 + \overline{V}$. Similarly, a put option traded at time $t = 0$ gives the holder the right to sell a unit of foreign currency at K_p units of US dollars at time $t = 1$. Its payoff at maturity is given by $\max\{K_p - e_1, 0\}$, where the strike price K_p is such that $e_0 - \overline{V} < K_p \leq e_0 + \overline{V}$. The sensitivity of each option value to changes in the price of the underlying is quantified by the option's delta, which corresponds to $\delta_c = (e_0 + \overline{V} - K_c)/2\overline{V}$ for the call option and $\delta_p = -(K_p + \overline{V} - e_0)/2\overline{V}$ for the put option. To further simplify our notation, we assume that call and put options are symmetric in their deltas by setting $|\delta_c| = |\delta_p| = L$.

Investors can trade in the spot market with a competitive risk-neutral market maker and/or

[8]The predictions of our model remain unchanged when we denote the dollar interest rate as i_0 and the foreign interest rate as $i_0^\star$. When investing in foreign currency while borrowing in US dollars, the excess return would be equal to $ln(e_1) - ln(e_0) + i_0^\star - i_0$ with $e_1 = e_0^{i_0 - i_0^\star} \pm \overline{V}$.

in the option market with another competitive risk-neutral market maker. Each market maker sets bid and ask prices that yield zero expected profits and that are endogenously determined in our model. We denote the bid (ask) price of the spot rate as b_s (a_s), the bid (ask) price of the call option as b_c (a_c), and the bid (ask) price of the put option as b_p (a_p). Also, market makers share the same information set and have the same expected value for the asset, thus implying that there is no role for arbitrageurs in our setting.

In our economy, trades arise between market makers and two types of traders. The first group consists of *uninformed* or *liquidity* traders, who infer the value of the risky asset using publicly available information and trade only for liquidity reasons that are exogenous to our model. In the option market, for example, many trades are likely to be driven by hedging motives. *Liquidity* traders have a probability mass of $1-\mu$ and their trading activity can be described as follows

$$\text{Liquidity Trading} = \begin{cases} q_1 &= \text{Prob}\,\{\text{buy the asset}\} \\ q_2 &= \text{Prob}\,\{\text{sell the asset}\} \\ q_3 &= \text{Prob}\,\{\text{buy the put}\} \\ q_4 &= \text{Prob}\,\{\text{sell the put}\} \\ q_5 &= \text{Prob}\,\{\text{buy the call}\} \\ q_6 &= \text{Prob}\,\{\text{sell the call}\}, \end{cases}$$

where $\sum_i q_i = 1$. We further ensure that liquidity trading is symmetric by making the following assumption:

Assumption 1. $q_1 = q_2,\ q_3 = q_4 = q_5 = q_6.$

The second group consists of *informed* traders, who privately know the true liquidating value of the risky asset and trade only for information reasons. They have a probability mass of

μ, are risk neutral, and competitive so that they are not allocated to a specific market, but decide where and what to trade based on the highest expected profit. We assume that *informed* investors enjoy a utility gain that amounts to m (with $m > 0$) from acquiring US dollars, i.e. by selling the foreign currency in the spot market, buying a put option, or writing a call option. In contrast, *informed* investors face a utility loss that corresponds to $-m$ when having a positive exposure to the foreign currency, i.e. by buying the foreign currency in the spot market, buying a call option, or writing a put option. Finally, *informed* traders are not allowed to simultaneously execute multiple trades as otherwise they would want to trade an infinite amount of the asset.

We can characterize the decision problem of an *informed* investor as follows. With bad news about the foreign currency, an *informed* investor knows that $e_1 = e_0 - \overline{V}$ and her utility can be quantified as follows

$$\underline{U} = \begin{cases} (b_s + \overline{V} - e_0) + m & \text{if sell the asset} \\ -a_p + (K_p + \overline{V} - e_0) + m & \text{if buy a put} \\ b_c + m & \text{if sell a call.} \end{cases}$$

In the case of good news, the investor knows that $e_1 = e_0 + \overline{V}$ and her utility is given by

$$\overline{U} = \begin{cases} -a_s + e_0 + \overline{V} - m & \text{if buy the asset} \\ b_p - m & \text{if sell a put} \\ -a_c + (e_0 + \overline{V} - K_c) - m & \text{if buy a call.} \end{cases}$$

Given the opportunity to trade, an *informed* trader selects the trade that maximizes her profit given her information set. When there is a positive signal about the foreign currency, we denote the fraction of *informed* traders active in the market by $\overline{q}$, the fraction of *informed* traders who choose to trade in the spot market by $\overline{\alpha}$, and the fraction of *informed* traders who choose to trade calls in the option market by $\overline{\beta}$. They can also decide not to engage in trading with probability $1-\overline{q}$, and in this case no trade is observed. When there is a negative signal about the foreign currency, in contrast, we label the fraction of *informed* traders active in the market by $\underline{q}$, the fraction of *informed* traders who choose to trade in the spot market by $\underline{\alpha}$, and the fraction of *informed* traders who choose to trade calls in the option market by $\underline{\beta}$. If they decide not to engage in trading with probability $1-\underline{q}$, no trade is observed.

The decision problem of an *informed* trader can be thus described as

$$\text{Informed Trading} = \begin{cases} \text{Good News} = \begin{cases} 1-\bar{q} & \text{if not active} \\ \bar{q}\,\overline{\alpha} & \text{if buy the asset} \\ \bar{q}(1-\overline{\alpha})\overline{\beta} & \text{if buy the call} \\ \bar{q}(1-\overline{\alpha})(1-\overline{\beta}) & \text{if sell the put} \end{cases} \\[2ex] \text{Bad News} \;\; = \begin{cases} 1-\underline{q} & \text{if not active} \\ \underline{q}\underline{\alpha} & \text{if sell the asset} \\ \underline{q}(1-\underline{\alpha})\underline{\beta} & \text{if sell the call} \\ \underline{q}(1-\underline{\alpha})(1-\underline{\beta}) & \text{if buy the put,} \end{cases} \end{cases}$$

where $(\underline{q},\ \underline{\alpha},\ \underline{\beta},\ \overline{q}\ \overline{\alpha},\ \overline{\beta})$ are determined in equilibrium with $\underline{q} \leq 1$ and $\overline{q},\ \underline{\alpha},\ \overline{\alpha},\ \underline{\beta},\ \overline{\beta} \geq 0$. We summarize the probabilistic structure of trading in Figure 1, where the game starts with an information event affecting the future value of the foreign currency, then proceeds with a random selection of a trader from the universe of all traders, and terminates with a trade outcome, i.e. buying or selling the asset, buying or writing a call, and buying or writing a put.

Figure 1 about here

Differently from Easley, O'Hara and Srinivas (1998), we assume that an *informed* trader incurs participation cost c to trade in a market, interpreted as an inventory or opportunity cost for missing alternative investment decisions. We assume $c > m$, so that an *informed* investor will trade in response to news about the foreign currency as described above, i.e. by buying the asset, selling a put, or buying a call when receiving good news about the foreign currency, and vice versa for bad news. With $m > c$, in contrast, an *informed* trader would ignore her private signal and hold US dollars even when receiving good news about the foreign currency. We further assume that c is less than the minimum trading profit enjoyed by *informed* traders in the spot market, hence ensuring that *informed* traders will be active in the market.[9] We can summarize the condition regarding m and c by making the following assumption.

Assumption 2. $\frac{2(1-\mu)q_1\overline{V}}{\mu+2(1-\mu)q_1} > c > m \geq 0.$

We now move to characterize the equilibrium prices in the spot and option market before deriving the key prediction of our model on the link between option volume and expected exchange rate returns.

2.2 Equilibrium Prices

To determine the equilibrium prices in the spot and option market, we require that market makers set prices so that their expected profits are zero given their beliefs about the behavior

[9]The minimum trading profit in the spot market depends on the bid and ask prices described in Section 2.2 and is equal to $\frac{1}{2}(b_s - (e_0 - \overline{V}) + (e_0 + \overline{V}) - a_s) = \frac{\overline{V}}{2}(\frac{2(1-\mu)q_2}{\underline{q}\underline{\alpha}\mu+2(1-\mu)q_2} + \frac{2(1-\mu)q_1}{\mu\overline{q}\overline{\alpha}+2(1-\mu)q_1}) \geq \frac{2(1-\mu)q_1\overline{V}}{\mu+2(1-\mu)q_1}$. Also, according to Lemma 1 described in Section 2.2, there is always a positive fraction of *informed* traders in the spot market such that their minimum trading profit is given by $\frac{2(1-\mu)q_1\overline{V}}{\mu+2(1-\mu)q_1}$.

of *informed* traders. We first derive the optimal bid and ask prices set by market makers given the probabilities of informed trading, and then derive conditions under which *informed* investors choose whether to trade in the spot market or the option market.

In the spot market, the bid (ask) price is the conditional expected value of the asset given that a trader wishes to sell (buy) the asset to the market maker. Using Bayes' rule, we obtain that the bid and ask prices are given by

$$b_s = \mathbb{E}[\text{Value Asset} \mid \text{Sell Asset}] = e_0 - \frac{\underline{q}\underline{\alpha}\mu\overline{V}}{\underline{q}\underline{\alpha}\mu + 2(1-\mu)q_2}$$

$$a_s = \mathbb{E}[\text{Value Asset} \mid \text{Buy Asset}] = e_0 + \frac{\mu\overline{q}\overline{\alpha}\overline{V}}{\mu\overline{q}\overline{\alpha} + 2(1-\mu)q_1}.$$

Similarly, the bid (ask) price for the call option is the conditional expected value of the call given that a trader wishes to sell (buy) the call to the market maker such that

$$b_c = \mathbb{E}[\text{Value Call} \mid \text{Sell Call}] = \frac{2(1-\mu)q_6 \times L\overline{V}}{\mu\underline{q}(1-\underline{\alpha})\underline{\beta} + 2(1-\mu)q_6}$$

$$a_c = \mathbb{E}[\text{Value Call} \mid \text{Buy Call}] = \frac{2\left[\mu\bar{q}(1-\overline{\alpha})\overline{\beta} + (1-\mu)q_5\right] \times L\overline{V}}{\mu\bar{q}(1-\overline{\alpha})\overline{\beta} + 2(1-\mu)q_5},$$

whereas the bid (ask) price for the put option corresponds to

$$b_p = \mathbb{E}[\text{Value Put} \mid \text{Sell Put}] = \frac{2(1-\mu)q_4 \times L\overline{V}}{\mu\bar{q}(1-\overline{\alpha})(1-\overline{\beta}) + 2(1-\mu)q_4}$$

$$a_p = \mathbb{E}[\text{Value Put} \mid \text{Buy Put}] = \frac{2\left[\mu\underline{q}(1-\underline{\alpha})(1-\underline{\beta}) + (1-\mu)q_3\right] \times L\overline{V}}{\mu\underline{q}(1-\underline{\alpha})(1-\underline{\beta}) + 2(1-\mu)q_3}.$$

These bid and ask prices depend on the expected presence of *informed* traders in each market, i.e. the probability of overall *informed* trading captured by μ, and the fraction of *informed* traders active in each market captured by $\underline{q}$, $\underline{\alpha}$, $\underline{\beta}$, $\bar{q}$ $\overline{\alpha}$, and $\overline{\beta}$.

2.3 Where Does Informed Trading Take Place?

In equilibrium, it can be shown that there are always *informed* investors ready to trade the asset in the spot market as summarized by the following lemma.

Lemma 1. *There is always a positive fraction of informed investors in the underlying asset.*

Proof. See Internet Appendix A.1. □

Next, we characterize the trading decision of *informed* traders and the corresponding asset pricing implications. In particular, we focus on the association between exchange rate changes and option trading volume, which we denote as V_o.

Proposition 1. *In this economy, the equilibrium is characterized by the following cases*:

1. There is no private benefit from holding US dollars ($m = 0$),

   (a) If $L \leq \frac{2(1-\mu)q_2}{\mu+2(1-\mu)q_2}$, *informed* investors only trade in the spot market and there is no association between option trading volume and future exchange rate changes, so that $Cov(e_1 - e_0, V_o) = 0$.

   (b) If $L > \frac{2(1-\mu)q_2}{\mu+2(1-\mu)q_2}$, there is a pooling equilibrium in which a positive fraction of *informed* investors is active in the option market. However, there is no association between option trading volume and future exchange rate returns.

2. There is a private benefit from holding US dollars ($m > 0$),

   (a) If $L \leq \frac{2(1-\mu)q_2}{\mu+2(1-\mu)q_2}$, no *informed* investors trade options and there is no association between option trading volume and future exchange rate changes.

   (b) If $L > \frac{2(1-\mu)q_2}{\mu+2(1-\mu)q_2}$, we can distinguish between two cases:

i. When $m \leq m^\star$, there is no association between option trading volume and future exchange rate returns, where $m^\star = \frac{2(1-\mu)q_1\overline{V}}{\mu\overline{\alpha}^\star+2(1-\mu)q_1} - c$ captures the difference between the minimum trading profit and the market participation costs of *informed* investors.

ii. When $m > m^\star$, there is a negative relationship between option trading volume and future exchange rate changes, i.e. $Cov(e_1 - e_0, V_o) < 0$.

