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Foreign Exchange Volume*

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We investigate the information contained in foreign exchange (FX) volume using a novel dataset from the over-the-counter market. We find that volume helps predict next day currency returns and is economically valuable for currency investors. Predictability implies a stronger currency return reversal for currency pairs with abnormally low volume today, and is driven by the component of FX volume unrelated to volatility, illiquidity, and order flow. We rationalize these findings via a simple model of exchange rate determination, in which volume helps reveal the degree of asymmetric information in currency markets. Testing this prediction shows that asymmetric information is uniform across currency pairs but varies across instruments.

Keywords: foreign exchange volume, currency returns, asymmetric information.
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1 Introduction

The foreign exchange (FX) market is enormous: On average, \$6.6 trillion is traded each day by a diverse set of key market participants, ranging from corporations to mutual funds, and from central banks to hedge funds, making FX volume over ten times larger than global equity market volume (BIS, 2019). But despite the size and importance of the FX market, studying its behavior is empirically challenging due to its decentralized, over the counter (OTC) structure, in which no central exchange records transaction data.[1] Recent important breakthroughs have begun to cast light on the market, however, by exploring the nature of trading liquidity (Mancini, Ranaldo, and Wrampelmeyer, 2013; Karnaukh, Ranaldo, and Söderlind, 2015; Hasbrouck and Levich, 2019) and differences in market participants' order flow (Menkhoff, Sarno, Schmeling, and Schrimpf, 2016; Ranaldo and Somogyi, 2021). Yet, FX volume remains largely unexplored. Does volume contain predictive information about future exchange rate returns? How is FX trading volume related to asymmetric information about the drivers of currency returns? Can currency investors employ the information embedded within volume in designing their asset allocation strategies? Until now, answers to these questions have remained tantalizingly unobtainable.

In this paper we make progress towards addressing these questions by developing a simple equilibrium model of exchange rate determination that generates a testable relationship between FX volume and future currency returns. We test the model's predictions using a novel dataset that provides the most comprehensive coverage of FX volume available at high frequency. Our data is from CLS Group, the world's largest FX settlement institution, and covers around 50% of OTC spot, forward, and swap market activity for 31 currency pairs, over six years, at hourly frequency.[2] Our main finding is that FX volume contains substantial predictive information about next day currency returns, which we find to be economically valuable for currency investors.

The model builds on the exchange rate determination framework of Bacchetta and Van Wincoop (2006), which we modify by assuming a nested information structure (such as, e.g. Llorente et al., 2002a; Vayanos and Wang, 2012a,b). The structure is simple: two countries (home, foreign)

[1]Following the G20 meeting in Pittsburgh in 2009, governments agreed that OTC derivative transactions would be reported to local trade repositories. This data has recently been analyzed to explain deviations from covered interest rate parity (Cenedese, Della Corte, and Wang, 2020), and to highlight the prevalence of trade price discrimination, in which less "sophisticated" customers are charged wider bid-ask spreads (Hau, Hoffmann, Langfield, and Timmer, 2021).

[2]See Galati (2002), Lindley (2008), and Kos and Levich (2016) for details of the CLS settlement process.

are inhabited by informed and uninformed agents who maximize short-term trading profits in an overlapping-generations (OLG) framework. In addition to a domestic bond, both agent classes can trade a foreign bond that serves as the key instrument for measuring the return and trading volume in the FX market. Bonds are risk-free in local currency. However, informed agents have a superior ability to forecast the fundamentals driving the foreign bond return (and hence the currency return), and thus speculate on their privileged information. Additionally, these agents hedge their exposure to a non-traded asset that is correlated with the exchange rate. Uninformed agents only trade based on their expectations of the next period currency return, thereby providing liquidity to the informed agents' trades.

We show that the model has a stationary linear equilibrium at which the exchange rate reflects the foreign bond fundamentals and the endowment shock to the non-traded asset, and proceed to study the dynamic relationship between currency returns and the demand for foreign bonds (i.e., FX volume). Similarly to Llorente et al. (2002a), two contrasting forces, reflecting traders' dual trading motive, drive the relationship. Volume realizations prompted by a hedging demand shock, being unanchored to fundamentals, have a mean reverting impact on future returns. Conversely, volume realizations traceable to demand shifts due to fundamental information have a persistent impact on returns. The latter effect becomes increasingly strong as the degree of asymmetric information in the market increases. This explains why, when expected returns are regressed on past returns and volume, an increase in asymmetric information predicts a weakening of the return reversal dynamic, eventually favoring return continuation. The model thus yields a parsimonious relationship between currency returns and FX volume, that has direct implications for the level of information asymmetry in the FX market, and which we proceed to test in the second part of the paper.

We explore the resulting relationship between FX volume, currency returns, and information asymmetry empirically, using daily data across a series of fixed-effects panel regressions. The coefficients we estimate imply a high level of information asymmetry across the entire market and hence, conditional on positive volume, the magnitude of return reversals weakens. We investigate if this result is driven by a particular group of currency pairs but find little heterogeneity—information asymmetry is high across both developed and emerging market pairs, and for pairs grouped by volume, liquidity, and volatility. The finding contrasts with results reported for the equity market by Llorente et al. (2002a), in which a large degree of heterogeneity exists across firms in terms of the level of privately held information. We rationalize this observation as reflecting the inherent structure of currency markets in which interbank dealers can become privately informed about currencies when intermediating trades, since many trades are known to contain substantial predictive content for future exchange rate returns (Menkhoff, Sarno, Schmeling, and Schrimpf, 2016). It follows that little variation should be expected across currency pairs in the level of privately held information.

While we do not observe much heterogeneity across currency pairs in the level of information asymmetry, we know the composition of trading by market participants differs markedly across instruments (BIS, 2019). Hedge funds and high-frequency traders, for example, typically enter speculative trades in spot and forward markets, while banks, institutional investors, and commercial corporations tend to hedge currency exposure and manage FX liquidity using FX swaps (Moore, Schrimpf, and Sushko, 2016). Given this asymmetry, it is reasonable to expect that the findings on privately informed trading should appear stronger when evaluated using either spot or forward market volume. And indeed, we find the coefficients indicating privately informed trading are large and significant when evaluated using spot and forward volume but become insignificant when evaluated using swap market volume.

The relationship we document between FX volume and currency returns implies that a currency trading strategy may yield economically sizable returns. We explore this possibility by constructing portfolios that are double sorted by currency returns and FX volume. Specifically, we find that a daily cross-sectional reversal strategy (that buys losing currencies and sells winners from the previous day) generates an annualized return of 17.6% and a Sharpe ratio of 1.7, when limited to currency pairs with the lowest volume. We refer to the strategy as the "low volume reversal in the cross-section" (LV R_{CS}). In the time series, a strategy that enters a reversal position in all currency pairs with low volume (LV R_{TS}) generates a smaller annualized return of 6.9% but an equally high Sharpe ratio of 1.7. We show the returns remain sizable after accounting for transaction costs and that the correlation of the strategies with other popular currency investment strategies including carry, value, and momentum, are low. Hence, large incremental diversification gains may be achieved when the LV R_{CS} and LV R_{TS} strategies are added to existing currency portfolios.

In additional analyses, we first investigate if FX volume contains information that is incremental to other theoretically related variables, such as order flow and volatility, and thus whether the predictive relationship we uncover is novel to volume. We find that volume and order flow, while both reflecting trading activity, are orthogonal to one another and that the portfolio returns generated using the predictive information in order flow, as documented by Menkhoff, Sarno, Schmeling, and Schrimpf (2016), are unrelated to the LV R_{CS} and LV R_{TS} strategies. Furthermore, we show that while volume is positively correlated with volatility, liquidity, and macroeconomic news, it is only the component of volume unrelated to these variables that helps predict currency returns.

Finally, we investigate the relative importance of the CLS volume data. We do so by obtaining data on FX volume from Thomson Reuters Dealing—an interbank electronic trading platform—for 13 currency pairs from 2011 to 2015. The period overlaps with our data from CLS but, unlike the CLS data that became available in 2016, was accessible by market participants. We find the LV R_{CS} strategy, using the Thomson Reuters data, also generates a high Sharpe ratio (of just over one) and a return statistically larger than the equivalent high volume strategy. However, using the CLS data for the same period and currency sample, we find that the Sharpe ratio increases by over 60%. Therefore, while market participants could have used other available FX volume data to formulate an investment strategy, the CLS data is particularly useful to fully exploit the information contained in volume, likely because of its larger coverage of the FX market and more precise measurement of trading volume.

Overall, our paper provides novel insights into the information content of FX volume. We are the first to theoretically model and empirically document a strong predictive link between FX volume and currency returns, which we find to be statistically significant, economically valuable for global currency investors, and indicative of a high level of asymmetric information across the entire currency market. These findings are important for academics seeking to better understand FX market behavior, for investors seeking novel sources of returns and diversification, and for regulators and market designers pursuing deeper insights into the information embedded within OTC FX market volume.

The remainder of the paper is organized as follows. Section 2 discusses related literature. Section 3 outlines the model. Section 4 describes the data and summary statistics. Section 5 contains our core empirical analysis. Section 6 reports findings from additional analyses. Section 7 concludes. An Internet Appendix contains further details on the model and results from additional empirical tests.

2 Related Literature

Our paper is closely related to three recent strands of FX market literature. First, we contribute to the growing literature on FX volume. Ranaldo and Santucci De Magistris (2019) present a theory of the relationship between FX volume, volatility, and liquidity, which they confirm using intraday data from CLS. Earlier studies have also explored the determination of FX volume and found FX volume reacts to macroeconomic news releases, FOMC announcements, and changes in financial regulation (Chaboud, Chernenko, and Wright, 2008; Fischer and Ranaldo, 2011; Levich, 2012). Hasbrouck and Levich (2019) observe individual settlement instructions from CLS for a sample period of one month, and confirm that the CLS volume data provides a close approximation to the true population of volume observed by the Bank for International Settlements in their triennial FX market surveys.[3] We differ from these papers by being the first to investigate theoretically and empirically the information content of FX volume and the mechanisms that link it with future currency returns.

Second, we contribute to the growing literature studying the predictability of currency returns and strategies that exploit this predictability, including carry (Lustig, Roussanov, and Verdelhan, 2011; Menkhoff et al., 2012a), value (Asness, Moskowitz, and Pedersen, 2013; Menkhoff et al., 2017), and momentum (Menkhoff et al., 2012b; Asness, Moskowitz, and Pedersen, 2013). We find that currencies with low trading volume are more likely to experience a return reversal and that simple, volume-conditioned, portfolios have impressive investment performance and low correlations with carry, value, and momentum strategies—resulting in a novel source of diversification gains.

Third, we build on the literature studying private information in currency markets. A number of studies have found proximate evidence of private information in FX markets. Ito, Lyons, and Melvin (1998), for example, identify private information using changes in intraday FX market volatility before and after a lunchtime trading ban in Tokyo. Private information may be acquired in FX markets because, unlike centralized markets, trades are not publicly disclosed and thus FX dealers

[3]Other researchers have used ultra-high-frequency data from inter-dealer trading platforms. This data is generally obtained for short samples to address market microstructure-related questions. Lyons (1995), for example, observes direct interdealer transactions of a single USDDEM dealer over five trading days. Payne (2003) observes the activity of multiple dealers on the Reuters electronic brokerage system for the same currency pair and over a similar trading interval. Berger et al. (2008) use one minute data from the EBS brokerage platform to study EURUSD and USDJPY, while Evans (2002) uses four months of direct interdealer data from the Reuters platform. Data on high-frequency trading activity has also been used to test various market microstructure models of dealer behavior (see, e.g. Bjønnes and Rime, 2005).

have a partial but potentially informed position (Peiers, 1997; Menkhoff et al., 2016).[4] We build on this literature by showing theoretically that the relationship between FX volume and currency returns is informative about the degree of information asymmetry in FX markets, while our empirical evidence highlights that information asymmetry is high and uniform across currency pairs and that the predictive information in volume is different from that contained in order flow.

3 Model

In this section, we present a stylized model of exchange rate determination that motivates our subsequent empirical work. The model builds on Bacchetta and Van Wincoop (2006), which we follow to set up the international economy, and Llorente et al. (2002a) which we use to study the link between expected currency returns, asymmetric information, and foreign exchange volume. The resulting model yields the testable prediction that we take to the data in the later empirical analysis.

Consider a two-country world in which at round $t = 1, 2, \ldots,$ both countries produce the same good whose (log) prices p_t and p^*_t (starred variables relate to the foreign country) satisfy purchasing power parity (PPP):

$$p_t = p^*_t + s_t, \tag{1}$$

where s_t denotes the log of the nominal exchange rate (home price of foreign currency).[5] In both countries, at each round t, a continuum of competitive agents in the interval [0, 1] are in the market, while the agents who entered at $t-1$ leave in an OLG fashion. Agents' preferences in both countries are represented by a CARA utility function of their short term profits (with unit risk aversion coefficient) which obtain from (i) home, real money holdings, (ii) home and foreign bond holdings (offering nominal returns i_t and i^*_t), and (iii) an income from production, obtained employing a technology that is in infinite supply and offers a real return r.[6] The home country is large, while the foreign country is small, implying that the equilibrium is determined by the conditions prevailing in the home country.

[4]Supporting the informed dealer perspective, Lyons (1995), Payne (2003) and Hau et al. (2021) show that dealers adjust spreads in response to privately informed order flow, while Michaelides, Milidonis, and Nishiotis (2018) find that local currency depreciations take place prior to sovereign debt downgrades.

[5]We can equivalently think of a basket of goods.

[6]See Lyons (2001) for evidence of short term trading behavior in the FX market.

Finally, we assume that money supply in the home (foreign) country is constant (stochastic), which implies that $i_t = r$.[7]

At round t, agents have a fixed endowment and know the money supply in both countries: m_t, and m^*_t. However, only a fraction $\omega \in [0,1]$ of them are "informed" (we denote them by the letter I) in that they have the ability to process the information to correctly anticipate and trade on the foreign country's t + 1-round money supply m^*_{t+1}.[8] As will become clear from the discussion that follows, this enables I-agents to correctly anticipate the interest rate differential between the two countries, improving their performance when trading the foreign bond. Investors belonging to the complementary fraction $(1 - \omega)$ obtain information by extracting a noisy signal from the round t exchange rate, and are thus "uninformed" (we denote them by the letter U). Additionally, we assume that, prior to round t, informed agents receive a random exposure in a non-tradable asset. We denote the t-round exposure by z_t, and assume that it follows an AR(1) process:

$$z_t = \rho_z z_{t-1} + \epsilon_t, \ \ \rho_z \in [0,1), \tag{2}$$

with ϵ_t i.i.d. over time. The value of the endowment at the following round of trade is denoted by n_{t+1}, and is correlated with the exchange rate.

Denoting the one-round return from investing in the foreign bond (i.e., the currency excess return) by

$$R_{t+1} = s_{t+1} - s_t + i^*_t - i_t, \tag{3}$$

we can write agents' budget constraints as follows:

$$w_{It+1} = (1 + i_t)w_{It} + R_{t+1}x_{It} + z_t n_{t+1} - i_t m_t + y_{t+1} \tag{4a}$$

$$w_{Ut+1} = (1 + i_t)w_{Ut} + R_{t+1}x_{Ut} - i_t m_t + y_{t+1}, \tag{4b}$$

where w_{it} denotes the wealth of a type $i \in \{I, U\}$ agent at round t, x_{it} is a type-i agent's demand for

[7]We do this for convenience, to keep the model tractable and in line with Bacchetta and Van Wincoop (2006). Note that this implies that, as will become clear in the following, at round t, the interest rate differential is entirely driven by the foreign country's money supply, so that its sign depends on the random variable realization that governs its evolution.

[8]See Menkhoff et al. (2016) for evidence on the superior predictive ability of certain groups of FX market participants.

the foreign bond, m_t denotes his real money holdings, while

$$y_{t+1} = -\frac{m_t}{\alpha}(\ln m_t - 1), \tag{5}$$

is the income agents derive from a decreasing returns to scale production technology, and $\alpha > 0$ a scaling parameter.[9]

The "fundamental" in the model is denoted by

$$g_t = m_t - m^*_t, \tag{6}$$

i.e., the difference between the logs of domestic and foreign money supply. We restrict attention to equilibria where at any round t the exchange rate is an affine function of the current and next round fundamentals (g_t and g_{t+1}), and the round-t components of the endowment shocks (i.e., z_{t-1} and ϵ_t):

$$s_t = a_0 g_{t+1} - a_1 \epsilon_t - a_3 z_{t-1} + a_2 g_t, \tag{7}$$

where a_0, a_1, a_2, a_3 are coefficients to be determined in equilibrium.

Due to our assumptions, at round t, an agent of type $i \in \{I, U\}$ in the home country maximizes

$$E_{it}[-\exp\{-w_{it+1}\}], \tag{8}$$

where the information set of a type-I agent is given by $\{s^t, g_{t+1}, m^t, (m^*)^t, z^t\}$, which includes the history of exchange rates $s^t \equiv \{s_1, s_2, \ldots, s_t\}$; money stocks at home and abroad $m^t \equiv \{m_1, m_2, \ldots, m_t\}$, $(m^*)^t \equiv \{m^*_1, m_2, \ldots, m_t\}$; and endowment shocks ($z_{t-1}$ and ϵ_t). An uninformed agent, instead, observes $\{s^t, m^t, (m^*)^t, z^{t-1}\}$. Therefore, at a trading round t, uninformed traders have access to the same information as informed traders, except for g_{t+1} and z_t, which they do not directly observe. However, as we will argue in the following, insofar as the exchange rate reflects these random variables, at round t uninformed traders recover some information which shapes their demand for the foreign bond.

[9]We drop the agent type subscript because, as we will show, agents' demand for money is type independent. According to this functional specification, real money holdings are essential for production, but as they grow too large, they become detrimental: $\lim_{m_t \to 0} y_{t+1} = 0$, and $y'_{t+1}(m_t) = -(1/\alpha)\ln m_t$, which is positive (negative) for $m_t < 1$ ($m_t > 1$). Additionally, for a given level of money holdings, a higher α reduces the importance of production as an engine of wealth creation.

Finally, assume that the random variables g_t, ϵ_t, and n_t are normally distributed: $\epsilon_t \sim N(0, \sigma^2_\epsilon)$, $n_t \sim N(0, \sigma^2_N)$, and $g_t \sim N(0, \sigma_G)$ with $E[g_{t+1} n_{t+1}] = \sigma_{GN}$, while all other random variables are mutually independent contemporaneously and over time.[10]

The model presented above replaces the assumption of dispersed information adopted by Bacchetta and Van Wincoop (2006) with that of a nested information structure (i.e., where the information sets of different agents' types can be completely ordered, as in Grossman and Stiglitz (1980), Vayanos and Wang (2012a,b)), which simplifies uninformed traders' signal extraction problem.[11]

To solve the model, we start by pinning down the equilibrium in the money market (see Section 3.1), and then use this result to show how the difference across money supplies in the two countries affects the equilibrium demand for foreign bonds (and thus foreign exchange volume) via the interest rate differential $i^*_t - i_t$, thus feeding, through the PPP condition (see Eq. (1)), into the determination of the equilibrium exchange rate (see Section 3.2).

3.1 Equilibrium in the money market

Under our assumptions, at a linear equilibrium the exchange rate (7) is a normal random variable, and we have:

$$E_{it}[-\exp\{-w_{it+1}\}] = -\exp\left\{-\left(E_{it}[w_{it+1}] - \frac{1}{2}Var_{it}[w_{it+1}]\right)\right\}, \tag{9}$$

where

$$E_{It}[w_{It+1}] = (1 + i_t)w_{It} + E_{It}[R_{t+1}]x_{It} + z_t E_{It}[n_{t+1}] - i_t\, m_t + y_{t+1} \tag{10a}$$

$$E_{Ut}[w_{Ut+1}] = (1 + i_t)w_{Ut} + E_{Ut}[R_{t+1}]x_{Ut} - i_t\, m_t + y_{t+1}, \tag{10b}$$

[10]Given that we assume the stock of money supply in the home country m_t is deterministic, due to (6) at every round t, $m^*_t = m_t - g_t$, implying that $m^t \sim N(m_t, \sigma_G)$.

[11]Compared to Llorente et al. (2002a), we introduce the possibility that informed traders' endowment shocks display persistence, which we see as a realistic feature and that, as we argue in Section 3.3, allows us to obtain the result that for a sufficiently large degree of asymmetric information, positive volume can predict positive return autocorrelation (similarly to Wang (1994)).

and

$$Var_{It}[w_{It+1}] = x^2_{It} Var_{It}[R_{t+1}] + z_t Var_{It}[n_{t+1}] + 2x_{It} z_t Cov_{it}[R_{t+1}, n_{t+1}] \quad (11a)$$

$$Var_{Ut}[w_{Ut+1}] = x^2_{Ut} Var_{Ut}[R_{t+1}]. \quad (11b)$$

Substituting (10a), (10b), (11a), and (11b) in the objective function of informed and uninformed traders, and equating to zero the first order conditions with respect to m_t and m^*_t, we find that the money demand functions for the two traders' types are identical in both countries, and decreasing in the interest rate, with semi-elasticity α:

$$\ln m_t = -\alpha i_t \quad (12a)$$

$$\ln m^*_t = -\alpha i^*_t. \quad (12b)$$

Imposing equilibrium in both countries' money markets by replacing the demand for money with the (logs of the) supply and prices yields:

$$m_t - p_t = -\alpha i_t \quad (13a)$$

$$m^*_t - p^*_t = -\alpha i^*_t. \quad (13b)$$

Substituting the PPP condition (Eq. (1)) in the home money market equilibrium condition (Eq. (13a)) and using it with the foreign money market equilibrium (Eq. (13b)), we compute the interest rate differential, obtaining:

$$i^*_t - i_t = \frac{m_t - m_t - s_t}{\alpha} = \frac{g_t - s_t}{\alpha} \quad (14)$$

Equation (14) relates the interest rate differential to the difference in money stocks across the two countries and the exchange rate. Given that the exchange rate is endogenous, the only variable of interest is g_t. Accordingly, when the foreign country's money supply stock is above the one in the home country, the interest rate differential decreases.[12] Knowledge of g_t is then useful to anticipate

[12]This effect is amplified as the relevance of the income from production increases in agents' budget constraints (as the money demand function becomes less elastic).

changes in the return from investing in the foreign bond market. Indeed, substituting Eq. (14) into the currency excess return (Eq. (3)) and using the expression for the exchange rate (Eq. (7)) yields:

$$R_{t+1} = \frac{\alpha(a_2 g_{t+1} - a_3 z_t + a_0(g_{t+2} - b\epsilon_{t+1})) - (1+\alpha)s_t + g_t}{\alpha}, \tag{15}$$

where $b \equiv a_1/a_0$. At equilibrium, informed traders correctly anticipate g_{t+1} and use it to trade in the bond market, contributing to the determination of the exchange rate s_t. This allows uninformed traders to recover the "informational content" of the exchange rate about g_{t+1} and ϵ_t, which obtains by rearranging Eq. (7):

$$\hat{s}_t \equiv \frac{s_t - a_2 g_t + a_3 z_{t-1}}{a_0} = g_{t+1} - b\epsilon_t. \tag{16}$$

3.2 Equilibrium in the foreign bond market

Differentiating the objective function of informed and uninformed traders (Eq. (9)) with respect to x_{It} and x_{Ut} and solving the first order conditions yields the following expressions for agents' demands for the foreign bond:

$$x_{It} = \frac{E_{It}[R_{t+1}] - a_2 \sigma_{GN} z_t}{\sigma^2_{IR}} \tag{17a}$$

$$x_{Ut} = \frac{E_{Ut}[R_{t+1}]}{\sigma^2_{UR}} \tag{17b}$$

According to Eq. (17a), at round t, informed agents have a dual motive for trading the foreign bond: informed speculation (captured by $E_{It}[R_{t+1}]$), to exploit their foreknowledge of the fundamentals, and hedging (captured by $-Cov_{It}[R_{t+1}, n_{t+1}]z_t = -a_2\sigma_{GN} z_t$), to share the risk due to their exposure to the non-tradable asset. Uninformed agents only trade based on their anticipation of the foreign bond return (see Eq. (17b)) (and thus are not hedging).[13] Imposing market clearing

$$\omega x_{It} + (1 - \omega)x_{Ut} = 0, \tag{18}$$

[13]Note that the result above proves existence of an equilibrium. When $\rho_z = 0$ we can also prove uniqueness. Our numerical simulations suggest, however, that even for $\rho_z = 0$, the equilibrium is unique.

and using Eq. (17a) and Eq. (17b) to solve for the equilibrium exchange rate, we prove the following result (see Section A of the Internet Appendix for a proof):

Proposition 1. There exists a stationary linear equilibrium in the dynamic model of exchange rate determination. At equilibrium, agents' demands for the foreign bond are given by

$$x_{It} = \frac{(\alpha a_2 - (1+\alpha)a_0)\hat{s}_t + (1+\alpha)a_3 z_{t-1}}{\alpha\sigma^2_{IR}}$$
$$= -\frac{1-\omega}{\omega} x_{Ut}, \tag{19}$$

where $\sigma^2_{IR} = Var_{It}[R_{t+1}] = a_0(\sigma_G + b^2\sigma_\epsilon)$, $\hat{s}_t = g_{t+1} - b\epsilon_t$, $a_2 = 1/(1+\alpha)$, and the expressions for $a_0 > 0$, $a_3 \geq 0$ if and only if $\rho_z \geq 0$, and $b > 0$ are provided in the Internet Appendix (see, respectively, (A.6a), (A.6c), and (A.6d)). The equilibrium exchange rate is given by:

$$s_t = a_2 g_t - a_3 z_{t-1} + \frac{a_0}{\gamma} E_{Ut}[g_{t+1}], \tag{20}$$

where $\gamma \equiv \sigma^2_G/(\sigma_G + b^2\sigma_\epsilon)$ and $g_t = m_t - m_t$.