Proof. See Internet Appendix A.2. □

This proposition has several implications. First, when there are no private benefits from holding US dollars, *informed* traders always enter the market since their trading profit is larger than the participation cost c (see Assumption 2 and Footnote 6), but option trading volume has no predictive power for future exchange rate returns. Akin to Easley, O'Hara and Srinivas (1998), there are two possible scenarios that depend on the option-embedded leverage: (a) *informed* traders only trade spot contracts when leverage is low, and (b) a pooling equilibrium where some *informed* investors trade options when leverage is sufficiently high. Intuitively, trading high-leverage options enables investors to better exploit their information advantage. Second, option trading volume can negatively predict future exchange rate returns only if both the option-embedded leverage and the private value of holding US dollar are high. Unsurprisingly, when there is no private benefit from holding US dollars, informed investors always buy the foreign currency (via buying in the spot market/buying call options or selling put options) when receiving good news about the foreign currency and always sell the foreign currency (via selling in the spot market/selling call options or buying put options). However, with positive benefits from holding US dollars, informed investors are disincentivized from holding foreign currency. We can therefore make the following empirical predictions.

Empirical Predictions

1. *FX option volume is negatively correlated with future exchange rate changes or, equivalently, correlated with a foreign currency depreciation.*

2. *The negative relationship between FX option volume and future exchange rate changes is larger in magnitude when the concentration of informed investors is higher.*

3. *The negative relationship between FX option volume and future exchange rate changes is larger in magnitude when the private utility gains from holding US dollars are higher.*

4. *The negative relationship between FX option volume and future exchange rate changes is larger in magnitude when option-embedded leverage is higher.*

3 Data Description and Summary Statistics

We first describe our granular dataset on foreign exchange (FX) options traded over the counter (OTC) and then present preliminary summary statistics.

3.1 Trade Repository Data

Understanding the nature of OTC markets is generally challenging, 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. However, regulatory efforts to enhance the transparency of OTC derivatives markets intensified after the Great Financial Crisis. 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 derivative 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. 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 the DTCC Derivatives Repository – 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 relative to the US dollar (USD): 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).[10]

3.2 Data Structure and Classification

The currency market consists of an interbank segment where dealers (typically large international banks) trade among themselves and a customer segment where financial and non-financial players trade with dealers or among themselves. Similar to Cenedese, Della Corte and Wang (2021) for FX forwards, we first identify dealers and clients using their legal entity identifiers (LEIs), and then group the corresponding transactions. We use a list of 17 dealer banks, which covers the largest banks by market share according to the 2015 and

[10] Options on European currencies like the Polish Zloty, Czech koruna, and Hungarian forint are mostly traded against the euro, and we observe only little trading activity against the US dollar. These currencies are therefore not included in our sample.

2016 Euromoney FX survey. Clients, moreover, are grouped into hedge funds, real money investors (asset managers, pension funds, insurance firms, sovereign institutions, and other financials), 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) as in Menkhoff et al. (2016).

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 taking place in the OTC FX option market. To shed light on this aspect, in Figure 2, we compare the average trading volume of our dataset with the summary statistics reported by publicly available sources such as the triennial survey of the Bank for International Settlements for global FX markets (BIS Survey) and the semi-annual survey of the London Foreign Exchange Joint Standing Committee (FXJSC survey) for the FX market in the UK.

Figure 2 about here

In April 2016, for example, the average FX option volume on all currency pairs amounts to more than $254 billion per day worldwide (BIS Survey) and is close to $110 billion per day in London (FXJSC survey). When restricting the analysis to options written on USD currency pairs, the average volume is larger than $218 billion per day on a global scale (BIS Survey), and close to $91 billion per day in London (FXJSC survey). We compare the coverage of our dataset to these publicly available statistics by first computing the volumes on each trading day, and then calculating the daily average for April 2016. We find an average volume of about $91 billion per day for the US dollar 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, 2016). We also report the average turnover for the full sample, which amounts to around

$130 billion per day. We, therefore, conclude that our sample covers a substantial amount of the overall trading activity in the OTC FX option market.

FIGURE 3 ABOUT HERE

We also present the average daily volume by currency pairs and counterparty sectors in Figure 3. The figure reveals that approximately 69% of the average daily volume (equivalent to $90 billion per day) is concentrated on the EUR (36%), JPY (25.4%), and GBP (7.6%) against the USD. An additional 14.4% (equivalent to $19 billion) 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. Other major currency pairs like the NOK and SEK account for less than $0.5 billion per day as they are mostly traded against the EUR. Finally, the most traded emerging markets currency pairs like the BRL, KRW, MXN, SGD, and TRY account for another 12.1% (equivalent to $15.8 billion) of the average daily volume.

FIGURE 4 ABOUT HERE

Finally, Figure 4 shows 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 Table A.1 and Table A.2 of the Internet Appendix. In our empirical analysis, volume is expressed in US dollars and constructed by aggregating transaction-level option volumes from the DTCC Derivatives Repository at 4pm London time on a daily basis.

3.3 Breakdown by Option Type and Trading Direction

In our dataset, we can also identify the direction of a client transaction thanks to new reporting guidelines introduced by ESMA in November 2015. In particular, we use a buy/sell indicator (reported in the counterparty side field of the trade repository) and define options such that the buyer of a call (put) has the right to buy (sell) a unit of foreign currency against a 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), moreover, has the obligation to sell (buy) one unit of the foreign currency at a given strike price if the option is exercised.

FIGURE 5 ABOUT HERE

We can therefore determine whether a client is buying or selling a given option, allowing us to identify a client's trading motives, her attitude towards risk, and her hedging demand. In Figure 5, we split trading volume by option type, currency pair, and trading direction. In Panel A, we show that the trading 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, Panel B shows that clients are net buyers in both call and put options. In particular, more than 60% of the dealer-client transactions are put options and less than 40% are call options. Also, hedge funds are the most active clients in put options, having traded 43.6% of all long puts and 42.8% of all short puts. Real money investors, in contrast, are the most active clients in call options, having traded 35.4% of all long calls and 30.9% of all short calls.

3.4 Spot and Forward Exchange Rates

We complement our transaction-level option data with high-frequency spot and forward exchange rates, quoted per second, from Refinitiv Tick History. Our analysis is at the daily frequency and requires overnight interest rates that are not directly observed for all countries in our sample. We thus synthesize overnight forward exchange rates (or, equivalently, interest rate differentials relative to the US dollar) from one-month forward exchange rates using the covered interest parity condition. Essentially, we assume that overnight forward premia are proportional to one-month forward premia similar to Cespa et al. (2021).[11]

We then simultaneously sample spot and forward exchange rates on each trading day at 4pm London time and construct both daily exchange rate returns and currency excess returns. Specifically, the daily exchange rate return of a given currency pair is computed as the log difference in spot exchange rates as

$$\Delta s_{t+1} = s_{t+1} - s_t,$$

where s_t is the log of the spot exchange rate on day t defined as units of US dollars per unit of foreign currency so that a positive exchange rate return corresponds to an appreciation of the foreign currency. Similarly, the daily currency excess return of a given currency pair is given by

$$rx_{t+1} = s_{t+1} - f_t$$

where f_t is the log of the synthetic overnight forward exchange rate observed at time t and define analogously to the spot exchange rate.

[11]While the approximation may not be exact due to deviations from covered interest parity (e.g., Du, Tepper and Verdelhan, 2018a; Cenedese, Della Corte and Wang, 2021), our analysis does not depend on whether this condition holds. As shown later in the paper, our results are entirely driven by changes in spot exchange rates with interest rate differentials playing a negligible role.

4 Baseline Empirical Results

This section empirically studies the FX return predictive power of FX option volume. First, we use simple portfolio sorting methods to assess the cross-sectional predictability of option volume for currency excess returns and exchange rate returns. Second, we employ panel regressions to account for the role of liquidity and volatility. Third, we provide evidence on the role of options' embedded leverage for return predictability. Finally, we examine exchange rate predictability during periods of high and low dollar demand.

4.1 Option Volume and Currency Return Predictability

We begin our empirical analysis by using conventional sorted portfolios (as in Lustig, Roussanov and Verdelhan, 2011) to evaluate the cross-sectional predictive power of FX option volume for currency returns. For this exercise, on each trading day t, we first measure the option volume $V_{i,t}$ for every currency pair i by aggregating the intraday volume of call and put options in dollar terms at 4pm London time. To mitigate the impact of heteroscedasticity and linear trends, we then follow Cespa et al. (2021) and construct a measure of abnormal option volume as

$$v_{i,t} = ln(V_{i,t}) - ln(\overline{V}_i), \tag{1}$$

where $\overline{V}_i = M^{-1}\sum_{s=1}^{M} V_{i,t-s}$ denotes the lagged option volume averaged over the past month (i.e., $M = 21$ trading days).[12] We then allocate our currency pairs to four baskets on the basis of $v_{i,t}$, so that the first basket comprises currencies with low option volume, and the last basket consists of currencies with high option volume. On the next trading day $t + 1$, we then compute the equally-weighted average of individual currency excess returns within each basket. In addition to using total option volume, we also consider portfolios sorted by interdealer option volume as well as portfolios sorted by customer option volume.

[12] In Section 6.1, we show that our results remain robust to using different rolling windows.

Table 1 about here

We summarize the performance of our daily-rebalanced portfolios in Table 1 (with t-stats in brackets based on Newey and West (1987) standard errors with a lag length of 21 days). Panel A focuses on *major currencies* with sizable option volumes (i.e., AUD, CAD, CHF, EUR, GBP, JPY, and NZD) whereas Panel B presents results for *all currencies* in our sample. We find statistically and economically significant evidence that option volume negatively predicts future currency excess returns, especially when conditioning on the dealer-client segment of the option market, in line with Prediction 1 and Prediction 2. As shown in Panel A of Table 1, portfolios of *major currencies* sorted by total option volume display monotonically decreasing average excess returns, with P_1 (portfolio of currencies with low option volume) significantly outperforming P_4 (portfolio of currencies with high option volume). It follows that buying P_1 while selling P_4 – a low-minus-high strategy dubbed LMH – generates an average excess return that is larger than 14% per annum. This estimate is not only statistically significant (with a t-stat well above 2), but also economically large with a Sharpe ratio close to 1.7 per annum.

We then divide the total option volume into interdealer and dealer-client volumes, which are likely to reflect different trading motives. While dealers accumulate inventories by trading with their clients and then trade among each other to balance out their inventories, clients tend to trade for information or liquidity reasons. As shown in Figure 4, our sample is dominated by real money investors and hedge funds, who are regarded as informed market participants (e.g., Menkhoff et al., 2016). We find that the predictive power of option volume for *major currencies* is weaker for the interdealer option volume but stronger for the client option volume. In particular, the LMH strategy based on interdealer volume generates a positive excess return that is only marginally statistically significant. In contrast, the same long-short strategy based on clients' option volume produces an excess return of 16.8% per annum, which is statistically significant with a t-stat of 2.72 and economically large with a Sharpe ratio of 1.86 per annum. Taken together, the findings reported in Panel A confirm the first two predictions of our model: FX option volume negatively predicts future currency returns, and the return predictability is larger for informed investors.

Panel B of Table 1 presents the results for portfolios using *all currencies*. We find that cross-sectional predictability only exists for client option volume. Specifically, when sorting by total volume or interdealer volume, the LMH strategy delivers an average excess return of about 6% per annum, which turns out to be statistically insignificant. Grouping currencies on the basis of client volume, however, delivers an average excess return of the long-short strategy that is close to 11% per annum. This estimate is statistically significant with a t-stat close to 2, and also economically sizable with a Sharpe ratio of 1.36 per annum. These findings confirm our prediction that option volume negatively predicts currency excess returns, especially when using client option volume.[13] Compared to *major currencies*, moreover, return predictability based on customer volume for *all currencies* is slightly weaker. This could be due to the fact that informed investors prefer to trade liquid options to more efficiently exploit their information advantage. We will further explore the informed trading hypothesis later in the paper.

TABLE 2 ABOUT HERE

Thus far, it remains unclear whether option volume predicts exchange rate returns or interest rate differentials. To shed light on this question, we strip out interest rate differentials and focus solely on the exchange rate return component of our sorted portfolios. We report the results in Table 2 and find qualitatively similar findings compared to those reported in Table 1. This means that our evidence of return predictability is largely driven by the fact

[13]Option volume for *all currencies* is highly unbalanced on a daily basis and this is likely to explain the lack of monotonically decreasing portfolio excess returns.

that option volume negatively predicts exchange rate returns, as suggested by our model. For example, when sorting by client option volume, the LMH strategy for *major currencies* delivers an average exchange rate return of 16.83% per annum, which is virtually indistinguishable from the average currency excess return of 16.80% per annum. For *all currencies*, the LMH strategy produces an average exchange rate return that is identical to its average excess return, i.e. 10.76% per annum. To sum up, in this section we show that FX option volume negatively predicts exchange rate returns, and the results are stronger when focusing on informed trading and more liquid currency pairs.