According to Eq. (19), a positive realization of the informational content of the exchange rate $\hat{s}_t$, or of informed agents' round $(t-1)$-exposure to the non-tradable asset z_{t-1}, leads informed agents to demand the foreign bond and uninformed agents to take the other side of the market (thus, uninformed agents act as liquidity providers).[14] Intuitively, for a given endowment shock exposure z_{t-1}, $\hat{s}_t$ is greater than zero when informed agents have either good news about the next period cross-country interest rate differential, or face a smaller exposure to the round-t innovation in the non-tradable asset (see Eq. (16)). Conversely, for a given $\hat{s}_t$, a positive z_{t-1} tames informed agents' long position in the asset (since a larger exposure to the risk factor leads them to scale down their position in the foreign bond), which depresses s_t and increases the anticipated short term return. In either case, uninformed agents take the other side of the market, trading at a price that incorporates the equilibrium compensation for facing higher adverse selection and/or exposure to the risky security.

The exchange rate (Eq. 23) reflects the current period fundamentals the more inelastic is the ~~demand for money, and reflects the next~~ period fundamental, via the uninformed traders' expectation

[14]This is because, as we show in Internet Appendix (Section A), at equilibrium $0 < a_0 < \alpha/(1+\alpha)^2$ and for $\rho_z \geq 0$, $a_3 \geq 0$ (see respectively (A.11) and (A.6c)).

$E_{Ut}[g_{t+1}]$. Additionally, s_t also reflects z_{t-1} since for $\rho_z > 0$, uninformed agents use their knowledge of z_{t-1} to anticipate the impact of z_t on R_{t+1} (via s_{t+1}), improving their inference from the exchange rate.[15]

In this model, as σ_G increases, informed traders have a stronger informational advantage over uninformed traders, as they know g_{t+1}. Thus, σ_G can be taken as a measure of asymmetric information.

3.3 Relation between expected currency returns and volume

At equilibrium, the aggregate order flow of informed agents must offset that of uninformed agents (Eq. (18)). Thus, without loss of generality, we can define volume as follows:

$$V_t = \omega|x_{It} - x_{It-1}|. \tag{21}$$

Indeed, in a model with two classes of agents, at equilibrium $\omega(x_{It} - x_{It-1}) = -(1-\omega)(x_{Ut} - x_{Ut-1})$, and (i) V_t is tantamount to observing the corresponding measure of foreign exchange volume one would obtain replacing x_{It} with x_{Ut} in Eq. (21), and (ii) for given information sets, foreign exchange volume offers no additional information to predict the exchange rate to an agent in the model.[16] Using Eq. (19) in Eq. (21) and rearranging yields:

$$V_t = \frac{\omega}{\alpha\sigma^2_{IR}}\left|(\alpha a_2 - (1+\alpha)a_0)(\hat{s}_t - \hat{s}_{t-1}) + (1+\alpha)a_3(z_{t-1} - z_{t-2})\right|. \tag{22}$$

We are now going to use foreign exchange volume to investigate its informational content from the point of view of an agent "outside the model" (such as an econometrician) who observes it, jointly with currency returns. Defining trading volume, scaled by the coefficient $\omega/\alpha\sigma^2_{IR}$, tofocusonthe informational content of the signal it contains a $V_t = (\alpha\sigma^2_{IR}/\omega)V_t$, wehavethefollowingresult(see ~~Section A of the Internet Appendix for a~~ proof):[17]

[15]This, in turn, introduces another factor, besides the fundamental value, having a persistent impact on the exchange rate. According to our assumptions, at round t uninformed traders observe z_{t-1} and extract information about ϵ_t from $\hat{s}_t$, both of which can be used to improve their forecast of s_{t+1}: $E_{U\,t}[s_{t+1}] = a_2 E_{U\,t}[g_{t+1}] - a_3(\rho_z z_{t-1} + E_{U\,t}[\epsilon_t])$. When $\rho_z = 0$, $a_3 = 0$, and the only useful information incorporated in $\hat{s}_t$ is the one about g_{t+1}.

[16]That is, at equilibrium, volume offers the same information that can be extracted from the exchange rate about the fundamentals exactly as Llorente et al. (2002a). In this respect, agents "in the model" do not improve their estimates of the fundamental by conditioning on volume. However, precisely because informed traders' strategies are driven by fundamental information and endowment shocks hedging, by conditioning on volume an agent "outside the model" can improve the estimation of R_{t+1}.

[17]This is akin to the normalization adopted by Llorente et al. (2002b). Note that in their case the scaling factor is

Corollary 1. At equilibrium,

$$E[R_{t+1}|R_t \; V_t] \approx -(\theta_1 + \theta_2 \tilde{V}^2_t) R_t. \tag{23}$$

where the expressions for the regression coefficients θ_1 and θ_2 are provided in the Internet Appendix (see, respectively, (A.18a) and (A.18b)).

We use numerical methods to investigate the behavior of θ_2 as a function of our measure of asymmetric information σ_G. Figure 1 displays the result of one of our numerical simulations, showing that for some parameter values, as σ_G increases, θ_2 declines, eventually turning negative for a sufficiently large degree of asymmetric information. The intuition is as follows. In our model, volume is driven by two different trading motives that have two potentially contrasting effects on the information that it conveys: informed traders' speculation on fundamental information and their hedging of endowment shocks. Suppose that $\rho_z = 0$. In this case, we find that $\theta_2 > 0$, even for large σ_G. Intuitively, at a given trading round, if a positive volume realization is due to informed traders selling for hedging reasons, s_t must decline to make the uninformed willing to take the other side of the trade (i.e., provide liquidity).[18] However, due to transience ($\rho_z = 0$), this selling pressure is likely to evaporate at the next round of trading, inducing a move up in s_{t+1}. This mean reversion effect is not present when informed traders' sell order is due to fundamental information, because such information has a persistent impact on the exchange rate. As $\theta_2 > 0$, this suggests that with $\rho_z = 0$ the mean reversion effect due to traders' risk aversion is never overturned by the impact of asymmetric information, not even when the effect is strong (i.e., when fundamentals are more likely to drive returns). With $\rho_z > 0$, however, the persistence of endowment shocks "adds" to that coming from the fundamentals in driving the exchange rate. Our simulations thus show that θ_2 can turn negative for a large enough σ_G (Figure 1). Thus, in this case, and similar to Wang (1994), we find that for some parameter values, a high degree of asymmetric information with positive volume predicts positively serially correlated returns. This latter numerical finding suggests the following:

given by the unconditional mean volume, since due to the endowment shock transience they assume, the endowment shock difference $z_{t-1} - z_{t-2}$ disappears from traders' demand, which allows to factor out the coefficient of the difference $\hat{s}_t - \hat{s}_{t-1}$, implying that normalized volume is proportional to $\hat{s}_t - \hat{s}_{t-1}$.

[18]This is because, due to risk aversion, buying the foreign security increases their exposure to fundamentals risk, which calls for a risk-based compensation for the trade to occur.

Empirical Prediction. With positive volume, higher asymmetric information favors return continuation: the impact of foreign exchange volume on expected currency returns, as measured by the coefficient of the interaction term in Eq. (23) (i.e., $-\theta_2$), turns from negative to positive as asymmetric information increases.

3.4 Model discussion

The model developed above is intended to strike a balance between tractability and realism, and deliver the main empirical prediction on the impact of asymmetric information on the coefficient of the interaction term $-\theta_2$. The empirical analysis below strongly supports this prediction. We are nonetheless aware of the potentially limiting role of some of the model's assumptions. For example, as remarked in Section 3.3, with only two types of agents volume has a limited informational role. Adding an extra set of agents (e.g., "dealers") would possibly deliver novel insights on the equilibrium role of foreign exchange volume as a signal to shape trading strategies. Furthermore, the assumption of a nested information structure cuts through the fixed point loop highlighted by the literature on Higher Order Expectations (see, e.g. Allen, Morris, and Shin (2006), Bacchetta and Van Wincoop (2006), and Cespa and Vives (2012, 2015)). As shown by Cespa and Vives (2015), differential information on a "long-lived" fundamental, coupled with the predictability of endowment shocks, has a strong effect on the set of equilibrium solutions, and the ensuing positive implications of the model. Additionally, long-lived information would allow for a better understanding of the long-term informational impact of foreign exchange volume for currency return predictability, although the empirical analysis developed in the paper shows that, in our data set, this is virtually non-existent.

4 Data and Summary Statistics

In this section, we begin by describing the data on volume and exchange rates, before presenting a set of summary statistics on FX volume—highlighting key features of the data across time, currency pairs, and instruments.

4.1 Foreign Exchange Market Volume

We obtain data on FX volume (recorded in U.S. dollars) from CLS, the world's largest FX settlement institution. The data is available from Quandl, a financial data provider, and is recorded hourly for six years starting in 2011, across spot, outright forward, and swap market instruments (we remove U.S. and U.K. public holidays from the sample, which are days that are typically characterized by especially low trading volume). Following an FX transaction, settlement members of CLS submit the details of the trade for authentication and matching. CLS records each transaction when the first instruction is received. In recent work, Hasbrouck and Levich (2019) find that CLS receives the majority of its instructions within ten seconds of the trade occurring. On the settlement date, CLS simultaneously settles both sides of the transaction, mitigating FX settlement risk. In aggregate, CLS settles around 50% of trades, providing them with a unique view of daily FX trading activity. The dataset spans a large cross section of 31 currency pairs and 17 major currencies including the Australian dollar (AUD), British pound (GBP), Canadian dollar (CAD), Danish krone (DKK), euro (EUR), Hong Kong dollar (HKD), Israeli shekel (ILS), Japanese yen (JPY), Mexican peso (MXN), New Zealand dollar (NZD), Norwegian krone (NOK), Singapore dollar (SGD), South African rand (ZAR), South Korean won (KRW), Swedish krona (SEK), Swiss franc (CHF), and US dollar (USD).[19]

4.2 Exchange Rate Returns and Currency Excess Returns

We supplement the FX volume data with daily WM/Reuters (WM/R) spot and one-week forward exchange rates obtained from Thompson Reuters via Datastream. The choice of exchange rate data is important to ensure that volume and returns are measured over precisely the same period. WM/R exchange rates are simultaneously recorded at 4pm in London. We calculate the daily exchange rate return as the log difference in spot exchange rates,

$$\Delta s_{t+1} = s_{t+1} - s_t. \tag{24}$$

Since we also analyze cross-rates in our analysis, we refer to "high" and "low" returns from the perspective of the base currency, meaning that s_t is defined as the price of the base currency in terms

[19]The Hungarian forint is also available although the series begins later, on 17 November 2015. We decide to maintain a balanced panel of data in our empirical investigation and therefore exclude the forint from the analysis.

of the quote currency. Currency excess returns are constructed as

$$r_{t+1} = \Delta s_{t+1} - (i_t - i^*_t), \tag{25}$$

where i_t and i^*_t are the overnight interest rates in the quote and base currencies, respectively. In practice we do not observe overnight money market rates for all 17 currencies in our sample and therefore extract information about interest rate differentials from forward rates using the covered interest rate parity (CIP) condition that $f_{k,t} - s_t \approx i_{k,t} - i^*_{k,t}$, where $f_{k,t}$ is the k-period forward rate observed at time t.[20]

4.3 Summary statistics

In Figure 2, we plot the monthly time series of average daily FX volume across spot, forward, and swap markets as well as for total volume (sum of spot, forward, and swap volume). The data is aggregated across currency pairs and is overlaid with a rolling six-month moving average. While total FX volume was largely steady across the sample, spot volume fell substantially after 2014. This reduction was driven by a drop in hedge fund and high-frequency trading due to a combination of banks either withdrawing or increasing the cost of prime brokerage services. It also reflects the introduction of "speed bumps" in trading by major inter-dealer platforms that reduced the profitability of high-frequency trading. In contrast, FX swap market activity has grown at pace, following an increase in currency hedging activity among institutional investors and corporates, and FX liquidity management among dealer banks (see Moore, Schrimpf, and Sushko, 2016, for further details).[21]

In Panel A of Table 1 we present summary statistics on the sample mean, standard deviation, and average trade size across individual currency pairs. Several facts emerge from these statistics. First,

[20]We use one-week forwards in our main analysis. We therefore assume that the daily forward premium is exactly proportional to the weekly forward premium. While this approximation is not exact, it has the advantage of not being estimated (by either interpolation or via bootstrap). We find qualitatively identical results using one-month forwards. Moreover, due to large deviations from CIP following the global financial crisis (see, e.g. Baba and Packer, 2009; Rime, Schrimpf, and Syrstad, 2017; Du, Tepper, and Verdelhan, 2018; Cenedese, Della Corte, and Wang, 2020), we also use the available euro-currency deposit rates for 13 currencies to estimate interest rate differentials. We find the results remain virtually unchanged. These results are available upon request.

[21]Figure B.1 of the Internet Appendix shows the average level of volume at hourly, daily, and monthly frequencies. We find volume typically concentrates in the early and later hours of the trading day in London and New York. The average level of trading activity is also moderately lower on Mondays and Fridays, but differences across days are not statistically significant. Across months, we find trading activity in spot and forward markets is reduced around the beginning of the year between February and April, and during U.S. and European summer and winter vacations. Swap activity remains steady across months and tends to remain high around quarter-ends, consistent with currency hedging activity.

the ranking of currency pairs by volume almost perfectly matches the BIS's triennial surveys, indicating that the data provides a representative sample for the full population of trades.[22] Second, the summary statistics reveal a positive relationship between the level and variability (standard deviation) of trading volume, suggesting that a standardization of volume is required to make meaningful comparisons across currency pairs in our subsequent analysis. Third, looking at the results disaggregated across instrument types, we see that volume is typically largest for swap and smallest for forward contracts, but that the average trade size (column labeled $\overline{\text{Trade}}$) is largest for swap and smallest for spot transactions. In fact, the average trade size for most currency pairs is only around \$1 million. This finding makes sense given the standardization of trade size in the FX spot market (a "standard" trade in the major currencies is for \$10mn) and the use of order-splitting algorithmic trades (BIS, 2018). In contrast, dealer banks typically accommodate large bespoke trades in forward and swap markets.

In Panel B we present the average (across pairs) pairwise correlation between the three instruments—computed using the daily (log) changes in volume. We find the correlations are positive, although not especially high. While spot and outright forward volume display a 40 percent correlation, swap volume has a more modest 21 percent correlation with both spot and forward volume, indicative that the underlying economic motives for trading are quite different across FX instruments.[23]

5 FX Volume and Currency Returns

In this section we explore the relationship between FX volume and currency returns. We begin by estimating the theoretically predicted relationship between currency returns and volume, and infer the implications for information asymmetry. Using these results, we analyze if a currency investor could use this information as part of their asset allocation decision making. Hence we construct and analyze the performance of currency strategies that condition on FX volume, and explore the extent to which these strategies can help diversify existing currency portfolios.

[22]In Table B.1 of the Internet Appendix, we confirm the reliability of the CLS data by comparing the average daily volume reported by CLS with the equivalent values from the 2013 and 2016 BIS Triennial Central Bank Surveys.
[23]We provide further summary analysis of the data in Internet Appendix Section B. In particular, we report results from a factor decomposition of FX volume in Figure B.2 that shows around 15 principal components are required to explain 80% of the variation in total FX volume. Moreover, Figure B.3 shows the R-square from regressing volume on the first principal component for each currency pair and indicates that the highest R-squares are associated with the most traded currency pairs.

5.1 Predictability and Information Asymmetry

Motivated by our earlier theoretical analysis, we empirically explore the dynamic relationship between currency returns and FX volume. We do so by running a series of fixed-effects panel regressions that correspond to the derived relationship between currency returns and volume presented in Equation (23). Specifically, we model currency returns as:

$$r_{i,t+1} = \alpha_i + \beta_1 r_{i,t} + \beta_2 \left(v_{i,t} r_{i,t} \right) + \beta_3 v_{i,t} + \gamma' x_{i,t} + \tau_t + \epsilon_{i,t+1}, \tag{26}$$

where $r_{i,t}$ is the log currency excess return for currency pair i at time t. To mitigate against heteroskedasticity and trends in the time series of volume, we include volume in the model as a normalized variable $v_{i,t} = \log(V_{i,t}) - \log\left(\frac{\sum_{s=1}^{N} V_{i,t-s}}{N}\right)$, setting N =21. Later we provide evidence that the results are qualitatively unaffected when the window is extended. The coefficients α_i and τ_t denote currency-pair and time fixed-effects, while $x_{i,t}$ denotes the vector of controls that includes currency-pair specific measures of volatility and liquidity. Volatility is measured by fitting a GARCH(1,1) to each series of excess returns, while we measure liquidity using the daily bid-ask spread for each currency pair. Standard errors are clustered in the currency-pair and time dimensions.

According to the model, β_1 (associated with lagged returns) is negative, while β_2 (associated with the interaction of lagged returns and volume) can take any sign. Specifically, we note from the model that a higher β_2 is consistent with a higher overall level of information asymmetry, as it indicates volume is relatively more driven by fundamental news. We initially estimate the coefficient for the aggregate market, in which we sum volume across spot, forward, and swap markets, and include all 31 currency pairs. The results are reported in Table 2. Column (1) contains coefficient estimates for the lagged values of currency returns (β_1) and FX volume (β_3). FX volume alone is uninformative about future currency returns but becomes informative once interacted with currency returns in Column (2)—the coefficient on the interaction term (β_2) is positive and highly statistically significant at the 1% level. The magnitude is also economically significant: a one standard deviation shift in volume below its average translates into a three times larger return reversal.

We find that the inclusion of volatility and liquidity controls (Column (3)) has no qualitative impact on the coefficients.[24] Overall, the estimate of β_2 is therefore consistent with an elevated level of information asymmetry for the aggregate currency market.

For comparison, previous studies have typically found opposite results for the aggregate stock market, or for the majority of individual stocks, for example finding negative and highly statistically significant values for β_2 (Campbell, Grossman, and Wang, 1993; Llorente et al., 2002a), suggesting that the level of information asymmetry in FX markets is higher than in the aggregate U.S. equity market. To better understand this result, we investigate if a particular group of currencies drives the result. We do this by splitting currencies into two equally sized groups by volume (Columns (4) and (5)), liquidity (Columns (6) and (7)), volatility (Columns (8) and (9)), and by considering only US dollar and euro pairs (Columns (10) and (11)). Looking across the columns it becomes immediately clear that the pattern in coefficients is similar. The estimates for β_2 are always positive, highly statistically significant, and of comparable magnitude—indicating that the level of information asymmetry is uniformly high across the entire currency market, while β_1 coefficients are always negative and typically statistically different from zero.[25] In contrast, in equity markets, Llorente et al. (2002a) find evidence of higher levels of information asymmetry (i.e., $\beta_2 > 0$) only for small illiquid stocks, which is intuitive given they are not extensively covered by equity market analysts.

It may appear puzzling therefore that the world's largest and most liquid market has similarities with small illiquid stocks. But a natural response is that the finding simply reflects a structural difference in the trading environments unrelated to liquidity. In particular, dealers in the FX market observe a subset of volume that is potentially informative, as it may reveal information about future macroeconomic states, the aggregate level of risk aversion, or the inventory of better informed market participants (Evans and Lyons, 2007; Breedon and Vitale, 2010; Evans, 2010). Indeed, Osler and Vandrovych (2009) and Menkhoff et al. (2016) show that certain demand-side investors enter trades that, once aggregated, predict FX returns. Dealers thus receive private information through the day-to-day course of their business and this information is not limited to a subgroup of currency pairs. It follows that given this inherent access to private information one may expect, a priori, that the

[24]We find the relationship between volume and subsequent returns is short lived; confined only to a single day ahead. See Figure C.1 in the Internet Appendix for further details.

[25]Indeed, we find that β_2 is positive for almost every currency pair when we estimate bilateral regressions. Furthermore, we also test if the β_2 coefficients estimated for the subgroups are statistically different from the 0.181 estimate for all pairs reported in Column (3) of Table 2. We find we are unable to reject the null hypotheses that the values are equal for all groups. These results are available on request.

information structure is heavily asymmetric across the entire market. This line of reasoning is also consistent with Cheung and Wong (2000), who provide survey evidence that dealers with access to more customer flows are viewed by other FX market participants as being better informed.

While we do not observe heterogeneity in coefficients estimated using total volume, it is possible that variation exists when coefficients are estimated using disaggregated volume across instruments, since the composition of market participants varies considerably across FX instruments. Hedge fund activity, for example, accounts for 13% (15%) of all spot (forward) market transactions but only 4% of swap market volume, while the combination of institutional investor and hedge fund activity accounts for 29% (37%) of spot (forward) volume but only 10% of swap market activity (BIS, 2019). Thus, based on our empirical prediction, we anticipate that the value of β_2 should be larger (in absolute terms) when estimated using either spot or forward volume than when estimated using swap market volume, while we would anticipate that β_1 is closer to zero and less likely to be statistically different from zero when estimated using swap market volume.

In Table 3, we therefore present results for the main regression specifications but replacing aggregate volume with spot, forward, and swap market volume, respectively. The coefficient estimates for β_2 display a clear declining pattern in absolute terms, ranging from 0.17 (significant at the 1% level) for spot volume, 0.07 for forward volume (significant at the 5% level), and 0.01 (statistically insignificant) for swap volume. Moreover, β_1 coefficients are increasing in value, displaying a negative and highly statistically significant value for spot volume but a coefficient not statistically different from zero for swap volume. These patterns are thus consistent with a higher degree of privately informed trading taking place in instruments that are known to be traded more extensively by informed agents, and thus provide further support to the prediction that, as asymmetric information declines, the continuation impact of traders' superior information on future returns wanes. In Internet Appendix Tables C.2, C.3, and C.4, we provide evidence that estimates of β_1 and β_2 coefficients across spot, forward, and swap volume are also consistent across different groups of currency pairs.

5.2 FX Volume in a Currency Investment Strategy

The above analysis indicates that FX volume reveals a predictable component in currency returns: if volume is abnormally low today, the expected currency return tomorrow is high (low) if today's return is negative (positive).[26] A return reversal strategy should therefore perform well when suitably conditioned on the level of FX volume, such that the strategy is implemented using only currency pairs with abnormally low levels of volume. We build on this insight by taking the perspective of an investor interested in understanding whether FX volume is economically valuable once incorporated within a currency investment strategy.

Constructing a reversal strategy can be achieved most transparently via either a simple cross-sectional or time-series strategy. Cross-sectional strategies are common in currency-based research and have been found to offer large returns when portfolios are formed according to various signals, including carry (Lustig, Roussanov, and Verdelhan, 2011), value (Menkhoff et al., 2017), momentum (Menkhoff et al., 2012b), and volatility risk premia (Della Corte, Ramadorai, and Sarno, 2016). Recent evidence has highlighted that time-series portfolios, which implement trading signals on assets individually (rather than relative to one another), can be equally effective and possibly generate quite different return profiles (Moskowitz, Ooi, and Pedersen, 2012; Menkhoff et al., 2012b; Baz et al., 2015).[27] We therefore begin by exploring the properties and performance of a cross-sectional portfolio strategy before turning to the time-series approach.

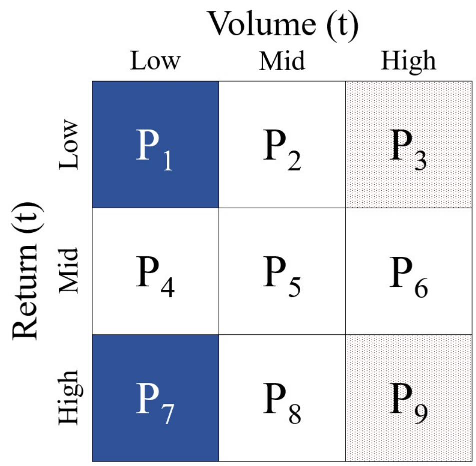
Cross-sectional Portfolios. A cross-sectional strategy that incorporates information in both FX volume and past returns can be achieved via a conditional double sort. In Exhibit A, we provide a graphical depiction of the double sort procedure. Currency pairs are initially allocated each day into three groups (from low to high) conditional on their returns over the previous 24 hours (in which the return is measured from the perspective of the base currency). Within these groups, the currency pairs are then allocated into a further three sub-groups (from low to high) conditional on volume ($v_{i,t}$) over the previous 24 hours. We thus form nine portfolios that are rebalanced daily. Reversal strategies are formed by taking long positions in low return currencies and short positions in high return currencies across the low ($P_1 - P_7$) and high ($P_3 - P_9$) volume groups. We denote these portfolios the low and high volume reversals in the cross section (LV R_{CS} , HV R_{CS}). The previous empirical analysis suggests that the LV R_{CS} portfolio should generate stronger investment performance than the HV R_{CS}

[26]From Table 2 we observe that the estimated marginal effect of returns at time t on t+1 equals $-0.025 + 0.181v_{i,t}$. It follows that when volume is abnormally low ($v_{i,t} < 0$), the expected currency return is high when today's return is negative and vice versa if the return today is positive.