4.2 Controlling for Liquidity and Volatility

Option volume may be associated with trading costs and price volatility (e.g., Stoll, 1978; Kyle, 1985), which could potentially drive our evidence on the currency return predictability. To examine whether this is the case, we run predictive regressions based on the following specification

$$rx_{i,t+1} = \alpha + \beta \tilde{v}_{i,t} + \gamma' x_{i,t} + fe + \varepsilon_{i,t+1}, \tag{2}$$

where $rx_{i,t+1}$ is the excess return between days t and $t+1$ for currency i, $\tilde{v}_{i,t}$ is the quartile rank of the standardized option volume $v_{i,t}$ for currency i relative to the total volume on day t, and $x_{i,t}$ includes country-level control variables, i.e. the forward premium, the realized volatility measured using intraday hourly exchange rates, and the bid-ask spread based on end-of-day quotes. We include time (calendar date) and currency fixed effects (*fe*), and cluster standard errors at the time dimension.

Table 3 about here

We show our results in Panel A of Table 3. $\tilde{v}_{i,t}$ in specifications (1) to (3) are constructed by using total, interdealer, and client volume, respectively, while controlling for time-variant omitted variables that are common to all currencies. All these specifications report statistically significant estimates of β, ranging between -1.677 (with a standard error of 0.813) and -2.396 (with a standard error of 0.823), thus confirming our empirical results in support of Prediction 1. Specifications (4) to (6), moreover, use $\tilde{v}_{i,t}$ based on both interdealer and client volumes, and we find statistically significant estimates for client volume but statistically insignificant results for interdealer volume, in line with our previous evidence for Prediction 2. For example, specification (6) controls for country-specific factors, time-variant unobserved factors, and time-invariant unobserved currency heterogeneity. The estimate of β for client volume is -2.119 with a standard error of 1.002, whereas the estimate on β for interdealer volume is -0.776 with a standard error of 0.950. In economic terms, these estimates imply that the future average currency excess return drops by 2.12% per annum when the current client volume increases by one standard deviation. In contrast, the future average currency excess return falls by 0.74% per annum when the current interdealer option volume increases by one standard deviation.

In Panel B of Table 3, we use exchange rate returns instead of currency excess returns as the dependent variable in Equation (2), and discover virtually identical results. This means that client option volume predicts the exchange rate return component as opposed to the interest rate differential component of currency excess returns. Taken together, these results suggest that client option volume contains valuable information that negatively predicts future currency returns beyond observable and unobservable factors. In contrast, interdealer option volume loses its predictive power once you control for clients' trading activity. Hence, the currency return predictability detected for interdealer volume in Table 1 may mechanically reflect the activity of their clients. We will further investigate informed trading using disaggregate customer volume in Section 5.

FIGURE 6 ABOUT HERE

A potential concern with our findings is that the short-term return predictability may result from price pressures due to temporary liquidity or hedging demand. If such trading motives would dominate, the correlation between option volume and currency returns should only be temporary and prices should revert to their fundamental values (e.g., Froot and Ramadorai, 2005). To address this concern, we calculate the post-formation performance of the LMH strategy based on client volume using a holding period of 30 days and then plot the cumulative excess returns in Figure 6. We find that the LHM portfolio continues to earn positive and significant excess returns over the longer horizon. Importantly, the observed return pattern exhibits no sign of a reversal. This helps us to rule out the possibility that option volume may reflect temporary liquidity or hedging demand.

4.3 Option Volume and Dollar Demand

In the previous sections, we have shown that the information embedded in FX option volume enables us to negatively predict future currency returns and that the predictive power is stronger for client option volume. We now move to an empirical test of Prediction 3, which forecasts a more pronounced negative correlation between option volume and future currency returns when private utility gains from holding US dollars are higher.

There is growing evidence that holding US dollars or dollar-denominated assets is particularly valuable during periods of stress in financial markets due to the stable nominal payoffs and high liquidity. These 'flight-to-safety' episodes are generally characterized by high levels of volatility coupled with investors' willingness to pay a premium to hold safe assets like US treasuries. Building on the prior literature, we rely on two different proxies to identify periods when holding US dollars is likely to deliver higher private benefits. The first one is the five-year US Treasury premium or convenience yield, which measures the yield difference between US treasuries and currency-hedged foreign government bonds with five-year maturities (e.g., Du, Im and Schreger, 2018b; Jiang, Krishnamurthy and Lustig, 2021). The second one is JP

Morgan's VXY index, a sort of VIX equivalent for FX markets, which tracks the aggregate expected volatility of major exchange rates and can be viewed as a measure of global risk (e.g., Menkhoff et al., 2012).

Table 4 about here

Armed with these measures, we first analyze periods of high dollar demand that occur when either the five-year US Treasury premium is high or the VXY index are high (above the sample median). We then repeat the portfolio sorting exercise described in Section 4.1 for periods of high and low dollar demand. We focus on major currency pairs and report the results for the exchange rate returns in Table 4. We find strong evidence that option volume negatively predicts exchange rate returns when dollar demand is high. However, option volume loses its predictive power when dollar demand is low, as suggested by our model. As shown in Panel A, for example, the average exchange rate return of the LMH portfolio amounts to 26.49% per annum (with a t-stat of 3.19) when the US Treasury premium is above the median and 19.09% per annum (with a t-stat of 2.82) when the VXY index is above the median. In Panel B, in contrast, we show that the average exchange rate return turns out to be statistically insignificant in periods with low dollar demand, regardless of whether we use the US Treasury premium or the VXY index. To sum up, in line with our Prediction 3, we show that option volume is a powerful cross-sectional predictor of future currency returns in periods with high dollar demand.

4.4 Option Volume and Leverage

A major appeal of option markets is that they provide relatively high leverage or 'bang for the buck'. Because of this *embedded leverage*, informed traders may prefer to trade options, rather than the underlying asset, to take advantage of their superior information set. On these grounds, our model's Prediction 4 suggests that the return predictability increases with the volume of options with higher embedded leverage.

To test this prediction, we focus on options traded between clients and dealers and use the strike-to-spot price ratio to classify them in terms of moneyness. For example, an option with a strike-to-spot price ratio of 1.05 is 5% out-of-the-money whereas an option with a strike-to-spot price ratio of 0.95 is 5% in-the-money. We then categorize options as deep out-of-the-money (DOTM) when the strike-to-spot price ratio is larger than 1.05, as out-of-the-money (OTM) when the strike-to-spot price ratio is between 1.05% and 1.02%, as near-the-money or close to being at-the-money (ATM) when the strike-to-spot price ratio is between 1.02 and 0.98, as in-the-money (ITM) when the strike-to-spot price ratio is between 0.98 and 0.95, and as deep in-the-money (DITM) when the strike-to-spot price ratio is less than 0.95. Finally, we rerun the portfolio sorting exercise described in Section 4.1 using $v_{i,t}$ based on options with different levels of moneyness.

Table 5 about here

We focus on major currency pairs and report summary statistics for exchange rate returns in Table 5. We find statistically and economically significant evidence that the average exchange rate return of the LMH portfolio increases monotonically with options' embedded leverage, consistent with Prediction 4. For example, the return for DOTM options (i.e. options with the highest level of embedded leverage) is close to 23% per annum (with a t-stat larger than 3). In contrast, the corresponding figure for DITM options (i.e. options with the lowest level of embedded leverage) is about -0.2% per annum (with a t-stat close to zero). In between, we further show that OTM options deliver a sizeable spread of about 11% per annum (with a t-stat of 2.13) whereas ATM and ITM options produce statistically insignificant exchange rate returns.

Table 6 about here

As an additional exercise, we also examine the return predictability based on options' time-to-expiration. This is based on the notion that for a given level of moneyness, short-dated options offer considerably higher leverage than long-dated options. To this end, we first group options on the basis of their time-to-expiration: within one month, between one month and three months, between three months and six months, and longer than six months. We then repeat the portfolio sorting exercise described in Section 4.1.

We focus on major currency pairs and report the results for exchange rate returns in Table 6. Our evidence highlights that the average exchange rate return of the LMH portfolio decreases monotonically with options' time-to-expiration, in line with our findings on moneyness. In particular, the exchange rate return is higher than 13% per annum (with a t-stat of 2.41) for options with a maturity up to one month, and it is close to 12% per annum (with a t-stat of 2.11) for the next bucket of options with a maturity between one month and three months. For long-dated options, like those with a maturity of more than six months, the average exchange rate return is both statistically insignificant and economically small, i.e., 1.64% per annum with a t-stat of 0.28. Overall, we show that the predictive power of option volume is more pronounced for options with higher embedded leverage, i.e. out-of-the money and short-maturity options, consistent with our model's Prediction 4.

5 Informed Trading in the Option Market

In this section, we provide additional insights on the role of informed trading by separating dealer-client trading volumes into volumes of different client types. First, we present evidence on exchange rate predictability when focusing on the FX option volume of informed client sectors. Second, we analyze informationally intensive periods by focusing on days with macroeconomic announcements. Third, we exploit further the granularity of our dataset and examine the information content of signed order flows in the FX option market. Finally, we examine the information content of FX forward volume and show that it is a poor predictor of future exchange rate returns.

5.1 Client Sectors

To better understand the implications of our previous findings on the return predictability of option volume, it is critical to identify traders that are more likely to possess value-relevant information compared to other market participants (e.g., Easley et al., 1998). In our model, this distinction is particularly important given that the predictive power of option volume increases with the concentration of informed traders, as suggested by Prediction 2. While identifying informed traders is generally difficult, the granularity of our dataset allows us to overcome this challenge since we directly observe investor identities. Similarly to Menkhoff et al. (2016) and Cenedese et al. (2021), we first classify investors on the client side as hedge funds, real money investors (e.g., asset managers, pension funds, insurance firms), non-dealer banks (e.g., commercial banks, prime-brokerage firms), and other clients (e.g., corporate firms, central banks), and then rerun our portfolio sorting exercise across different types of investors, so that we can directly test our model's prediction.[14]

Table 7 about here

We focus on major currency pairs and report the results for exchange rate returns in Table 7. We find statistically significant evidence that the option volume of informed investors significantly predicts future exchange rate returns. In contrast, the estimates are statistically insignificant for uninformed clients. For example, the average exchange rate return is about

[14]Menkhoff et al. (2016), for example, show that FX market participants like hedge funds and real money investors possess superior information processing skills compared to other investors in the spot market.

14.26% per annum (with a t-stat of 2.60) for hedge funds and 15.06% per annum (with a t-stat of 2.45) for real money investors. As shown in Figure 4, these investors are also particularly active in the FX option market and account for more than two-thirds of client volume. This in line with the argument that informed traders tend to place their bets in the option market as the embedded leverage of options can amplify their potential gains. For nondealer banks, moreover, we find that the average exchange rate return is slightly higher than 8.4% per annum (with a t-stat of 1.43). While this estimate is statistically insignificant, its economic magnitude is fairly large and, according to Figure 4, the sector intermediates nearly 20% of client volume. A possible explanation is that non-dealer banks act on behalf of different types of market participants, including small hedge funds and asset management firms, and their trading volume could be a noisy proxy for informed trading. Finally, for other clients, we find that the average exchange rate return spread is about 6% per annum (with a t-stat of 0.95), which is also statistically insignificant. To sum up, these results further strengthen the information-based interpretation of our findings.

5.2 Macroeconomic Announcements

To further support our argument that the predictive power of option volume is driven by information, we exploit the heterogeneity in information intensity in the time series by analyzing days with macroeconomic announcements relative to non-announcement days. Intuitively, announcement days are usually associated with high levels of trading activity and should therefore offer ideal trading opportunities for informed investors. This argument is well documented in the literature. For example, prior studies on the equity market document a spike of informed trading prior to earnings announcements (e.g., Krinsky and Lee, 1996; Brennan et al., 2018), whereas existing work on the FX market finds similar evidence around macroeconomic announcements (e.g., Andersen et al., 2003; Evans and Lyons, 2008). In the context of options, moreover, 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.

Table 8 about here

Building on the analysis described in Section 5.1, we now examine the exchange rate return performance of different client types on days with and without macroeconomic announcements (i.e. FOMC, non-farm payrolls, PMI, PPI, CPI, GDP), and we report the results in Table 8. We find that the option volume of different investor groups generates higher average exchange rate returns on announcement days as opposed to non-announcement days. This pattern is particularly pronounced for hedge funds. While the average exchange rate return is about 24.5% per annum (with a t-stat of 2.8) on days with macroeconomic announcements, it is only close to 11.4% per annum (with a t-stat of 1.7) on non-announcement days. For real money investors, the average exchange rate return is similar on days with and without announcements, but it is statistically more significant on non-announcement days. For other investors (i.e. non-dealer banks and other clients), we show that the average exchange rate returns are statistically insignificant across both sets of days. To wrap up, we find evidence that informed trading is more intensive on announcement days.

5.3 Client Net Demand

Our empirical analysis thus far relates unsigned option volumes to future exchange rate changes. However, this begs the question of whether signed volumes would produce results consistent with our previous findings. To address this question, our dataset offers the possibility to examine the predictive power of *client net demand* (or equivalently, the client-dealer order flow), albeit for a shorter sample period between November 2015 and December 2016 (due to a regulatory change in 2015). Intuitively, if informed investors (e.g., hedge funds) have superior information, the corresponding net demand of put (call) options should negatively (positively) predict future exchange rate returns.

For each client group and on each trading day, we measure the *net demand* of put (or call) options as buy volume minus sell volume divided by total volume (to make client net demand comparable across currency pairs). We then build four currency portfolios sorted by client net demand so that the first (last) portfolio contains currencies with low (high) option net demand. In the case of put options, the first (last) portfolio contains currencies with low (high) option selling pressure, and the low-minus-high portfolio should deliver positive currency returns. For call options, in contrast, the first (last) portfolio contains currencies with low (high) option demand pressure, and the low-minus-high portfolio should produce negative currency returns.