[27]The difference between the two approaches has been analytically decomposed by Goyal and Jegadeesh (2018). See also Georgopoulou and Wang (2016) and Huang et al. (2019), who further investigate the additional benefits of time-series momentum originally documented by Moskowitz, Ooi, and Pedersen (2012).

Exhibit A

3×3 Conditional Double Sort



strategy.

In Table 4, we report summary statistics for the nine portfolios formed from the conditional double sort. Three results stand out. First, the majority of portfolio returns are not statistically significantly different from zero, and thus sorting on past returns is not mechanically guaranteed to generate a positive return. In fact, apart from the two LV R_{CS} portfolios, only P_2 (low return, mid volume) generates a statistically significant return. Second, the turnover of the portfolios is high. On average, each portfolio exhibits over 80% turnover each day, and thus no single currency pair dominates any of the portfolios. Third, the standard deviation and average bid-ask spread is similar across all portfolios and thus the cross-sectional dispersion in average returns does not appear to be driven by differences in volatility or liquidity.

In Panel A of Table 5 we report results on the reversal strategy returns when employing all 31 currency pairs. The LV R_{CS} portfolio delivers a high excess return. The out-of-sample annualized average return is 17.6%, which is statistically different from zero at the one percent significance level. In contrast, the return of the HV R_{CS} portfolio is only about 4.0% and not statistically distinguishable from zero. The relatively strong performance of the LV R_{CS} strategy is also clear when computing Sharpe ratios. The LV R_{CS} Sharpe ratio is 1.70, which is statistically larger than the 0.34 Sharpe ratio generated by the HV R_{CS} strategy.[28] While the Sharpe ratio is commonly used to assess investment

[28]We test whether two Sharpe ratios are statistically different using the procedure proposed by Ledoit and Wolf (2008). We thank Michael Wolf for kindly making the code available on his website at www.econ.uzh.ch/en/people/faculty/wolf.

performance, it exhibits certain drawbacks. For example, the statistic does not take into account the effects of non-normality (Jondeau and Rockinger, 2012), which may be particularly important in a small-sample setting. We therefore also report the theta (Θ) performance measure proposed by Ingersoll et al. (2007), which re-estimates the sample mean by putting less weight on outlier returns. We show that for both strategies, Θ is only slightly lower than the average return, indicating that neither outliers nor non-normality are driving the strategies' returns, which is further confirmed in the cumulative returns reported in Figure 3 that show a steadily increasing pattern over the sample.

Panel A also reports the equivalent results for strategies formed using the volume for each individual FX instrument. We find the performance of the LV R_{CS} strategy is always superior, especially when replacing total volume with either spot or outright forward volume. The results when conditioning on swap volume are slightly weaker, which is consistent with the earlier panel regression results.

Incorporating Transaction Costs. The majority of trading strategies proposed in the FX literature are rebalanced monthly and thus the issue of transaction costs has been largely innocuous (see e.g., Lustig, Roussanov, and Verdelhan, 2011, 2014; Menkhoff et al., 2012b, 2017). The volume strategy we propose, however, requires daily rebalancing and thus transaction costs may have a material impact on the returns available to investors. Researchers have typically used the average of dealer quoted spreads recorded at 4pm in London by WM/R. These quoted spreads are much higher than the effective spreads actually paid in the FX market, and thus much of the literature has employed an arbitrary scaling of 50% of the quoted bid-ask spread to proxy for the effective spread available (e.g. Menkhoff et al., 2012b, 2017). Even this number has been viewed as conservative. Gilmore and Hayashi (2011), for example, find bid-ask spreads are likely much lower than 50% of the quoted spread for emerging market currencies.

We therefore investigate transaction costs using a variety of alternative sources of FX data including (i) inter-dealer quotes provided by Olsen Financial Technologies (Olsen), the leading provider of interbank FX quotes; (ii) proprietary quoted spreads charged on the single-bank platform of a large global bank (the identity of which we keep anonymous for confidentiality purposes); and, (iii) quoted spreads from the retail aggregator platform of Dukascopy Bank (Dukascopy), a Swiss based FX broker that services active traders, hedge funds, and banks. The data from Olsen and Dukascopy is hourly and covers the full sample. The data from the global bank is available as an average quote across

London trading hours (9am to 5pm) for a portion of our sample. Figure 4 displays the daily median bid-ask spread (as a percentage of the mid price) across currency pairs at 4pm for WM/R, Olsen, and Dukascopy. The time-series pattern is similar across each series—falling during the second half of 2013 before rising and then falling again at the start of 2015. The level of spreads is, however, markedly different across the series. While Olsen and Dukascopy spreads largely overlap, WM/R spreads are substantially higher. From 2014 to the end of 2017, the median spread was around 0.05% according to the WM/R data, but only around 0.01% according to the Olsen and Dukascopy data. Indeed, it appears that even a 50% scaling of the WM/R spread is still around twice the actual market spread.[29]

The results from incorporating Olsen bid-ask spreads are reported in Panel B of Table 5. As expected, transaction costs reduce the profitability of the LV R_{CS} strategy. When forming portfolios using total volume, we observe a reduction in the annualized out-of-sample mean return of around 7.6%. Nevertheless, the net return is still high (10%) and statistically significant at the 5% level. Moreover, the Sharpe ratio remains over 0.90. In contrast, the average return to the HV R_{CS} strategy turns negative, indicating that there are no economic gains from conditioning on high volume. Furthermore, the values for theta confirm that non-linearities and outliers are not driving the result. Compared to the results reported in Panel A, the differences between FX instruments are more apparent. The average returns to the LV R_{CS} strategy are significantly higher than the returns to the HV R_{CS} strategies when conditioning on spot and forward volume but not when conditioning on swap volume, consistent with swap volume containing less information about future currency returns.[30]

Time-series Portfolios. We construct daily time-series portfolios by entering return reversal strategies on all currency pairs with abnormally low volume, which we define as having a negative level of abnormal volume ($v_{i,t} < 0$). The number of currency pairs entering the strategy therefore varies

[29]In Table B.2 of the Internet Appendix, we provide a currency-by-currency breakdown of the average bid-ask spread at 4pm for WM/R and Olsen (columns one and two). In the third column we report the ratio of the average spread from WM/R and Olsen. On average, Olsen spreads are 22% the level of WM/R spreads, although the ratio varies from a low of 0.14 for EURJPY to 1.76 for EURDKK (which is the only currency pair in which Olsen spreads are larger than WM/R). In contrast the ratio of the average spreads between Olsen and the global bank and between Olsen and Dukascopy equal 0.95 and 1.01, respectively. We conclude that, at least for strategies covering recent years, a WM/R 50% scaling likely overstates the best bid-ask spreads an investor can expect when adopting a currency strategy, whereas a scaling coefficient closer to 25% more accurately reflects the best bid-ask spread faced by currency investors.

[30]We are unable to incorporate all transaction costs, since we rely on the best bid-ask spreads, at which only a finite amount of liquidity is available. Additional costs include price “slippage” and wider spreads being charged when transaction sizes are particularly large. Both of these effects would lower our reported returns and should be incorporated by market participants. Nonetheless, our returns should still provide a fair reflection of the returns available to many market participants whose trades do not have a large price impact.

over time and is higher (lower) when, on average, the aggregate level of FX volume is low (high). We refer to the strategy as the Low Volume Reversal in the time-series (LV R_{TS}). For comparison, we also construct the alternative High Volume Reversal (HV R_{TS}) strategy, in which reversal positions are entered on all currency pairs exhibiting an abnormally high level of volume over the day ($v_{i,t} > 0$).

Results are reported in Table 6. In Panel A, we present results for the full sample of 31 currency pairs. Across all measures of volume the LV R_{TS} portfolio generates a lower average return than the LV R_{CS} portfolio, but an equally high Sharpe ratio. The Sharpe ratio is again highest for total volume (1.68) and lowest for swap volume (1.19), while the average returns are considerably larger than those generated by the HV R_{TS} strategy. After transaction costs the average returns are weaker, which reflects the high cost associated with rebalancing the entire portfolio each day. However, we find that when we restrict the sample to only the most liquid currency pairs, including the G9 currencies traded against the U.S. dollar, and the highly traded EUR crosses, including EURGBP, EURJPY, EURCHF, EURNOK and EURSEK, the after cost performance remains impressive (see Panel B of Table 6).[31] The after cost average returns are all statistically significantly different from zero, while the Sharpe ratios remain high, ranging from 0.69 for swap volume to 1.17 for spot volume.

5.3 Diversification with FX Volume

The high returns to the LV R strategies raise the prospect that global currency investors can enhance the investment performance of their portfolios by conditioning on FX volume. We therefore analyze the performance of a currency portfolio that combines standard currency market portfolios including carry, value, momentum, and dollar strategies, before including the LV R_{CS} and LV R_{TS} strategies.[32] We rebalance the portfolios monthly. In Panel A of Table 7, we present descriptive statistics for the previously documented currency strategies during our sample period. Carry was the best performer, generating an annualized return of 3.26% and Sharpe ratio of 0.48. Momentum and value strategies were less successful. In fact, the momentum portfolio generated a negative return over the period. The

[31]The G9 currencies include the Australian dollar (AUD), British pound (GBP), Canadian dollar (CAD), euro (EUR), Japanese yen (JPY), New Zealand dollar (NZD), Norwegian krone (NOK), Swedish krona (SEK), and Swiss franc (CHF).
[32]The portfolios are formed by first sorting currencies by either forward premia (carry), past three-months exchange rate returns (momentum) or deviations from the real exchange rate (value) before constructing an equally weighted high-minus-low (top-3 minus bottom-3) strategy. The "dollar" portfolio allocates equal weight to all currencies against the U.S. dollar. We use the after-cost LV R strategies and include the LV R_{TS} strategy calculated using liquidly traded currency pairs. We build value portfolios following Asness, Moskowitz, and Pedersen (2013).

U.S. dollar appreciated strongly since 2014, which accounts for the underperformance of the dollar strategy. In the third and fourth rows, we show the monthly correlations between the returns to these strategies and to the LVR_{CS} and LVR_{TS} portfolios. In each case the correlation is low, indicating that substantial diversification benefits could arise from adding the strategies to existing portfolios.

In Panel B, we begin by presenting the investment performance of three currency portfolios that combine carry, value, momentum, and dollar strategies: an equally weighted portfolio (EW), a global minimum variance portfolio (MV), and the mean-variance tangency portfolio (TG).[33] The Sharpe ratios are found to fluctuate between 0.07 for the naive equally weighted strategy to 0.60 for the tangency portfolio. These values are dwarfed, however, when we include either or both the LVR_{CS} and LVR_{TS} strategies. For the equally weighted portfolio, the Sharpe ratio increases to 0.76 when adding both LVR_{CS} and LVR_{TS} strategies. In the case of the optimized tangency portfolios, the inclusion of the LVR strategies almost doubles the Sharpe ratio. Overall, these results point towards FX volume providing a novel source of diversification for currency investors.

5.4 Robustness of the LVR_{CS} Strategy

We test the robustness of the LVR_{CS} strategy in various ways. Specifically we consider: (i) alternative trading times; (ii) alternative trading costs; (iii) end-of-the-month and end-of-the-quarter effects; (iv) alternative measures of unexpected volume; (v) portfolios involving only USD pairs; (vi) the consistency of the result across different sub-samples of currency pairs; and (vii) small sample estimation problems. All results are presented in Internet Appendix Section D, where we concentrate on the LVR_{CS} returns but find similar (unreported) results for the LVR_{TS} strategy.

[33] The equally weighted portfolio simply assigns 25% weight to each strategy every month. The global minimum variance portfolio is the portfolio with the lowest return volatility, representing the solution to the following optimization problem: $\min w'\Sigma w$ subject to the constraint that the weights sum to unity $w'\iota = 1$, where w is the $N \times 1$ vector of portfolio weights on the risky strategies, ι is a $N \times 1$ vector of ones, and Σ is the $N \times N$ covariance matrix of the strategies' returns. The weights of the global minimum variance portfolio are given by $w = \frac{\Sigma^{-1}\iota}{\iota'\Sigma^{-1}\iota}$. The tangency portfolio maximizes the Sharpe ratio, the weights for which are given by $w = \frac{\Sigma^{-1}\mu}{\iota'\Sigma^{-1}\mu}$ where μ is the $N \times 1$ vector of expected strategy returns. We compute the optimal weights across our entire sample.

6 Additional Analysis

In this section, we undertake two additional analyses. First, we investigate if the predictive information in FX volume is novel or common to other variables that correlate with volume. Second, we analyze if the CLS volume data is uniquely valuable or whether the predictive information could have been extracted from other available datasets.