TABLE 9 ABOUT HERE

We focus on major currencies and report the results for exchange rate returns in Table 9. Our results reveal that the option net demand of hedge funds is a strong predictor of future exchange rate returns, both statistically and economically. For example, a strategy that buys currencies with low selling pressure and sells currencies with high selling pressure in the put option market (LMH strategy) produces an average exchange rate return of approximately 18% per annum (with a t-stat of 2.38). Similarly, buying currencies with high demand pressure while selling currencies with low demand pressure in the call option market (the opposite of the LMH strategy) generates an average exchange rate return of about 17% per annum (with a t-stat of 2.68). Results are slightly weaker for real money investors: the LMH strategy based on put option net demand yields an average exchange rate return close to 17.5% per annum (with a t-stat of 1.76), whereas the opposite of the LMH strategy based on call option net demand generates an average exchange rate return close to 16% per annum (with a t-stat of 1.28). Finally, we find no statistically significant evidence for non-dealer banks and other clients, similar to our findings based on the unsigned trading volume.

5.4 FX Forward Volume

In addition to FX option volume, we also explore the predictive power of FX forward volume based on transaction-level contracts from DTCC Derivatives Repository (for a detailed description see Cenedese et al., 2021). We report our results in Table 10, and find that forward volume has no significant predictive power for future exchange rate returns. For example, the LMH strategy sorted by the forward volume of hedge funds produces an average exchange rate return of 4% per annum (with a t-stat of 0.95) for major currency pairs and 1.43% per annum (with a t-stat of 0.43) for all currency pairs. These results suggest that informed investors tend to use options rather than forwards to take advantage of their superior information set not at least due to options' embedded leverage.

6 Robustness Checks and Extensions

In this section, we conduct additional exercises to examine the robustness of our findings. First, we use different rolling windows as well as formation periods to calculate option volumes. Second, we examine the correlation between our low-minus-high strategy based on option volume with existing currency risk factors. Finally, we extend our analysis to an alternative source of FX option volume data.

6.1 Different Volume Scaling Methods

In our main analysis, we measure abnormal option volume using a rolling window of one month ($M = 21$) coupled with a formation period of one day ($N = 1$). For robustness, Internet Appendix Table A.4 shows that our key results remain qualitatively similar when using a rolling window of one week ($M = 5$) or three months ($M = 63$) while keeping the same formation period. For example, with a shorter window of one week, the LMH strategy based on total volume for major currencies (top panel) produces an average excess return of 15.04% per annum (with a t-stat of 2.61), which is very close to the 14.63% per annum (with a t-stat of 2.66) reported in Table 1. Moreover, the results improve slightly with a longer window of three months: the LMH strategy based on total volume for major currencies (middle panel) produces an average excess return of 17.57% per annum (with a t-stat of 2.88). In the same table, we further show that our key results are robust to using a formation period of three days ($M = 21$ and $N = 3$). The LMH strategy based on total volume for major currencies (bottom panel) yields an average excess return of 18.75% per annum (with a t-stat of 2.79).

6.2 Correlation with Currency Factors

We also analyze whether option volume captures any information beyond common currency factors in the literature. We regress the excess returns for the LMH portfolio based on client volume on a variety of existing currency factors such as the dollar, carry, value, momentum, volatility, liquidity, risk-reversal, and volatility risk premium factors. As shown in Internet Appendix Table A.3, the LMH portfolio is persistently profitable even after controlling for all currency risk factors. These results confirm that the return predictability of FX option volume cannot be explained by other well-known currency factors. We, therefore, conclude that FX option volume indeed captures information beyond common currency factors in the literature.

6.3 Alternative Data

Our main analysis is based on regulatory data obtained on a confidential basis from the Bank of England. As an alternative source of data, we also use the DTCC transaction-level FX option data available on Bloomberg between March 2013 and December 2020. This dataset is less granular as we do not observe investor identities, and it provides a smaller coverage since it mostly covers FX options traded in the US market. For example, for options written on US dollar currency pairs, we uncover a daily average volume of about \$26 billion as of April 2013 (approximately 9% of the global trading activity reported by the 2013 BIS Survey), \$44 billion as of April 2016 (approximately 20% of the global trading activity reported by the 2016 BIS Survey), \$54 billion per day as of April 2019 (approximately 21% of the global trading activity reported by the 2019 BIS Survey).

Armed with these data, we rerun the analysis described in Section 4.1 for total option volume, and report the results in Internet Appendix Table A.5. We find that option volume negatively predicts future currency excess returns (in Panel A) and exchange rate returns (in Panel B) for our sample of major currencies. For example, the average exchange rate return on the LMH strategy is about 9% per annum (with a t-stat of 2.86). When we extend the analysis to the larger sample of 20 currencies, the LMH strategy generates an insignificant return, similar to our results in Table 1. Internet Appendix Table A.6 further shows that the currency predictability is more pronounced during periods with high dollar demand. Overall, these findings using publicly-available data corroborate our baseline results on FX option volume.

7 Conclusion

In this paper, we examine the informational content of FX option volume 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 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 out-of-the-money 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.

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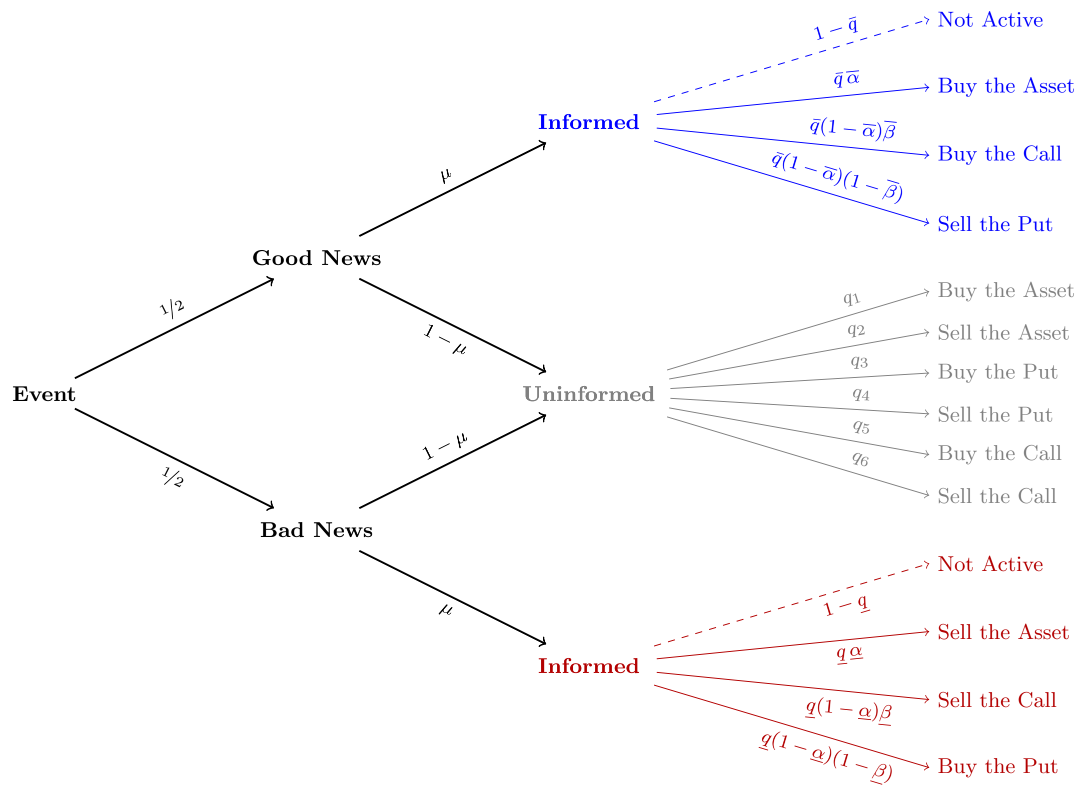


Figure 1. Structure of Trading

This diagram displays the probabilistic structure of trading, which starts with an information event and then proceeds with the trader's selection probabilities. When an information event occurs, the news about the foreign currency is either good or bad with equal probabilities. μ $(1-\mu)$ denotes the fraction *informed* (*uninformed*) traders, $\overline{q}$ $(\underline{q})$ is the fraction of *informed* traders active when the news is good (bad), $1-\overline{q}$ $(1-\underline{q})$ is the fraction of *informed* traders not active when the news is good (bad), $\overline{\alpha}$ $(\underline{\alpha})$ is the fraction of *informed* traders who choose to trade in the spot market when the news is good (bad), and $\overline{\beta}$ $(\underline{\beta})$ is the fraction of *informed* traders who choose to use calls given that they trade in the options markets when the news is good (bad). $q_1 = q_2$, $q_3 = q_4$, and $q_5 = q_6$ quantify the propensity of *uninformed* traders to trade in the spot or option market.

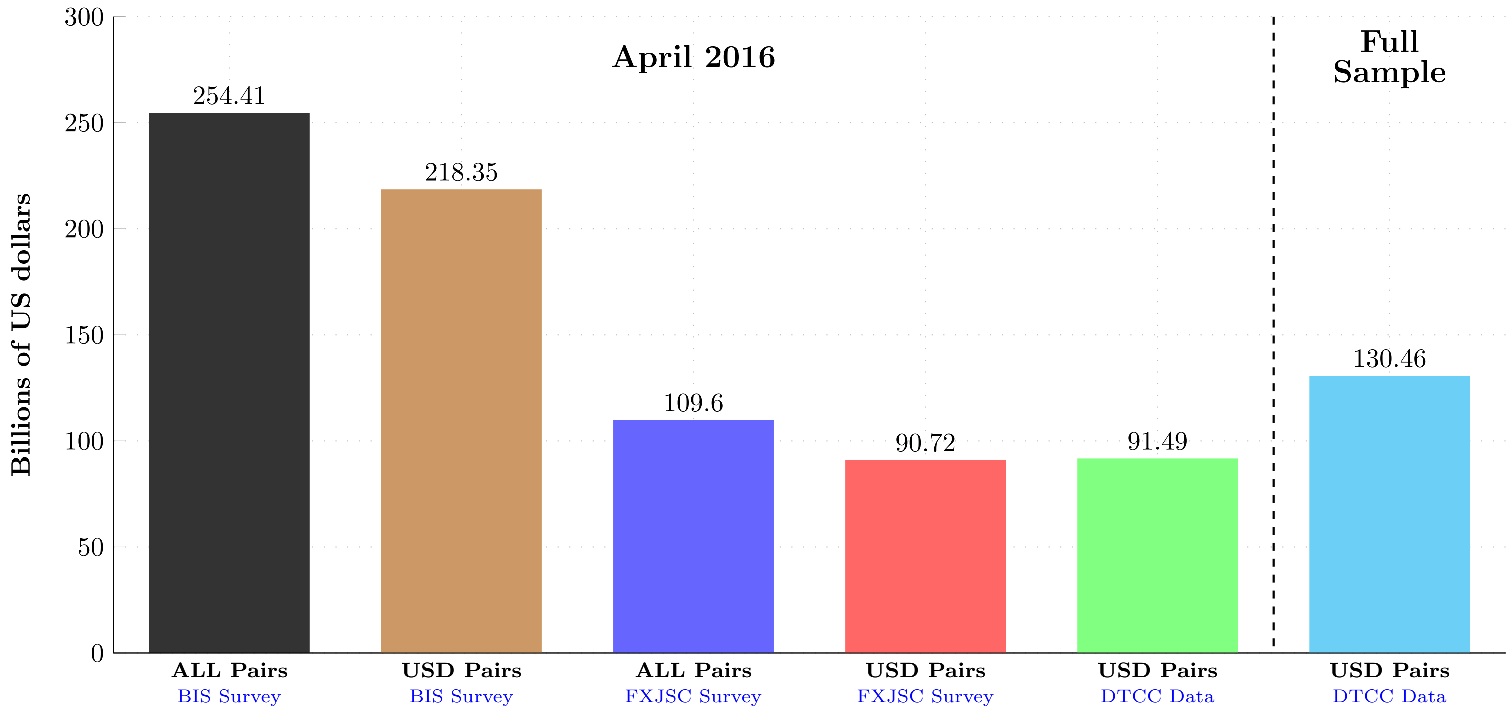


Figure 2. Daily Average Volume on FX Options

This figure displays, in billions of US dollars, the daily average volume of foreign exchange (FX) options traded over the counter (OTC). BIS Survey indicates the Triennial Central Bank Survey of Foreign Exchange and OTC Derivatives Markets Activity undertaken by the Bank for International Settlements. FXJSC denotes the Semi-Annual FX Turnover Surveys in April 2016 of the London Foreign Exchange Joint Standing Committee. DTCC refers to all FX option transactions submitted to the DTCC Derivatives Repository in which at least one of the counterparties is a UK-regulated entity. We first synchronize these transactions with exchange rates from Refinitiv Tick History to express volume in US dollars and then aggregate them at 4pm London time daily. DTCC volume is computed as of April 2016 (for comparison) and for the full sample that runs daily between December 2014 and December 2016.