6.1 How important is FX volume?

We investigate the novelty of the predictive information in FX volume in two ways. We begin by comparing the information with that contained in order flow, which is a closely related variable constructed from trading data that has also been found to contain predictive information for future exchange rate returns. We then expand the analysis and consider the relationship between FX volume and a large set of theoretically motivated macroeconomic and financial variables in multivariate regressions. This second test allows us to extract the "unexplained" (i.e. residual) component of volume and compare it in predictive regressions with the "explained" (i.e. fitted) component of volume to assess the underlying source of the predictive information stemming from FX volume.

6.1.1 Order flow

Order flow is "signed" volume, calculated as total buyer-initiated minus seller-initiated volume. Evans and Lyons (2002) find in their seminal study that FX returns are highly correlated with contemporaneous order flow from Thomson Reuters interdealer market, while Rime, Sarno, and Sojli (2010) show that order flow from the same interdealer platform also predicts next-day FX returns. More recently, Menkhoff et al. (2016) present more granular evidence that order flow predicts FX returns. Specifically, they show that high order flow (i.e. more buyer than seller initiated flow) predicts a continuation in the exchange rate and that the effect is amplified when the order flow is constructed using only orders of more informed-type agents, such as buy-side investors. It is natural to question, therefore, whether volume is capturing similar predictive information to order flow, and thus if the LV R strategies are simply relabeling existing order flow based strategies. We investigate this possibility by obtaining a smaller dataset on order flow from CLS. The dataset covers around one-third of the trades in our larger volume dataset and begins one year later, but is available for the same 31 currency pairs in our study. Further details on the data can be found in the recent paper by Ranaldo and Somogyi (2021).

To begin the comparison we first construct a measure of volume using the order flow dataset, i.e. we add, rather than subtract, the dollar amount of buyer and seller initiated orders. This first step allows us to assess if the order flow dataset is representative of our larger dataset on volume. We present correlations between volume and order-flow-implied volume, for each currency pair, in Table E.1 of the Internet Appendix. The majority of correlations are high, and typically over 80%. Indeed, the average correlation across all 31 currency pairs is 89%. In the remaining columns of Table E.1, we present the correlations between volume and order flow—split across different customer types, including “funds”, “non-bank financials”, and “corporates”, and with the aggregate of all buy-size order flow. In contrast to the previous result, relationships are all weak, with correlations all close to zero. Indeed, across the four groups of order flow, the average correlation ranges from only -0.3% to 1.3%, supporting the assertion that order flow and volume are orthogonal.

While the two underlying series are unrelated, it is still possible that the economic information in the LV R strategies is related to that contained in order flow. We test this possibility by forming an order flow strategy following Menkhoff et al. (2016). To do so, we first calculate order flow for all U.S. dollar currency pairs, rank them from high to low, and split them into three equally sized groups. We then form a simple zero-cost, high-minus-low, portfolio that is equally long all currencies in the highest order flow group, and equally short all currencies in the lowest order flow group. We rebalance the portfolio each day.

In Figure 5, we plot the cumulative returns to the order flow strategy when constructed using either “fund” or “corporate” order flow. As noted earlier, Menkhoff et al. (2016) find the strategy generates stronger investment performance when constructed using the order flow of more informed type agents. Consistent with this result, we find the strategy conditioned on “fund” order flow that includes hedge fund trades, generates an impressive Sharpe ratio of 1.41 over the sample period. In contrast the strategy conditioned on “corporate” order flow generates a Sharpe ratio of -0.16.

If the “funds” strategy contains similar predictive information to that contained in volume, we would anticipate the returns of the two strategies to be strongly and positively correlated. Instead, we find the correlation with the LV R_{CS} strategy is only -1.2%. The correlation is also similarly weak, equal to 6.5%, with the LV R_{TS} strategy. The return profile and information content of the strategies are thus quite different, reinforcing the point that volume and order flow are distinct and reflect quite different predictive information content.

6.1.2 The relationship between FX volume and other economic and financial variables

We investigate the relationship between FX volume and various economic and financial variables in a series of panel regressions. We emphasize that the purpose of this analysis is not to prove causality, but to determine how much of the variability in volume is explainable, and hence whether the predictability we document stems from the unexplained component of volume. Specifically, we consider the following model:

$$v_{i,t} = \log(V_{i,t}) = \alpha_i + \beta v_{i,t-1} + \sum_{k=1}^{K} \gamma_k X_{ik,t} + \tau_t + \varepsilon_{i,t} \tag{27}$$

where $V_{i,t}$ is the volume (either spot, forward, or swap) of currency pair i at time t, $X_{k,t}$ is the value of the independent variable k at time t. We include variables on volatility, liquidity, macroeconomic news announcements, order flow, and other asset returns. Finally, β and γ_k denote coefficients. We include time (τ) and currency-pair (α) fixed effects and cluster standard errors across time and currency-pair dimensions. In the Internet Appendix Section F we provide a full list of all the predictor variables we consider and the theoretical motivation for their inclusion in the model.

We report panel regression results in Table 8. To ease the comparison across coefficients, we standardize the regressors to have zero mean and unit variance.[34] The first 12 columns report results for total volume in which we include only lagged volume and one independent variable, while the last four columns report results from multivariate regressions that include all regressors, both for total volume and separately for spot, forward, and swap market volume. The three proxies for volatility are, as expected, all positively related to FX volume, with the effect being highly statistically significant for spot and forward volume. The number and total relevance of U.S. macroeconomic data announcements is also found to be strongly positively related to FX spot volume although the sign and significance of the relationship is mixed across forward and swap markets. We also find that high levels of liquidity are associated with higher FX volume. Finally, equity and bond market return differentials are strongly

[34]It follows that for every one standard deviation change in a regressor, the percentage change in FX volume is given by $100(e^{\zeta} - 1)$, where ζ is the reported coefficient in Table 8.

related to FX spot and forward volume levels. In the multivariate regressions we observe a clear dispersion in adjusted R-square statistics across spot, forward, and swap volume. For spot volume the adjusted R-square is 33%, but is only 10% for swap volume, reflecting the fact that only seven variables have a significant relationship with swap volume at the 90% confidence level (relative to 11 for spot volume).

The important question stemming from this analysis is whether the fitted values from these regressions explain the previously documented predictability between volume and currency returns. To answer this question we re-run our earlier regressions reported in Tables 2 and 3, replacing volume with either the residuals or fitted component of volume. The results are reported in Table 9. We find the estimates of β_2 are always qualitatively identical to the previous estimates when we replace volume with the residuals, i.e. the unexplained component of volume. In contrast, we do not observe any relationship between currency returns and the fitted (or explained) value of volume across total, spot, forward, or swap volume—none of the coefficients are statistically different from zero—indicating that the predictive information we uncover is driven by novel information in FX volume.

6.2 How important is CLS volume?

The data on FX volume became available from CLS in 2016. A potential concern is that, until 2016, the LV R strategies were unavailable to market participants. While true that the CLS data were not publicly disseminated, alternative data on volume were available in the market. In particular, the largest dealers in the FX market observe a large and potentially representative share of volume, and could thus extract the information from the trades they intermediate. Moreover, FX volume data are available from interbank order books. One of the major interbank platforms is operated by Thomson Reuters (Thomson Reuters Dealing), from which we obtain a daily dataset from 2011 to 2015 for 13 currency pairs including: EURUSD, USDJPY, GBPUSD, AUDUSD, USDCAD, USDCHF, USDSGD, USDILS, USDZAR, USDMXN, NZDUSD, EURNOK, and EURSEK.

In Table 10 Panel A, we report the correlations between the normalized daily spot volume from CLS and Thomson Reuters. The correlations are generally high and above 90% for over half the sample, and below 50% only for USDCHF. In Panel B, we report statistics on the rank correlations across the two samples. Specifically, each day we calculate the correlation in the ranking obtained by sorting pairs by the CLS and Thomson Reuters volume and report the time-series average. We also report values for various percentiles of the distribution. The mean and median are high, estimated to be 67% and 72% respectively, confirming that the alternative dataset provides similar information to that contained in the dataset from CLS.

Using the Thomson Reuters Dealing data, we construct the LV R_{CS} and HV R_{CS} strategies. In Panel C, we report the investment performance. The LV R_{CS} strategy generates a return of 13.5% and Sharpe ratio of 1.01, which compares favorably with the HV R_{CS} strategy that generates a return and Sharpe ratio essentially equal to zero. However, when we construct the equivalent portfolios—same time-period and currency pairs—using the data from CLS, we find the return and Sharpe ratio of the LV R_{CS} strategy increase substantially to 22.7% and 1.65, which are both statistically larger than the equivalent statistics for the HV R_{CS} strategy. The correlation between the two LV R_{CS} strategies is high, albeit not perfect, at 70%.

These results are important in two respects. First, they highlight that market participants could have extracted information from alternative sources of data. While CLS data only became available in 2016, FX volume was informative about future currency returns and sizeable investment returns were available across our entire sample. Second, it is clear that obtaining the most comprehensive dataset on FX volume is valuable: the data from CLS covers a more comprehensive and diverse set of trades, which is reflected in the stronger overall investment performance.

7 Conclusions

Given the FX market's decentralized OTC structure, researchers' ability to study the properties and information content of FX volume has been hampered by a sparsity of data. In this paper we use a novel dataset to investigate the information contained in FX volume across a large cross-section of currency pairs. We find that volume helps forecast next-day currency returns: when volume is abnormally low for a given currency pair, we typically observe a return reversal over the following day. We explain the findings via a simple equilibrium model of exchange rate determination with information asymmetry. The model generates a predictive relationship between FX volume and currency returns, and further implies that the nature of the predictive relationship is informative about the degree of information asymmetry in currency markets. Our empirical findings are consistent with the level of informed trading being uniformly high across currency pairs but varying across FX instruments—higher levels being observed in the spot and forward markets compared to the swap market.

Overall, the results shed new light on currency markets and, in particular, on the nexus between FX volume and currency returns. Given these results, future empirical work could analyze individual OTC trades to provide a clearer understanding of the sources and timing of privately informed trades and their relationship, more broadly, with volatility and liquidity. For theorists, a better understanding of how the strategic interaction between dealers and (possibly informed) customers impacts volume, within a large decentralized network, appears to be a fruitful direction forwards.

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Table 1: Summary Statistics

Panel A: Summary Statistics Across Foreign Exchange Instruments and Currency Pairs

	Total		Spot			Forward			Swap		
	Mean	Std dev	Mean	Std dev	$\overline{\text{Trade}}$	Mean	Std dev	$\overline{\text{Trade}}$	Mean	Std dev	$\overline{\text{Trade}}$
G9 USD pairs											
EURUSD	500.54	85.30	158.89	51.62	1.27	23.33	16.63	8.37	318.32	61.63	128.55
USDJPY	248.11	62.45	91.26	38.59	1.07	10.93	8.42	5.57	145.93	36.74	110.85
GBPUSD	189.74	34.68	51.00	15.27	1.22	9.32	7.51	5.75	129.42	27.28	113.10
AUDUSD	121.15	27.09	42.16	14.42	0.90	5.54	2.37	3.78	73.45	16.25	73.70
USDCHF	87.04	16.91	15.55	5.32	0.95	3.22	2.80	5.21	68.27	14.31	114.09
USDCAD	82.76	16.21	43.91	9.34	1.44	5.58	2.38	3.30	33.27	10.39	64.16
NZDUSD	32.84	7.97	10.86	3.98	0.71	1.88	1.05	1.48	20.09	4.99	27.30
USDSEK	28.41	7.14	2.91	1.07	1.02	1.15	1.08	2.28	24.34	6.54	69.25
USDNOK	22.78	4.99	2.54	0.93	1.07	0.92	0.60	1.90	19.32	4.57	68.85
Other USD pairs											
USDMXN	28.06	6.79	11.34	3.77	1.01	2.16	0.90	3.67	14.56	3.67	33.39
USDHKD	27.17	7.39	6.21	2.12	1.86	0.73	0.50	7.03	20.23	5.93	60.80
USDSGD	26.83	5.88	8.61	3.05	1.20	1.29	0.61	3.10	16.93	3.91	43.42
USDZAR	20.60	4.49	6.96	2.17	0.95	1.17	0.46	2.36	12.47	3.09	26.51
USDKRW	17.27	3.57	7.89	1.86	1.82	0.39	0.42	30.48	9.00	2.23	55.27
USDDKK	14.42	3.61	0.73	0.48	1.63	0.32	0.35	4.29	13.37	3.48	69.15
USDILS	4.39	1.41	1.30	0.58	1.62	0.29	0.20	2.51	2.80	0.98	27.65
EUR pairs											
EURGBP	35.03	8.02	15.62	4.71	1.11	3.36	1.74	7.41	16.05	4.85	51.41
EURJPY	23.40	9.60	16.54	8.94	0.88	1.45	1.24	5.89	5.41	2.36	34.14
EURCHF	22.41	7.67	9.56	5.22	1.16	1.45	1.02	7.58	11.39	3.76	52.79
EURSEK	10.06	3.09	6.42	2.14	1.12	0.83	0.47	3.81	2.81	1.35	24.59
EURNOK	8.14	2.62	5.65	1.97	1.10	0.58	0.39	2.94	1.91	1.01	22.19
EURAUD	5.75	2.00	3.51	1.32	0.82	0.56	0.44	4.36	1.68	1.17	19.54
EURDKK	5.17	2.42	2.31	1.04	2.96	0.30	0.38	10.36	2.56	1.67	57.49
EURCAD	3.57	1.24	1.84	0.65	0.77	0.35	0.33	3.28	1.38	0.81	22.13
GBP pairs											
GBPJPY	6.17	2.67	4.38	2.12	0.70	0.49	0.65	4.04	1.30	0.99	25.99
GBPCHF	2.15	0.92	0.66	0.34	0.61	0.19	0.29	3.90	1.31	0.72	32.68
GBPAUD	1.97	0.79	1.13	0.49	0.64	0.29	0.27	3.55	0.54	0.44	13.77
GBPCAD	1.41	0.71	0.72	0.43	0.64	0.18	0.27	3.21	0.50	0.42	17.60
Other pairs											
AUDJPY	5.29	1.89	4.28	1.72	0.54	0.42	0.30	3.48	0.58	0.40	14.40
AUDNZD	3.04	1.30	2.36	1.04	0.66	0.35	0.23	1.71	0.33	0.39	3.45
CADJPY	0.91	0.47	0.58	0.30	0.36	0.12	0.21	3.09	0.21	0.21	14.29