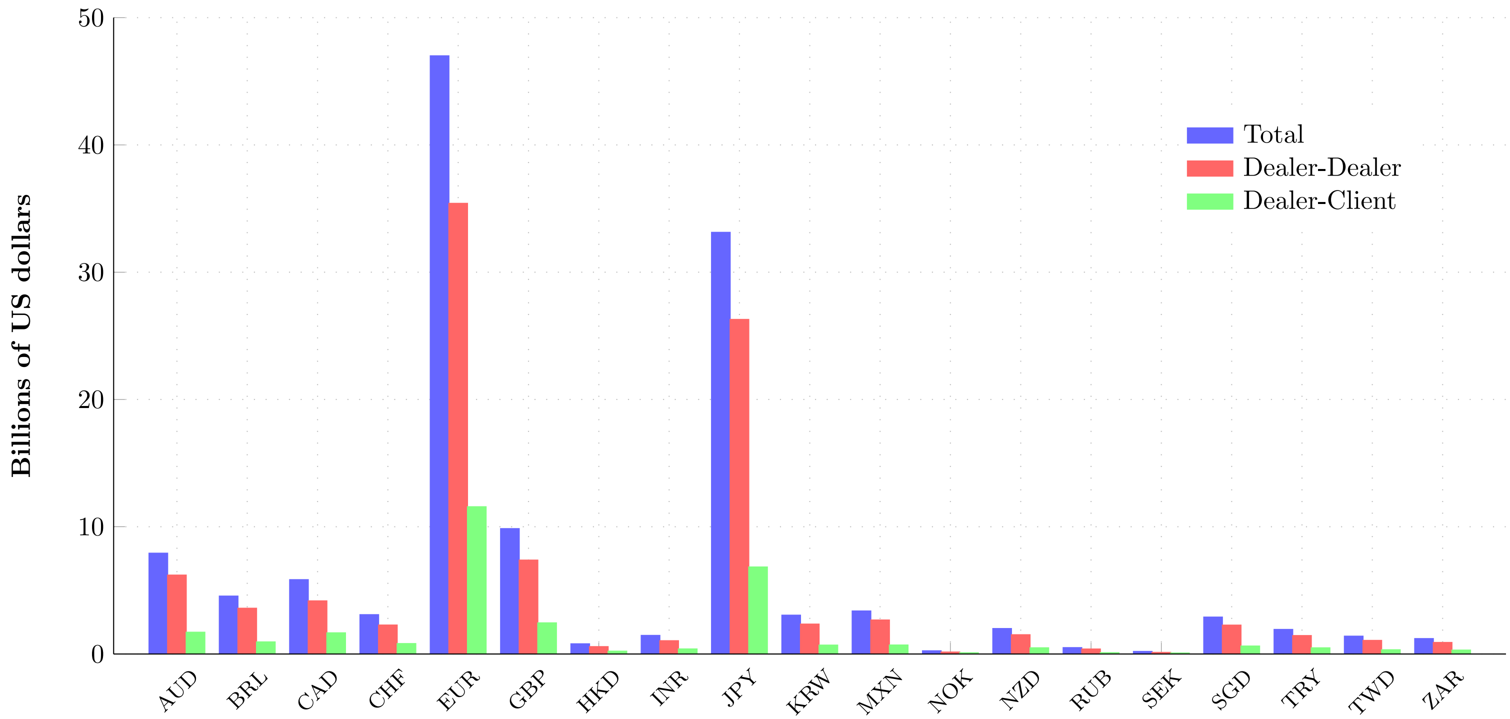


Figure 3. Daily Average Volume on FX Options by Currency Pairs

This figure displays, in billions of US dollars, the daily average volume of foreign exchange (FX) options traded over the counter based on transactions submitted to the DTCC Derivatives Repository in which at least one of the counterparties is a UK-regulated entity. We first synchronize these transactions with exchange rates from Refinitiv Tick History to express volume in US dollars and then aggregate them at 4pm London time daily. Option volume is calculated using all (Total), interdealer (Dealer-Dealer), and customer (Dealer-Client) transactions. The sample runs daily between December 2014 and December 2016.

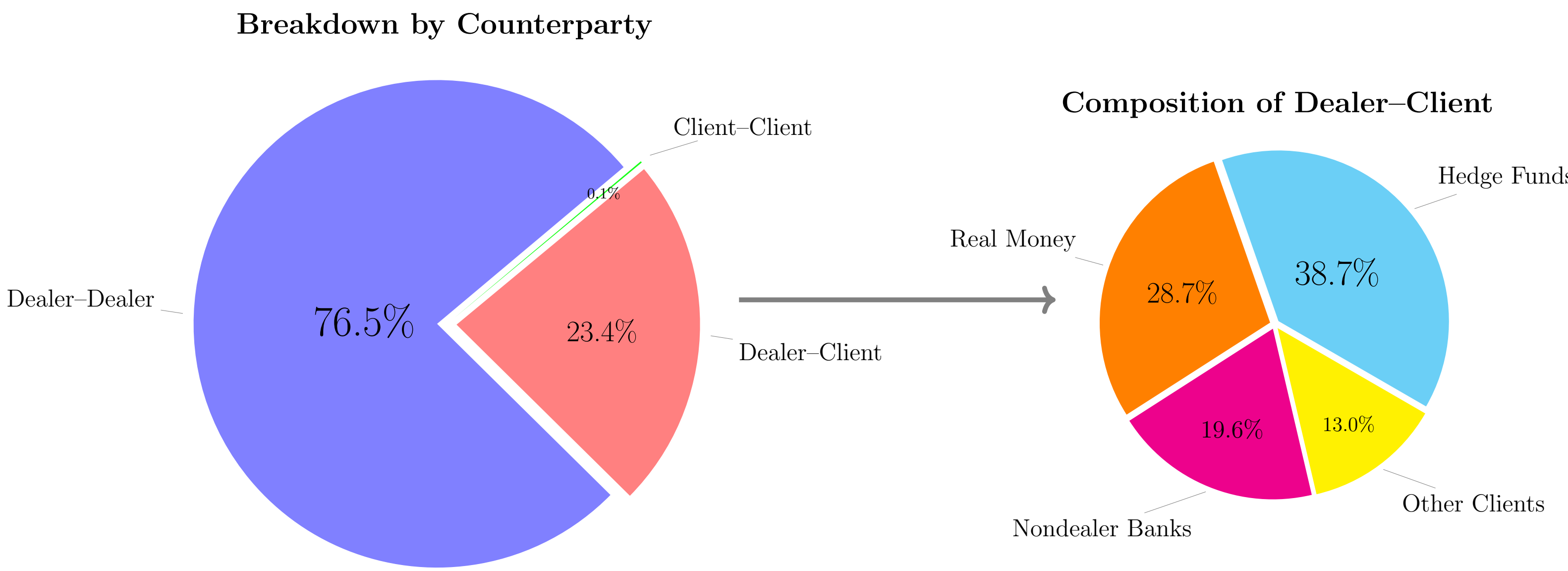
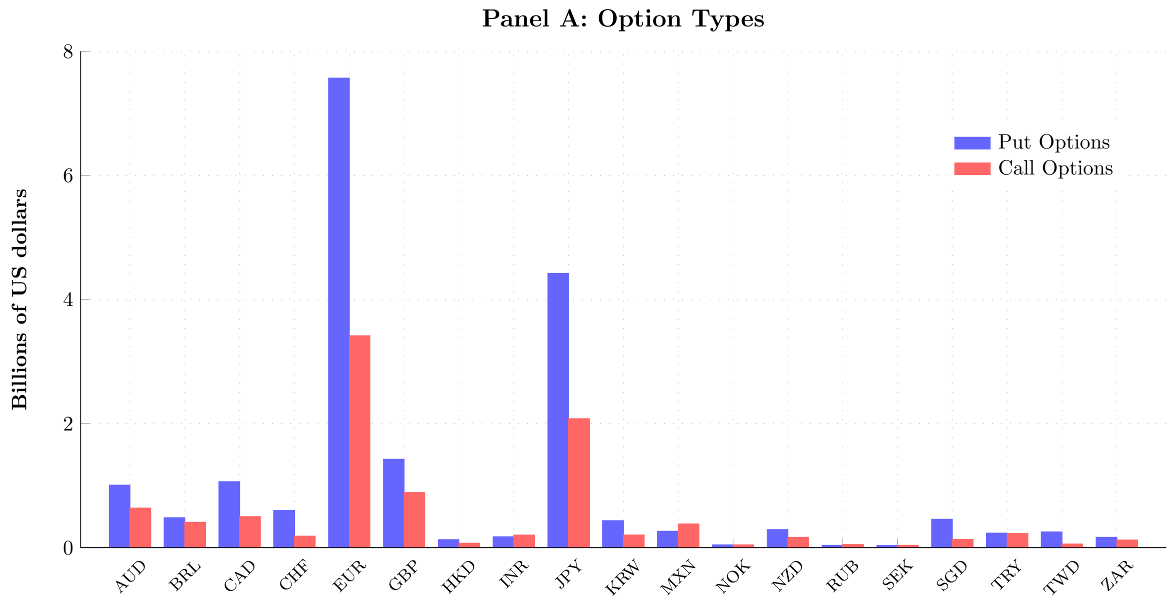


Figure 4. Daily Average Volume on FX Options by Counterparty Sectors

This figure displays, in billions of US dollars, the daily average volume of foreign exchange (FX) options traded over the counter based on transactions submitted to the DTCC Derivatives Repository in which at least one of the counterparties is a UK-regulated entity. We first synchronize these transactions with exchange rates from Refinitiv Tick History to express volume in US dollars and then aggregate them at 4pm London time daily. Option volume is calculated using interdealer (Dealer-Dealer) and customer (Dealer-Client) transactions. The latter segment is further disaggregated into real money investors (asset managers, pension funds, insurance firms, sovereign institutions, and other financials), 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). The sample runs daily between December 2014 and December 2016.



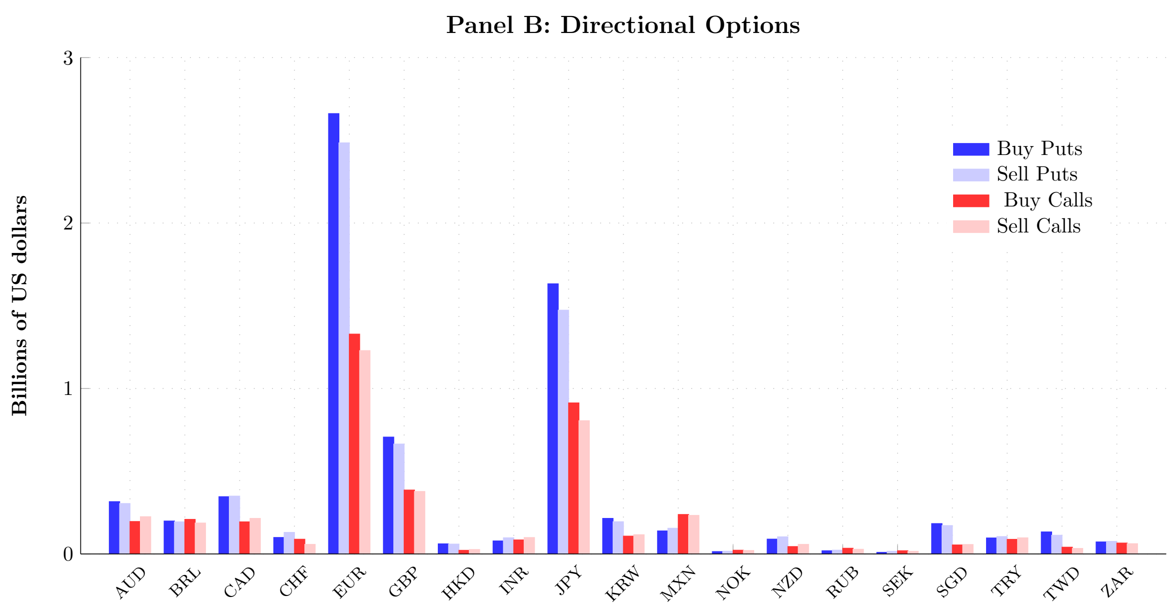


Figure 5. Customer Segment and Trading Direction

This figure displays, in billions of US dollars, the daily average volume of foreign exchange (FX) options traded over the counter based on transactions submitted to the DTCC Derivatives Repository in which at least one of the counterparties is a UK-regulated entity. We first synchronize these transactions with exchange rates from Refinitiv Tick History to express volume in US dollars and then aggregate them at 4pm London time daily. Option volume is calculated using customer (Dealer-Client) transactions for which a buy-sell indicator is available for a shorter sample that runs daily between November 2015 and December 2016.

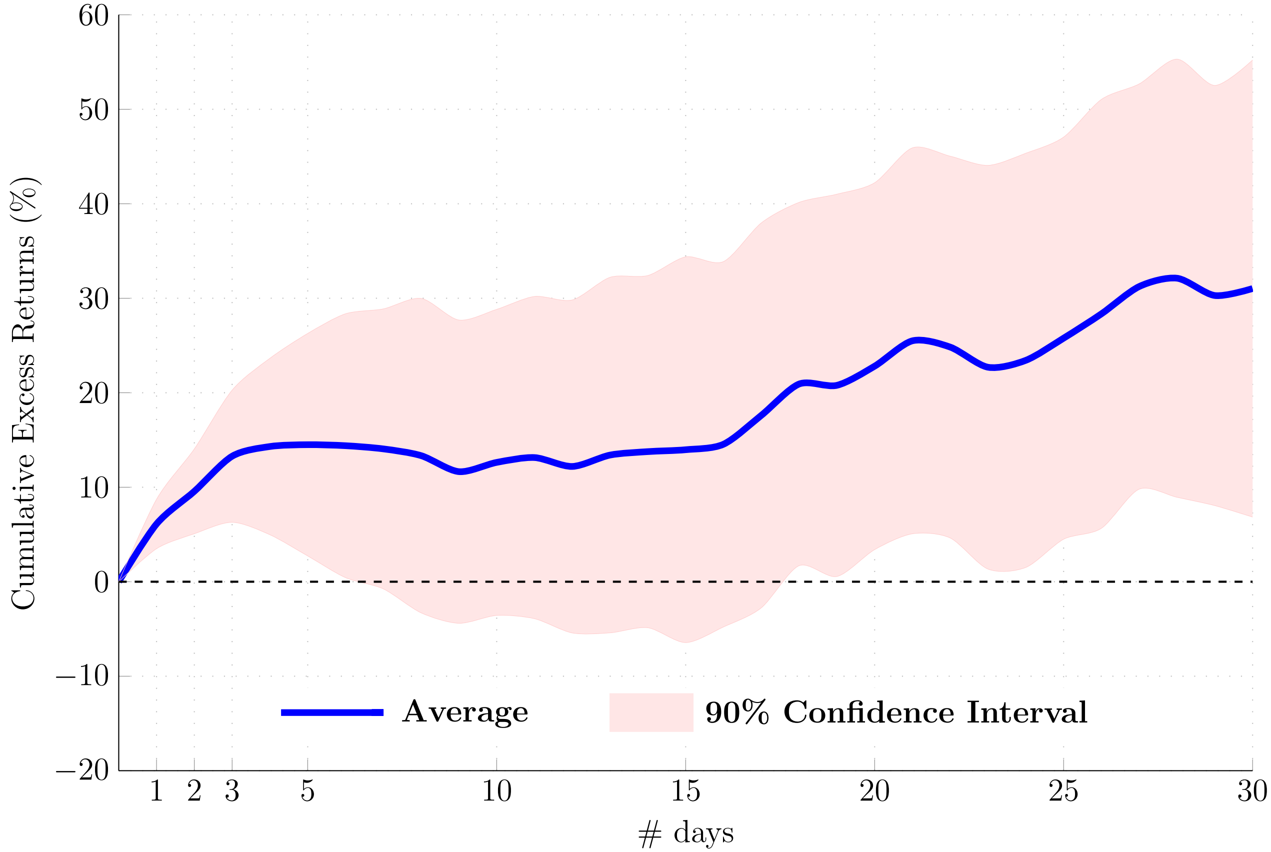


Figure 6. Post-Formation Excess Returns

This figure displays the average post-formation currency excess return up to thirty trading days of a long-short strategy sorted on the lagged abnormal foreign exchange (FX) option volume based on customer transactions. The strategy buys currencies with the lowest abnormal option volume and sells currencies with the highest abnormal option volume. Portfolios are rebalanced daily and abnormal volume is constructed as in Cespa et al. (2021) using a rolling window of 21 trading days. The 90% confidence interval is based on block-bootstrapped standard errors. Volume is expressed in US dollars and constructed by aggregating transaction-level option volume from DTCC Derivatives Repository at 4pm London time daily. The sample runs daily between December 2014 and December 2016.

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

This table presents average excess returns for currency portfolios sorted on the lagged abnormal foreign exchange (FX) option volume. Portfolios are rebalanced daily and abnormal volume is constructed as in Cespa et al. (2021) using a rolling window of 21 trading days. Portfolio 1 (P_1) contains currencies with the lowest abnormal volume, whereas Portfolio 4 (P_4) comprises currencies with the highest abnormal volume. LMH is the low-minus-high strategy that buys P_1 and sells P_4. We report means, standard deviations, and Sharpe ratios of excess returns in percentage per annum. Numbers in brackets are t-statistics based on Newey and West (1987) standard errors with a lag length of 21 days. Volume is expressed in US dollars and constructed by aggregating transaction-level option volume from DTCC Derivatives Repository at 4pm London time daily. Option volume is calculated using all (Total), interdealer (Dealer-Dealer), and customer (Dealer-Client) transactions. The sample runs daily between December 2014 and December 2016.

		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 presents average exchange rate returns for currency portfolios sorted on the lagged abnormal foreign exchange (FX) option volume. Portfolios are rebalanced daily and abnormal volume is constructed as in Cespa et al. (2021) using a rolling window of 21 trading days. Portfolio 1 (P_1) contains currencies with the lowest abnormal volume, whereas Portfolio 4 (P_4) comprises currencies with the highest abnormal volume. LMH is the low-minus-high strategy that buys P_1 and sells P_4. We report means, standard deviations, and Sharpe ratios of exchange rate returns in percentage per annum. Numbers in brackets are t-statistics based on Newey and West (1987) standard errors with a lag length of 21 days. Volume is expressed in US dollars and constructed by aggregating transaction-level option volume from DTCC Derivatives Repository at 4pm London time daily. Option volume is calculated using all (Total), interdealer (Dealer-Dealer), and customer (Dealer-Client) transactions. The sample runs daily between December 2014 and December 2016.

		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 presents panel regression estimates of currency excess returns (or exchange rate returns) on the quartile rank of the lagged abnormal foreign exchange (FX) option volume. Abnormal volume is constructed as in Cespa et al. (2021) using a rolling window of 21 trading days. The set of control variables includes the forward premium, FX realized volatility based on intraday hourly exchange rates, and FX bid-ask spread based on end-of-day quotes. We include time (calendar date) and currency fixed effects (fe). Standard errors (in parentheses) are clustered by time. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Volume is expressed in US dollars and constructed by aggregating transaction-level option volume from DTCC Derivatives Repository at 4pm London time daily. Option volume is calculated using all (Total), interdealer (Dealer-Dealer), and customer (Dealer-Client) transactions. The sample runs daily between December 2014 and December 2016.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Currency Excess Returns					
Total Volume	−1.968**					
	(0.796)					
Dealer-Dealer Volume		−1.677**		−0.753	−0.778	−0.776
		(0.813)		(0.848)	(0.849)	(0.950)
Dealer-Client Volume			−2.396***	−2.057**	−2.088**	−2.119**
			(0.823)	(0.861)	(0.859)	(1.002)
Forward Premium					−0.001	−0.046
					(0.010)	(0.042)
Realized Volatility					0.103	0.049
					(0.295)	(0.214)
Bid-Ask Spread					−0.597	−0.470
					(0.818)	(0.732)
Adj R^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
	Panel B: Exchange Rate Returns					
Total Volume	−1.971**					
	(0.796)					
Dealer-Dealer Volume		−1.682**		−0.755	−0.777	−0.779
		(0.812)		(0.847)	(0.849)	(0.949)
Dealer-Client Volume			−2.402***	−2.062**	−2.089**	−2.119**
			(0.823)	(0.860)	(0.859)	(1.001)
Forward Premium					−0.003	−0.049
					(0.010)	(0.042)
Realized Volatility					0.065	0.049
					(0.295)	(0.215)
Bid-Ask Spread					−0.660	−0.471
					(0.818)	(0.732)
Adj R^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	✓	✓	✓	✓	✓	✓
Currency fe						✓

Table 4. Portfolios sorted by FX Option Volume: Dollar Demand

This table presents average exchange rate returns for currency portfolios sorted on the lagged abnormal foreign exchange (FX) option volume for periods of high dollar demand periods (Panel A) and low dollar demand (Panel B). Portfolios are rebalanced daily and abnormal volume is constructed as in Cespa et al. (2021) using a rolling window of 21 trading days. Portfolio 1 (P_1) contains currencies with the lowest abnormal volume, whereas Portfolio 4 (P_4) comprises currencies with the highest abnormal volume. LMH is the low-minus-high strategy that buys P_1 and sells P_4. Periods of high dollar demand occur when the five-year US Treasury premium is high (above its sample median) or the VXY index is high (above its sample median), and vice versa for periods of low dollar demand. We report means, standard deviations, and Sharpe ratios of exchange rate returns in percentage per annum. Numbers in brackets are t-statistics based on Newey and West (1987) standard errors with a lag length of 21 days. Volume is expressed in US dollars and constructed by aggregating transaction-level option volume from DTCC Derivatives Repository at 4pm London time daily. Option volume is calculated using all transactions for major currency pairs. The sample runs daily between December 2014 and December 2016.

		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*				
US 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
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 5. Portfolios sorted by FX Option Volume: Moneyness

This table presents average exchange rate returns for currency portfolios sorted on the lagged abnormal foreign exchange (FX) option volume for different levels of moneyness. Options are classified using the strike-to-spot price ratio as deep out of the money (ratio higher than 1.05), out of the money (ratio between 1.05% and 1.02%), near the money (ratio between 1.02 and 0.98), in the money (ratio between 0.98 and 0.95), and deep in the money (ratio lower than 0.95). Portfolios are rebalanced daily and abnormal volume is constructed as in Cespa et al. (2021) using a rolling window of 21 trading days. Portfolio 1 (P_1) contains currencies with the lowest abnormal volume, whereas Portfolio 4 (P_4) comprises currencies with the highest abnormal volume. LMH is the low-minus-high strategy that buys P_1 and sells P_4. We report means, standard deviations, and Sharpe ratios of exchange rate returns in percentage per annum. Numbers in brackets are t-statistics based on Newey and West (1987) standard errors with a lag length of 21 days. Volume is expressed in US dollars and constructed by aggregating transaction-level option volume from DTCC Derivatives Repository at 4pm London time daily. Option volume is calculated using customer transactions (Dealer-Clients) for major currency pairs. The sample runs daily between December 2014 and December 2016.

		P_1 (Low)	P_2	P_3	P_4 (High)	LMH
Deep out of the money	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
Out of the money	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
In the money	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
Deep in the money	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 6. Portfolios sorted by FX Option Volume: Time-to-Maturity

This table presents average exchange rate returns for currency portfolios sorted on the lagged abnormal foreign exchange (FX) option volume for different time to maturity options. Portfolios are rebalanced daily and abnormal volume is constructed as in Cespa et al. (2021) using a rolling window of 21 trading days. Portfolio 1 (P_1) contains currencies with the lowest abnormal volume, whereas Portfolio 4 (P_4) comprises currencies with the highest abnormal volume. LMH is the low-minus-high strategy that buys P_1 and sells P_4. We report means, standard deviations, and Sharpe ratios of exchange rate returns in percentage per annum. Numbers in brackets are t-statistics based on Newey and West (1987) standard errors with a lag length of 21 days. Volume is expressed in US dollars and constructed by aggregating transaction-level option volume from DTCC Derivatives Repository at 4pm London time daily. Option volume is calculated using customer transactions (Dealer-Clients) for major currency pairs. The sample runs daily between December 2014 and December 2016.

		P_1 (Low)	P_2	P_3	P_4 (High)	LMH
Maturity $\leq$ 1 month	mean	4.29	−8.77	−8.65	−8.97	13.26
	t-stat	[0.68]	[−1.40]	[−1.16]	[−1.35]	[2.41]
	std	9.15	8.98	11.03	9.57	8.23
	SR	0.47	−0.98	−0.78	−0.94	1.61
1 month $<$ Maturity $\leq$ 3 months	mean	1.68	−3.78	−7.32	−10.25	11.93
	t-stat	[0.27]	[−0.58]	[−1.13]	[−1.59]	[2.11]
	std	9.26	9.14	10.28	9.24	8.18
	SR	0.18	−0.41	−0.71	−1.11	1.46
3 months $<$ Maturity $\leq$ 6 months	mean	0.47	−3.02	−9.69	−8.35	8.83
	t-stat	[0.08]	[−0.45]	[−1.33]	[−1.25]	[1.66]
	std	8.85	9.89	10.64	9.86	8.07
	SR	0.05	−0.31	−0.91	−0.85	1.09
Maturity $>$ 6 months	mean	−7.40	−3.42	0.90	−9.04	1.64
	t-stat	[−1.20]	[−0.47]	[0.14]	[−1.37]	[0.28]
	std	9.26	10.59	10.22	9.50	8.50
	SR	−0.80	−0.32	0.09	−0.95	0.19

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

This table presents average exchange rate returns for currency portfolios sorted on the lagged abnormal foreign exchange (FX) option volume disaggregated across different client sectors. Portfolios are rebalanced daily and abnormal volume is constructed as in Cespa et al. (2021) using a rolling window of 21 trading days. Portfolio 1 (P_1) contains currencies with the lowest abnormal volume, whereas Portfolio 4 (P_4) comprises currencies with the highest abnormal volume. LMH is the low-minus-high strategy that buys P_1 and sells P_4. We report means, standard deviations, and Sharpe ratios of exchange rate returns in percentage per annum. Numbers in brackets are t-statistics based on Newey and West (1987) standard errors with a lag length of 21 days. Volume is expressed in US dollars and constructed by aggregating transaction-level option volume from DTCC Derivatives Repository at 4pm London time daily. Option volume is calculated using customer transactions (Dealer-Clients) for major currency pairs. The sample runs daily between December 2014 and December 2016.