Panel B: Correlations Between Foreign Exchange Instruments

	Spot and Forward	Forward and Swap	Spot and Swap
Correlation (%)	40	21	21

The table presents summary statistics on FX volume. Panel A presents statistics for each currency pair across spot, forward, swap, and total (the sum of spot, forward, and swap) volume. The statistics Mean and Std dev denote the sample mean and standard deviation of volume (in \$ billions). $\overline{\text{Trade}}$ denotes the average trade size, computed as the ratio of dollar volume to the number of trades (in \$ millions). Panel B displays the average pairwise correlation (in percent across all currency pairs) between the three FX instruments.

Table 2: Foreign Exchange Volume and Currency Excess Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
				Volume		Bid-Ask Spread		Volatility			
		All Pairs		High	Low	High	Low	High	Low	USD	EUR
$Return_t$	-0.005	-0.025*	-0.025*	-0.030*	-0.031*	-0.031*	-0.034**	-0.028	-0.045***	-0.033*	-0.103***
	(0.022)	(0.015)	(0.015)	(0.018)	(0.017)	(0.019)	(0.015)	(0.019)	(0.015)	(0.018)	(0.018)
$Volume_t$	-0.009	-0.010	-0.010	-0.052	-0.007	0.015	-0.011	0.063	-0.017	-0.011	-0.037
	(0.011)	(0.011)	(0.011)	(0.040)	(0.011)	(0.040)	(0.010)	(0.046)	(0.010)	(0.011)	(0.045)
$Return_t * Volume_t$		0.180***	0.181***	0.272***	0.123***	0.127***	0.276***	0.132***	0.242***	0.168***	0.274***
		(0.058)	(0.058)	(0.077)	(0.043)	(0.043)	(0.075)	(0.048)	(0.078)	(0.058)	(0.090)
Controls	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj-R^2	0.02	0.02	0.02	0.02	0.03	0.04	0.02	0.04	0.03	0.03	0.10
Nobs	46,199	46,199	46,199	22,379	23,820	22,379	23,820	22,379	23,820	23,820	13,428

e table presents coefficient estimates and associated double-clustered standard errors (reported in parentheses) for the following fixed el regression:

$$r_{i,t+1} = \alpha_i + \tau_t + \beta_1 r_{i,t} + \beta_2 \left(r_{i,t} v_{i,t} \right) + \beta_3 v_{i,t} + \gamma' x_{i,t} + \epsilon_{i,t+1},$$

ere α_i and τ_t denote currency-pair and time fixed effects, $r_{i,t}$ is the log currency excess return for currency pair i at time t, $v_{i,t}$ is the (log) iation of total volume (sum of spot, forward and swap) from its recent trend, defined as $v_{i,t} = \log(Volume_{i,t}) - \log\left(\frac{1}{21}\sum_{s=1} Volume_{i,t-s}\right)$, $x_{i,t}$ is tor of controls relative to pair i and $\epsilon_{i,t+1}$ is the model error term. The values reported in columns (1) to (3) are based on all 31 currency pair sample while in columns (4) to (9) currency pairs are split based on median Volume (columns 4 and 5), median Bid-Ask spread (columns 6 nd median Volatility (8 and 9). The values reported in columns (10) and (11) are calculated for samples including only USD and EUR-base pa efficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 3: Foreign Exchange Volume and Currency Excess Returns

	(1) Spot	(2) Forward	(3) Swap
$Return_t$	-0.039***	-0.009	-0.003
	(0.015)	(0.019)	(0.021)
$Volume_t$	-0.002	-0.004	-0.012
	(0.011)	(0.009)	(0.012)
$Return_t * Volume_t$	0.170***	0.065**	0.012
	(0.057)	(0.030)	(0.023)
Controls	YES	YES	YES
adj-R^2	0.02	0.02	0.02
Nobs	46,199	46,199	46,199

The table presents coefficient estimates and associated double-clustered standard errors (reported in parentheses) for the following fixed-effects panel regression:

$$r_{i,t+1} = \alpha_i + \tau_t + \beta_1 r_{i,t} + \beta_2 \left(r_{i,t} v_{i,t} \right) + \beta_3 v_{i,t} + \gamma' x_{i,t} + \epsilon_{i,t+1},$$

where α_i and τ_t denote currency-pair and time fixed effects, $r_{i,t}$ is the log currency excess return for currency pair i at time t, $v_{i,t}$ is the (log) deviation of volume from its recent trend, defined as $v_{i,t} = \log(Volume_{i,t}) - \log\left(\frac{\sum_{s=1}^{21} Volume_{i,t-s}}{21}\right)$, $x_{i,t}$ is a vector of controls relative to pair i and $\epsilon_{i,t+1}$ is the model error term. Results in columns (1), (2) and (3) are based on Spot, Forward and Swap volume respectively. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 4: Double-Sorted Currency Portfolios

	Low Past Returns			Mid Past Returns			High Past Returns		
	Low Volume P1	Mid Volume P2	High Volume P3	Low Volume P4	Mid Volume P5	High Volume P6	Low Volume P7	Mid Volume P8	High V F
ean (%)	10.01***	4.95*	2.60	-1.20	2.31	-1.03	-7.59***	-1.52	-1
R	1.46	0.75	0.39	-0.22	0.46	-0.24	-1.26	-0.23	-0
d (%)	6.84	6.55	6.75	5.57	5.04	4.38	6.05	6.58	7
ew	0.47	0.28	-0.43	-2.99	-0.84	-0.48	-0.75	-0.81	-2
urt	6.6	6.7	15.7	48.8	19.9	7.2	9.4	11.3	5
c(1)	-0.03	-0.04	-0.04	0.01	-0.01	0.00	0.01	-0.04	-0
dd (%)	6.4	10.5	11.2	20.0	7.5	11.0	45.6	14.9	2
o (%)	87.8	88.8	81.6	82.7	86.6	77.6	84.6	83.8	8
d-ask (%)	0.014	0.013	0.014	0.014	0.013	0.013	0.014	0.013	0.

e table presents descriptive statistics for currency portfolios sorted by past returns and abnormal volume. Portfolios are rebalanced daily. ort the annualized mean, with the superscripts ***, **, * representing statistical significance of the portfolio return at the 1%, 5% and 1 nificance levels using Newey and West (1987) corrected standard errors. In addition we report the Sharpe ratio (SR), standard deviation (s wness (skew), kurtosis (kurt), first-order autocorrelation coefficient (ac(1)), the maximum drawdown (mdd), average turnover (t/o) and rage bid-ask spread (bid-ask) for each portfolio.

Table 5: Cross-Sectional Portfolios

Panel A: Portfolio Performance Excluding Transaction Costs

	Total			Spot		
	LV R_{CS}	HV R_{CS}	LMH	LV R_{CS}	HV R_{CS}	LMH
mean (%)	17.61***	3.95	13.66***	17.04***	3.25	13.79***
SR	1.70	0.34	1.36***	1.63	0.27	1.36***
Θ (%)	16.01	1.97		15.41	1.18	
MDD	9.02	19.06		6.81	18.73	

	Forward			Swap		
	LV R_{CS}	HV R_{CS}	LMH	LV R_{CS}	HV R_{CS}	LMH
mean (%)	16.99***	3.31	13.68***	13.64***	2.47	11.17***
SR	1.60	0.31	1.29***	1.28	0.24	1.04***
Θ (%)	15.31	1.58		11.94	0.83	
MDD	5.58	20.88		16.20	15.54	

Panel B: Portfolio Performance Including Transaction Costs

	Total			Spot		
	LV R_{CS}	HV R_{CS}	LMH	LV R_{CS}	HV R_{CS}	LMH
mean (%)	10.00**	-2.87	12.87***	7.27*	-2.08	9.35**
SR	0.91	-0.24	1.15***	0.66	-0.17	0.83**
Θ (%)	8.19	-5.06		5.48	-4.34	
MDD	17.50	39.69		18.98	36.55	

	Forward			Swap		
	LV R_{CS}	HV R_{CS}	LMH	LV R_{CS}	HV R_{CS}	LMH
mean (%)	9.53**	-3.46	12.99***	3.27	-1.04	4.31
SR	0.85	-0.30	1.15***	0.29	-0.09	0.39
Θ (%)	7.67	-5.45		1.39	-2.91	
MDD	14.02	38.55		32.52	28.01	

The table presents the out-of-sample economic performance of cross-sectional currency reversal strategies, excluding (Panel A) and including (Panel B) transaction costs. The LV R_{CS} strategy takes positions in currency pairs with abnormally low volume, with long positions in currencies which previously depreciated and short positions in currencies which previously appreciated. The HV R_{CS} strategy is the analogous strategy that takes positions in currency pairs with abnormally high volume. Results are reported separately for spot, forward, swap, and total (sum of spot, forward, and swap) volume. We report the annualized average return (mean), annualized Sharpe ratio (SR), 'theta' performance measure (Θ) proposed by Ingersoll et al. (2007), and the maximum drawdown (M DD). The values in the LMH column denote the difference between the annualized average return and Sharpe ratio between the LV R_{CS} and HV R_{CS} strategies. We test whether the individual annualized average returns (and their difference) are statistically different from zero with Newey and West (1987) adjusted t-statistics. We test whether the two Sharpe ratios are statistically different using the procedure proposed by Ledoit and Wolf (2008). Values marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 6: Time-Series Portfolios

Panel A: All Currency Pairs

	Total			Spot		
	LV R_{TS}	HV R_{TS}	LMH	LV R_{TS}	HV R_{TS}	LMH
$mean_{gross}$ (%)	6.85***	1.85	5.00***	5.17***	2.00	3.17*
SR_{gross}	1.68	0.43	1.25***	1.33	0.44	0.89**
$mean_{net}$ (%)	3.16*	-1.39	4.55***	1.55	-1.26	2.81
SR_{net}	0.73	-0.31	1.04***	0.38	-0.26	0.65

	Forward			Swap		
	LV R_{TS}	HV R_{TS}	LMH	LV R_{TS}	HV R_{TS}	LMH
$mean_{gross}$ (%)	5.68***	2.59*	3.09**	4.96***	2.71*	2.24
SR_{gross}	1.41	0.66	0.75**	1.19	0.69	0.50
$mean_{net}$ (%)	2.60	-1.07	3.67***	1.44	-0.86	2.30
SR_{net}	0.62	-0.26	0.88**	0.33	-0.21	0.54

Panel B: Most Liquid Currency Pairs

	Total			Spot		
	LV R_{TS}	HV R_{TS}	LMH	LV R_{TS}	HV R_{TS}	LMH
$mean_{gross}$ (%)	8.51***	5.96**	2.55	9.50***	5.33**	4.18
SR	1.60	1.00	0.60	1.81	0.93	0.88*
$mean_{net}$ (%)	5.04**	2.43	2.61	6.11***	1.79	4.33
SR	0.94	0.41	0.54	1.17	0.31	0.85

	Forward			Swap		
	LV R_{TS}	HV R_{TS}	LMH	LV R_{TS}	HV R_{TS}	LMH
$mean_{gross}$ (%)	8.54***	4.93**	3.61*	6.96***	5.39***	1.57
SR	1.62	0.96	0.66	1.35	1.03	0.32
$mean_{net}$ (%)	5.19**	1.37	3.81*	3.56*	1.87	1.69
SR	0.98	0.27	0.71*	0.69	0.36	0.33