		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	−0.61	−13.16	−8.41	−6.57	5.96
	t-stat	[−0.10]	[−1.89]	[−1.24]	[−1.03]	[0.95]
	std	9.06	10.46	10.08	9.64	9.66
	SR	−0.07	−1.26	−0.84	−0.68	0.62

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

This table presents average exchange rate returns for currency portfolios sorted on the lagged abnormal foreign exchange (FX) option volume disaggregated across different client sectors for announcements (i.e., FOMC, non-farm payrolls, PMI, PPI, CPI, GDP) and otherwise days. Portfolios are rebalanced daily and abnormal volume is constructed as in Cespa et al. (2021) using a rolling window of 21 trading days. Portfolio 1 (P_1) contains currencies with the lowest abnormal volume, whereas Portfolio 4 (P_4) comprises currencies with the highest abnormal volume. LMH is the low-minus-high strategy that buys P_1 and sells P_4. We report means, standard deviations, and Sharpe ratios of exchange rate returns in percentage per annum. Numbers in brackets are t-statistics based on Newey and West (1987) standard errors with a lag length of 21 days. Volume is expressed in US dollars and constructed by aggregating transaction-level option volume from DTCC Derivatives Repository at 4pm London time daily. Option volume is calculated using customer transactions (Dealer-Clients) for major currency pairs. The sample runs daily between December 2014 and December 2016.

		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	−1.47	−4.60	−22.06	−25.94	24.47	1.43	−1.04	8.32	−9.98	11.41
	t-stat	−0.09	−0.34	−1.35	−1.77	2.80	0.21	−0.15	0.99	−1.33	1.71
	std	10.25	9.63	11.24	9.84	7.20	8.63	9.60	11.31	9.29	8.59
	SR	−0.14	−0.48	−1.96	−2.63	3.40	0.17	−0.11	0.74	−1.07	1.33
Real Money	mean	−7.05	−14.77	−9.77	−19.81	12.76	5.22	−2.71	−9.04	−10.51	15.73
	t-stat	−0.45	−0.99	−0.84	−1.17	1.04	0.76	−0.36	−1.10	−1.39	2.05
	std	9.71	10.45	10.45	9.71	8.41	8.95	10.02	10.26	9.59	8.95
	SR	−0.73	−1.41	−0.93	−2.04	1.52	0.58	−0.27	−0.88	−1.10	1.76
Non-dealer Banks	mean	1.57	−24.51	−16.12	−16.26	17.82	3.36	−8.34	−4.75	−2.27	5.64
	t-stat	0.12	−1.72	−1.00	−1.00	1.33	0.49	−1.33	−0.58	−0.31	0.86
	std	9.27	9.31	10.80	10.26	7.76	9.05	8.49	10.79	9.31	8.29
	SR	0.17	−2.63	−1.49	−1.58	2.30	0.37	−0.98	−0.44	−0.24	0.68
Other Clients	mean	−8.42	−20.97	−30.34	−19.54	11.12	1.71	−10.84	−1.89	−2.71	4.42
	t-stat	−0.60	−1.42	−1.95	−1.51	0.81	0.27	−1.31	−0.23	−0.37	0.60
	std	9.90	9.92	9.84	9.73	8.59	8.80	10.62	10.12	9.61	9.97
	SR	−0.85	−2.11	−3.08	−2.01	1.29	0.19	−1.02	−0.19	−0.28	0.44

Table 9. Portfolios sorted by FX Option Volume: Net Demand

This table presents average exchange rate returns for currency portfolios sorted on the lagged net demand of options. Portfolios are rebalanced daily and net demand is constructed as difference between buy volume and sell volume, divided by total volume. Portfolio 1 (P_1) contains currencies with the lowest net demand of options, whereas Portfolio 4 (P_4) comprises currencies with the highest net demand of options. LMH is the low-minus-high strategy that buys P_1 and sells P_4. We report means, standard deviations, and Sharpe ratios of exchange rate returns in percentage per annum. Numbers in brackets are t-statistics based on Newey and West (1987) standard errors with a lag length of 21 days. Volume is expressed in US dollars and constructed by aggregating transaction-level option volume from DTCC Derivatives Repository at 4pm London time daily. Option volume is calculated using customer transactions (Dealer-Clients) for major currency pairs. The sample runs daily between November 2015 and December 2016.

		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 Demand					*Panel B: Call Option Net Demand*				
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 presents average exchange rate returns for currency portfolios sorted on the lagged abnormal foreign exchange (FX) forward volume disaggregated across different client sectors. Portfolios are rebalanced daily and abnormal volume is constructed as in Cespa et al. (2021) using a rolling window of 21 trading days. Portfolio 1 (P_1) contains currencies with the lowest abnormal volume, whereas Portfolio 4 (P_4) comprises currencies with the highest abnormal volume. LMH is the low-minus-high strategy that buys P_1 and sells P_4. We report means, standard deviations, and Sharpe ratios of exchange rate returns in percentage per annum. Numbers in brackets are t-statistics based on Newey and West (1987) standard errors with a lag length of 21 days. Volume is expressed in US dollars and constructed by aggregating transaction-level option volume from DTCC Derivatives Repository at 4pm London time daily. Forward volume is calculated using customer transactions (Dealer-Clients) for major currency pairs. The sample runs daily between December 2014 and December 2016.

		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*				
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

Internet Appendix to

"FX Option Volume"

(not for publication)

Abstract

In the Internet Appendix, we present additional results which are not included in the main body of the paper.

A On the Co-Existence of Spot and Option Markets

A.1 Proof of Lemma 1

We first consider the case where informed investors know $e_1 = e_0 - \overline{V}$. The sufficient condition for a positive fraction of informed investors in the underlying asset is that:

$$\overline{V} > -\frac{2\left[\mu \underline{q}(1-\underline{\beta}) + (1-\mu)q_3\right] \cdot L\overline{V}}{\mu \underline{q}(1-\underline{\beta}) + 2(1-\mu)q_3} + 2L\overline{V}$$

$$\overline{V} > \frac{2(1-\mu)q_6 \cdot L\overline{V}}{\mu \underline{q\beta} + 2(1-\mu)q_6}$$

As we can see, the above equations always hold, which suggests that when informed investors know $e_1 = e_0 - \overline{V}$, there is always a positive fraction of informed investors in the underlying asset regardless of $\underline{q}$.

Similarly, when informed investors know $e_1 = e_0 + \overline{V}$, the sufficient condition for a positive fraction of informed investors in the underlying asset is that:

$$\overline{V} > \frac{2(1-\mu)q_4 \cdot L\overline{V}}{\mu \bar{q}(1-\overline{\beta}) + 2(1-\mu)q_4}$$

$$\overline{V} > -\frac{2\left[\mu \bar{q}\overline{\beta} + (1-\mu)q_5\right] \cdot L\overline{V}}{\mu \bar{q}\overline{\beta} + 2(1-\mu)q_5} + 2L\overline{V}$$

As we can see, the above equations always hold, which suggests that when informed investors know that $e_1 = e_0 + \overline{V}$, there is always a positive fraction of informed investors in the underlying asset regardless of $\bar{q}$.

A.2 Proof of Proposition 1

Proof of Case 1. We focus on the case in which informed investors know $e_1 = e_0 - \overline{V}$; the proof for the case in which informed investors know $e_1 = e_0 + \overline{V}$ follows similar steps. For the pooling equilibrium, we have: $b_s + \overline{V} = b_c = -a_p + (K_p - \overline{V})$

We first solve $\underline{\beta}$, which is the solution to the following equation:

$$b_c = \frac{2(1-\mu)q_6 \cdot L\overline{V}}{\mu(1-\underline{\alpha})\underline{\beta} + 2(1-\mu)q_6} = 2L\overline{V} - \frac{2\left[\mu(1-\underline{\alpha})(1-\underline{\beta}) + (1-\mu)q_3\right] \cdot L\overline{V}}{\mu(1-\underline{\alpha})(1-\underline{\beta}) + 2(1-\mu)q_3}$$

We can solve that $\underline{\beta} = \frac{q_6}{q_3+q_6} = \frac{1}{2}$.

$$\overline{V} - \frac{\underline{\alpha}\mu\overline{V}}{\underline{\alpha}\mu + 2(1-\mu)q_2} = \frac{2(1-\mu)q_6 \cdot L\overline{V}}{\mu(1-\underline{\alpha})\underline{\beta} + 2(1-\mu)q_6}$$

$$\underline{\alpha}^* = \frac{q_2[\mu + 2(1-\mu)(q_3+q_6)(1-L)]}{\mu\left[q_2 + L(q_3+q_6)\right]}$$

We can get the same solution when informed investors know that $e_1 = e_0 + \overline{V}$.

After we characterize the equilibrium, we can characterize the association between $e_1 - e_0$ and option trading volume. We denote the option trading volume as V_o. The option trading volume takes the following form:

$$V_o = \begin{cases} \sum_{i=3}^{i=6} q_i + \overline{\alpha} & \text{When } e_1 = e_0 + \overline{V} \\ \sum_{i=3}^{i=6} q_i + \underline{\alpha} & \text{When } e_1 = e_0 - \overline{V} \end{cases}$$

As we can see, $\overline{\alpha} = \underline{\alpha}$ and $Cov(e_1 - e_0, V_o) = 0$.

Proof of Case 2(a). We take two steps to prove this case. In the first step, we show that when $e_1 = e_0 + \overline{V}$, informed investors will still not trade options. In the second step, we show that $Cov(e_1 - e_0, V_o) = 0$.

Step 1: When $\overline{\alpha} = 1$, the trading profit of selling a put is $b_p = L\overline{V}$, and the trading profit of buying a call is $-a_c + (\overline{V} - K_c) = 2L\overline{V} - a_c = L\overline{V}$. The trading profit of buying the underlying asset is $\overline{V} - \frac{\mu\bar{q}\overline{\alpha}\overline{V}}{\mu\bar{q}+2(1-\mu)q_1}$

$$\begin{aligned}\overline{V} - a_s &= \overline{V} - \frac{\mu\bar{q}\overline{V}}{\mu\bar{q} + 2(1-\mu)q_1} \\ &= \overline{V}\frac{2(1-\mu)q_1}{\mu\bar{q} + 2(1-\mu)q_1}.\end{aligned}$$

Because $L \leq \frac{2(1-\mu)q_2}{\mu+2(1-\mu)q_2}$, we can obtain that $L\overline{V} \leq \overline{V}\frac{2(1-\mu)q_1}{\mu\bar{q}+2(1-\mu)q_1}$ as $\bar{q} \leq 1$. Thus, we conclude that when $e_1 = e_0 + \overline{V}$, informed investors will still not trade options.

Step 2: Since no informed investors trade options, the option volume $V_o = \sum_{i=3}^{i=6} q_i$. We can directly obtain that $Cov(e_1 - e_0, V_o) = 0$.

Proof of Case 2(b). We take two steps to prove this case. In the first step, we pin down m^*. Since $L > \frac{2(1-\mu)q_2}{\mu+2(1-\mu)q_2}$, when all informed investors participate in the market, it is a pooling equilibrium where $\bar{\alpha}^* = \frac{q_1[\mu+2(1-\mu)(q_2+q_5)(1-L)]}{\mu[q_2+L(q_2+q_5)]}$ and $\bar{\beta} = \underline{\beta} = \frac{1}{2}$. In this case, we denote the trading profit from participating in the market as π^*, and we calculate π^* as follows:

$$\frac{2(1-\mu)q_1\overline{V}}{\mu\overline{\alpha}^* + 2(1-\mu)q_1}.$$

Let $m^* = \frac{2(1-\mu)q_1\overline{V}}{\mu\overline{\alpha}^*+2(1-\mu)q_1} - c$. When $m \leq m^*$, all informed investors participate in the market. We can directly calculate that $\bar{\alpha}^* = \underline{\alpha}^*$ and have the same option trading volumes in the cases with $e_1 = e_0 + \overline{V}$ and $e_1 = e_0 - \overline{V}$. Thus, $Cov(e_1 - e_0, V_o) = 0$.

In the second step, we show that when $m > m^*$, $V_o(e_1 = e_0 + \overline{V}) < V_o(e_1 = e_0 - \overline{V})$.

When $m > m^*$, not all informed investors participate in the market and thus $\bar{q} < 1$. We have two scenarios.

Scenario (1): no informed investors trade options.

In this case, we have $\overline{V}\frac{2(1-\mu)q_1}{\mu\bar{q}+2(1-\mu)q_1} = m + c$ and $\overline{V}\frac{2(1-\mu)q_1}{\mu\bar{q}+2(1-\mu)q_1} > L\overline{V}$.

These two conditions suggest that $m > L\overline{V} - c$. In this case, $\overline{\alpha}^* = 0$, and the option trading volume takes the following form:

$$V_o = \begin{cases} \sum_{i=3}^{i=6} q_i & \text{When } e_1 = e_0 + \overline{V} \\ \sum_{i=3}^{i=6} q_i + \underline{\alpha}^* & \text{When } e_1 = e_0 - \overline{V} \end{cases}.$$

Thus, we have $Cov(e_1 - e_0, V_o) < 0$.

Scenario (2): informed investors trade options. As in reality, there is always a positive fraction of informed investors in the underlying asset. In this scenario, the condition is $\overline{V}\frac{2(1-\mu)q_1}{\mu\bar{q}\overline{\alpha}+2(1-\mu)q_1} = m + c$ and $\overline{\alpha}^*$, $\bar{\beta}$ are pinned downed by:

$$\overline{V} - \frac{\mu\overline{q}\overline{\alpha}\overline{V}}{\mu\overline{q}\overline{\alpha} + 2(1-\mu)q_1} = \frac{2(1-\mu)q_4 \cdot L\overline{V}}{\mu\bar{q}(1-\overline{\alpha})(1-\overline{\beta}) + 2(1-\mu)q_4}$$

$$2L\overline{V} - \frac{2\left[\mu\bar{q}(1-\overline{\alpha})\overline{\beta} + (1-\mu)q_5\right] \cdot L\overline{V}}{\mu\bar{q}(1-\overline{\alpha})\overline{\beta} + 2(1-\mu)q_5} = \frac{2(1-\mu)q_4 \cdot L\overline{V}}{\mu\bar{q}(1-\overline{\alpha})(1-\overline{\beta}) + 2(1-\mu)q_4}$$

We have $\bar{\beta} = \frac{q_5}{q_5+q_4}$. $\overline{\alpha}^{**} = \frac{q_1[\bar{q}\mu+2(1-\mu)(q_4+q_5)(1-L)]}{\bar{q}\mu[q_1+L(q_4+q_5)]}$ and $\bar{q} < 1$. Thus, the option trading volume of informed investors is $\bar{q}(1-\overline{\alpha}^{**})$, which is

$$\begin{aligned}
\bar{q}(1-\overline{\alpha}^{**}) &= \bar{q}(1 - \frac{q_1[\bar{q}\mu + 2(1-\mu)(q_4+q_5)(1-L)]}{\bar{q}\mu\left[q_1 + L(q_4+q_5)\right]}) \\
&= \bar{q}\frac{\bar{q}\mu L(q_4+q_5) - 2(1-\mu)(q_4+q_5)(1-L)q_1}{\bar{q}\mu\left[q_1 + L(q_4+q_5)\right]} \\
&= \frac{\bar{q}\mu L(q_4+q_5) - 2(1-\mu)(q_4+q_5)(1-L)q_1}{\mu\left[q_1 + L(q_4+q_5)\right]} \\
&< \frac{\mu L(q_4+q_5) - 2(1-\mu)(q_4+q_5)(1-L)q_1}{\mu\left[q_1 + L(q_4+q_5)\right]} \\
&= 1 - \underline{\alpha}^*.
\end{aligned}$$

This suggests that $V_o(e_1 = e_0 + \overline{V}) < V_o(e_1 = e_0 - \overline{V})$, and thus we have $Cov(e_1 - e_0, V_o) < 0$.

Table A.1. FX Option Volume: Currency Pairs

This table displays, in billions of US dollars, the daily average foreign exchange (FX) option volume disaggregated by currency pairs. Volume is expressed in US dollars and constructed by first synchronizing transaction-level option volume from DTCC Derivatives Repository with exchange rates from Refinitiv Tick History, and then aggregating transactions at 4pm London time daily. Option volume is calculated using all (Total), interdealer (Dealer-Dealer), and customer (Dealer-Client) transactions. The sample runs daily between December 2014 and December 2016.

	Total	Dealer-Dealer	Dealer-Client	Client-Client
AUD	7.919	6.200	1.711	0.008
CAD	5.837	4.173	1.663	0.000
CHF	3.094	2.275	0.818	0.001
EUR	47.001	35.408	11.570	0.023
GBP	9.851	7.377	2.446	0.027
JPY	33.132	26.288	6.837	0.007
NZD	2.001	1.514	0.486	0.000
BRL	4.547	3.595	0.951	0.001
HKD	0.800	0.578	0.222	0.000
INR	1.460	1.042	0.398	0.020
KRW	3.049	2.349	0.698	0.001
MXN	3.378	2.671	0.707	0.000
NOK	0.251	0.153	0.097	0.000
RUB	0.499	0.392	0.104	0.003
SEK	0.205	0.125	0.080	0.000
SGD	2.896	2.269	0.626	0.001
TRY	1.932	1.447	0.484	–
TWD	1.400	1.067	0.332	0.000
ZAR	1.215	0.906	0.307	0.001
ALL	**130.465**	**99.832**	**29.414**	**0.094**

Table A.2. FX Option Volume: Client Sectors

This table displays, in billions of US dollars, the daily average foreign exchange (FX) option volume disaggregated by client sectors. Volume is expressed in US dollars and constructed by first synchronizing transaction-level option volume from DTCC Derivatives Repository with exchange rates from Refinitiv Tick History, and then aggregating transactions at 4pm London time daily. Option volume is calculated using customer (Dealer-Client) transactions. We group clients into hedge funds, real money investors (asset managers, pension funds, insurance firms, sovereign institutions, and other financials), 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). The sample runs daily between December 2014 and December 2016.

	Hedge Funds	Real Money	Non-dealer Banks	Other Clients
AUD	0.603	0.454	0.472	0.181
CAD	0.545	0.652	0.267	0.198
CHF	0.420	0.181	0.112	0.106
EUR	4.622	3.268	2.136	1.544
GBP	0.811	0.727	0.508	0.401
BRL	0.149	0.387	0.312	0.103
HKD	0.103	0.053	0.037	0.028
INR	0.119	0.085	0.042	0.152
JPY	3.004	1.895	1.187	0.752
KRW	0.281	0.233	0.094	0.091
MXN	0.257	0.201	0.160	0.089
NOK	0.028	0.018	0.035	0.016
NZD	0.193	0.146	0.092	0.055
RUB	0.016	0.040	0.024	0.023
SEK	0.006	0.020	0.037	0.017
SGD	0.295	0.142	0.126	0.063
TRY	0.106	0.098	0.223	0.057
TWD	0.174	0.094	0.026	0.039
ZAR	0.078	0.080	0.111	0.038
Total	**11.809**	**8.775**	**6.001**	**3.974**

Table A.3. Exposure to Currency Factors

This table presents least squares estimates. The dependent variable is the excess return of the LHM strategy for major currencies based on customer (Dealer-Client) option volume described in Table 1. The set of explanatory variables includes the excess returns of the dollar, carry, value, momentum, volatility, liquidity, risk-reversal, and volatility risk premium factors. α denotes the unexplained excess return in percentage per annum. Numbers in brackets are Newey and West (1987) standard errors with a lag length of 21 days. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample runs daily between December 2014 and December 2016.

	(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)
$Adj R^2$ (%)	-0.2	0.1	1.0	2.5
# Observations	512	512	512	512

Table A.4. Portfolios sorted by FX Option Volume: Alternative Scaling Methods

This table presents average excess returns for currency portfolios sorted on the lagged abnormal foreign exchange (FX) option volume. Portfolios are rebalanced daily and abnormal volume is constructed using a rolling window of M trading days and a formation period of N trading days. Portfolio 1 (P_1) contains currencies with the lowest abnormal volume, whereas Portfolio 4 (P_4) comprises currencies with the highest abnormal volume. LMH is the low-minus-high strategy that buys P_1 and sells P_4. We report means, standard deviations, and Sharpe ratios of excess returns in percentage per annum. Numbers in brackets are t-statistics based on Newey and West (1987) standard errors with a lag length of M days. Volume is expressed in US dollars and constructed by aggregating transaction-level option volume from DTCC Derivatives Repository at 4pm London time daily. Option volume is calculated using all (Total), interdealer (Dealer-Dealer), and customer (Dealer-Client) transactions. The sample runs daily between December 2014 and December 2016.

		P_1 (Low)	P_2	P_3	P_4 (High)	LMH	P_1 (Low)	P_2	P_3	P_4 (High)	LMH
		Panel A: Currency Excess Returns					*Panel B: Exchange Rate Returns*				
$M = 5$ and $N = 1$	mean	4.57	−0.43	−11.79	−10.49	15.06	4.40	−0.50	−11.96	−10.64	15.04
	t-stat	[0.76]	[−0.07]	[−1.76]	[−2.20]	[2.61]	[0.73]	[−0.08]	[−1.78]	[−2.24]	[2.61]
	std	9.98	9.36	10.98	9.53	9.84	9.98	9.37	10.99	9.52	9.83
	SR	0.46	−0.05	−1.07	−1.10	1.53	0.44	−0.05	−1.09	−1.12	1.53
$M = 63$ and $N = 1$	mean	7.23	−2.03	−6.19	−10.35	17.57	7.17	−2.12	−6.30	−10.47	17.64
	t-stat	[1.23]	[−0.36]	[−0.79]	[−2.09]	[2.88]	[1.23]	[−0.38]	[−0.80]	[−2.11]	[2.90]
	std	8.95	8.72	11.00	9.99	9.00	8.95	8.72	11.00	9.98	9.00
	SR	0.81	−0.23	−0.56	−1.04	1.95	0.80	−0.24	−0.57	−1.05	1.96
$M = 21$ and $N = 3$	mean	−6.82	−2.24	−10.24	−11.93	18.75	6.68	−2.35	−10.34	−12.09	18.78
	t-stat	1.13	−0.41	−1.40	−2.17	2.79	1.11	−0.43	−1.41	−2.21	2.80
	std	10.28	8.98	11.03	9.98	10.55	10.27	8.98	11.03	9.98	10.54
	SR	0.66	−0.25	−0.93	−1.19	1.78	0.65	−0.26	−0.94	−1.21	1.78

Table A.5. Portfolios sorted by FX Option Volume: Bloomberg Data

This table presents average excess returns for currency portfolios sorted on the lagged abnormal foreign exchange (FX) option volume. Portfolios are rebalanced daily and abnormal volume is constructed as in Cespa et al. (2021) using a rolling window of 21 trading days. Portfolio 1 (P_1) contains currencies with the lowest abnormal volume, whereas Portfolio 4 (P_4) comprises currencies with the highest abnormal volume. LMH is the low-minus-high strategy that buys P_1 and sells P_4. We report means, standard deviations, and Sharpe ratios of excess returns in percentage per annum. Numbers in brackets are t-statistics based on Newey and West (1987) standard errors with a lag length of 21 days. Volume is expressed in US dollars and constructed by aggregating transaction-level option volume from DTCC Derivatives Repository at 4pm London time daily. Option volume is calculated using all transactions. The sample runs daily between March 2013 and December 2020.

		P_1 (Low)	P_2	P_3	P_4 (High)	LMH	P_1 (Low)	P_2	P_3	P_4 (High)	LMH
		Panel A: Currency 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	[1.48]	[−0.57]	[−0.59]	[−1.71]	[2.86]	[1.56]	[−0.48]	[−0.47]	[−1.61]	[2.86]
	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	[−0.78]	[−0.03]	[−1.19]	[−1.26]	[0.69]	[−1.36]	[−0.50]	[−1.66]	[−1.80]	[0.71]
	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

Table A.6. Portfolios sorted by Bloomberg FX Option Volume: Dollar Demand

This table presents average exchange rate returns for currency portfolios sorted on the lagged abnormal foreign exchange (FX) option volume for periods of high and low dollar dollar demand. Portfolios are rebalanced daily and abnormal volume is constructed as in Cespa et al. (2021) using a rolling window of 21 trading days. Portfolio 1 (P_1) contains currencies with the lowest abnormal volume, whereas Portfolio 4 (P_4) comprises currencies with the highest abnormal volume. LMH is the low-minus-high strategy that buys P_1 and sells P_4. Periods of high dollar demand occur when the five-year US Treasury premium is high (above its sample median), and vice versa for periods of low dollar demand. We report means, standard deviations, and Sharpe ratios of exchange rate returns in percentage per annum. Numbers in brackets are t-statistics based on Newey and West (1987) standard errors with a lag length of 21 days. Volume is expressed in US dollars and constructed by aggregating transaction-level option volume from DTCC Derivatives Repository at 4pm London time daily. Option volume is calculated using all transactions. The sample runs daily between March 2013 and December 2020.

		P_1 (Low)	P_2	P_3	P_4 (High)	LMH	P_1 (Low)	P_2	P_3	P_4 (High)	LMH
		Currency Excess Returns					*Exchange Rate Returns*				
		Panel A: Major Currencies									
High Dollar Demand	mean	4.64	−0.05	−1.37	−7.67	12.31	4.91	0.23	−1.07	−7.41	12.32
	t-stat	[0.96]	[−0.01]	[−0.30]	[−1.57]	[2.84]	[1.02]	[0.05]	[−0.24]	[−1.51]	[2.85]
Low Dollar Demand	mean	4.42	−2.64	−1.73	−2.09	6.51	4.63	−2.47	−1.44	−1.84	6.46
	t-stat	[1.12]	[−0.79]	[−0.54]	[−0.52]	[1.45]	[1.17]	[−0.73]	[−0.45]	[−0.46]	[1.44]
		Panel B: All Currencies									
High Dollar Demand	mean	0.06	0.77	0.13	−2.68	2.74	−1.31	−0.53	−1.14	−4.10	2.79
	t-stat	[0.02]	[0.18]	[0.03]	[−0.68]	[0.90]	[−0.32]	[−0.13]	[−0.26]	[−1.04]	[0.92]
Low Dollar Demand	mean	−3.98	−1.11	−6.73	−4.12	0.14	−5.41	−2.41	−8.01	−5.59	0.18
	t-stat	[−1.22]	[−0.33]	[−2.18]	[−1.17]	[0.04]	[−1.66]	[−0.71]	[−2.59]	[−1.59]	[0.05]