The table presents the out-of-sample economic performance of time-series currency reversal strategies. The LV R_{TS} strategy takes positions in all currency pairs with abnormally low volume ($v_t < 0$), with long positions in currencies which previously depreciated and short positions in currencies which previously appreciated. The HV R_{TS} strategy is the analogous strategy that takes positions in all currency pairs with abnormally high volume ($v_t > 0$). Results are reported separately for spot, forward, swap, and total (sum of spot, forward, and swap) volume. We report the annualized average return (mean) and annualized Sharpe ratio (SR) before (gross) and after transaction costs (net). In Panel A, all 31 currency pairs could be included in the strategy. In Panel B, the set of currency pairs is reduced to include only the most liquid pairs, including the G9 pairs and liquid EUR crosses (see Section 5.2 for further details). The values in the LMH column denote the difference between the annualized average return and Sharpe ratio between the LV R_{TS} and HV R_{TS} strategies. We test whether the individual annualized average returns (and their difference) are statistically different from zero with Newey and West (1987) adjusted t-statistics. We test whether the two Sharpe ratios are statistically different using the procedure proposed by Ledoit and Wolf (2008). Values marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 7: Diversification Gains

Panel A: Common Currency Strategies

	CAR	DOL	MOM	VAL
mean (%)	3.26	-1.66	-2.41	1.83
SR	0.48	-0.26	-0.44	0.36
ρ_{CS}	-0.11	0.12	0.12	-0.02
ρ_{TS}	0.06	0.13	-0.10	0.13

Panel B: Diversification Gains

	ex. LVR Strategies			inc. LVR_{CS}		
	EW	MV	TG	EW	MV	TG
mean (%)	0.26	0.44	2.54	2.21	1.16	5.12
SR	0.07	0.14	0.60	0.60	0.40	1.11
$\omega_{LVR_{CS}}$ (%)				20.00	6.38	34.08

	inc. LVR_{TS}			inc. LVR_{CS} and LVR_{TS}		
	EW	MV	TG	EW	MV	TG
mean (%)	1.24	1.36	4.12	2.70	1.41	4.92
SR	0.40	0.50	1.04	0.76	0.52	1.17
$\omega_{LVR_{TS}}$ (%)	20.00	21.67	58.12	16.67	20.28	29.61
$\omega_{LVR_{CS}}$ (%)				16.67	0.96	20.86

The table presents results on the diversification benefits of the LVR_{CS} and LVR_{TS} strategies. Panel A presents summary statistics on the average annualized returns (mean) and Sharpe ratios (SR) of common currency strategies and their correlation with LVR_{CS} (ρ_{CS}) and LVR_{TS} (ρ_{TS}) strategies. The common currency strategies we consider include carry (CAR), dollar (DOL), momentum (MOM), and value (VAL) (see Section 5.2 for further details). In Panel B, we report the investment performance of broad currency portfolios that include the common currency strategies and LVR_{CS} and LVR_{TS} strategies. The portfolio weights are determined using an equal weighting scheme (EW), an estimation of optimal weights when minimizing the portfolio variance (MV), and an estimation of optimal weights at the tangency point (TG) on the efficient frontier. In the final two rows, we report the average weights allocated to the LVR_{CS} ($\omega_{LVR_{CS}}$) and LVR_{TS} ($\omega_{LVR_{TS}}$) strategies within each portfolio.

Table 8: Explaining Foreign Exchange Volume

	Total Volume													Spot	Forward	Swap
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
gged volume																
og(V_{t-1})	0.609***	0.614***	0.614***	0.613***	0.610***	0.613***	0.187	0.577***	0.192	0.611***	0.201	0.613***	0.161	0.231*	0.190***	0.261***
	(0.018)	(0.017)	(0.017)	(0.018)	(0.019)	(0.017)	(0.122)	(0.011)	(0.125)	(0.015)	(0.126)	(0.017)	(0.108)	(0.135)	(0.054)	(0.095)
latility																
$\|r_{FX}\|$	0.073***												0.061***	0.098***	0.088***	0.005
	(0.012)												(0.008)	(0.007)	(0.009)	(0.004)
VIX		0.060***											0.041***	0.034***	0.077***	0.045***
		(0.009)											(0.006)	(0.006)	(0.012)	(0.010)
VXY			0.096***										0.025**	0.078***	0.044**	-0.039**
			(0.017)										(0.012)	(0.016)	(0.017)	(0.018)
croeconomic news																
lacroeconomic announcements				0.008									-0.007***	0.013***	-0.009	-0.024***
				(0.005)									(0.002)	(0.003)	(0.006)	(0.004)
Relevance of announcements					0.030***								0.030***	0.033***	0.042***	0.029***
					(0.004)								(0.003)	(0.003)	(0.005)	(0.005)
uidity																
BA						-0.038***							-0.031*	-0.052***	-0.032	-0.015
						(0.011)							(0.016)	(0.015)	(0.023)	(0.019)
OrderF low|							0.067***						0.048***	0.090***	0.075***	0.017**
							(0.008)						(0.008)	(0.010)	(0.009)	(0.006)
TED								-0.030**					-0.019	-0.052***	-0.099***	-0.023
								(0.013)					(0.012)	(0.013)	(0.022)	(0.023)
der flow																
Order flow									0.004				0.003	0.004	-0.001	0.005
									(0.004)				(0.003)	(0.004)	(0.007)	(0.003)
rtfolio rebalancing																
$r_{mm,home} - r_{mm,foreign}\|$										0.049			0.015	-0.003	0.052*	-0.012
										(0.036)			(0.022)	(0.027)	(0.029)	(0.029)
$r_{bond,home} - r_{bond,foreign}\|$											0.019***		0.009***	0.016***	0.013***	0.001
											(0.003)		(0.002)	(0.003)	(0.004)	(0.004)
$r_{stock,home} - r_{stock,foreign}\|$												0.030***	0.011***	0.013***	0.010***	0.005*
												(0.005)	(0.002)	(0.003)	(0.003)	(0.003)
s	46,879	46,879	46,879	46,879	46,879	46,879	40,540	46,446	40,540	46,879	44,706	46,879	38,585	38,585	38,585	38,585
. R^2		0.18	0.17	0.17	0.17	0.17	0.16	0.15	0.14	0.17	0.14	0.17	0.23	0.33	0.12	0.10
		0.17														

table presents coefficient estimates and associated double-clustered standard errors (reported in parentheses) for fixed-effects panel regress laily (log) volume on a set of financial and economic variables. The independent variables are described in Internet Appendix Section F. endent variable in columns (1)-(13) is total volume (sum of spot, forward, and swap volume), while the dependent variables in columns (14) are spot, forward, and swap volume, respectively. The regressors are standardized to have zero mean and unit variance. Coefficients mar ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 9: Foreign Exchange Volume and Currency Excess Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Residuals				Fitted			
	Total	Spot	Forward	Swap	Total	Spot	Forward	Swap
$Return_t$	-0.007	-0.017	-0.002	0.008	-0.106	-0.221*	-0.170	-0.006
	(0.023)	(0.021)	(0.022)	(0.024)	(0.110)	(0.130)	(0.123)	(0.090)
$Volume_t$	-0.023	-0.001	-0.005	-0.029	-0.008	-0.049	0.020	0.079
	(0.037)	(0.032)	(0.013)	(0.024)	(0.072)	(0.058)	(0.040)	(0.059)
$Return_t * Volume_t$	0.131***	0.139***	0.052**	0.021	0.005	0.010	0.009	0.001
	(0.042)	(0.039)	(0.022)	(0.020)	(0.005)	(0.006)	(0.007)	(0.004)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
adj-R^2	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.02
Nobs	38,526	38,526	38,526	38,526	38,526	38,526	38,526	38,526

The table presents coefficient estimates and associated double-clustered standard errors (reported in parentheses) for the following fixed-effects panel regression:

$$r_{i,t+1} = \alpha_i + \tau_t + \beta_1 r_{i,t} + \beta_2 \left(r_{i,t} v_{i,t} \right) + \beta_3 v_{i,t} + \gamma' x_{i,t} + \epsilon_{i,t+1},$$

where α_i and τ_t denote currency-pair and time fixed effects, $r_{i,t}$ is the log currency excess return for currency pair i at time t, $x_{i,t}$ is a vector of controls relative to pair i and ϵ_{t+1} is the model error term. In columns (1) to (4), $v_{i,t}$ is the residual from regressions described in Section 5 while in columns (5) to (8) is the fitted value. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 10: A Comparison with Thomson Reuters Dealing

Panel A: Time-Series Correlations

G9 USD pairs		Other USD pairs		EUR pairs	
EURUSD	0.81	USDSGD	0.92	EURNOK	0.91
USDJPY	0.67	USDILS	0.73	EURSEK	0.90
GBPUSD	0.87	USDZAR	0.90		
AUDUSD	0.93	USDMXN	0.91		
USDCAD	0.89	NZDUSD	0.92		
USDCHF	0.40				

Panel B: Ranking Correlations

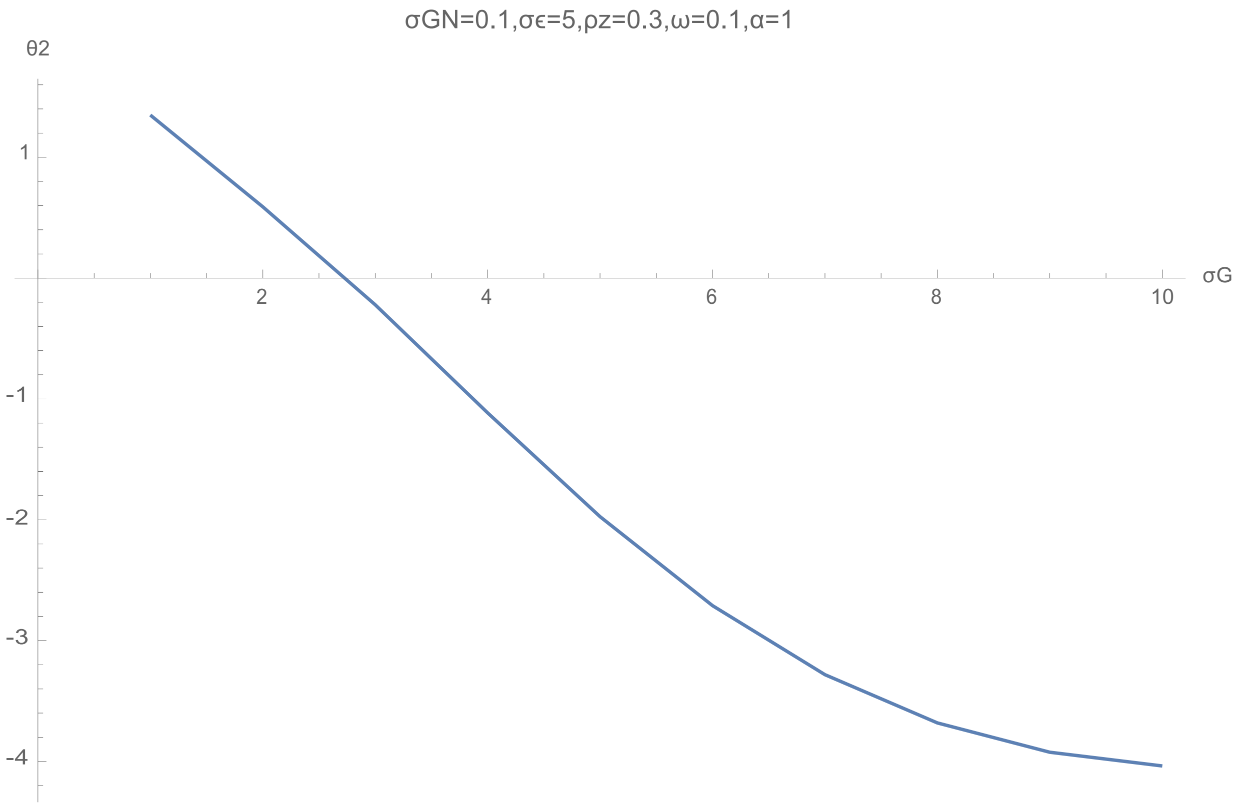
Mean	Median	Std	p10	p25	p70	p90
0.67	0.72	0.2	0.35	0.55	0.83	0.89

Panel C: Portfolio Performance

	Reuters			CLS		
	LV R_{CS}	HV R_{CS}	LMH	LV R_{CS}	HV R_{CS}	LMH
mean (%)	13.53**	-0.13	12.68*	22.72***	1.10	21.62***
SR	1.01	-0.01	1.02	1.65	0.08	1.57***
Θ (%)	10.82	-2.42		19.90	-1.51	
MDD	9.35	21.34		8.79	20.16	
$\rho(LVR)_{CLS,TR}$	0.70					

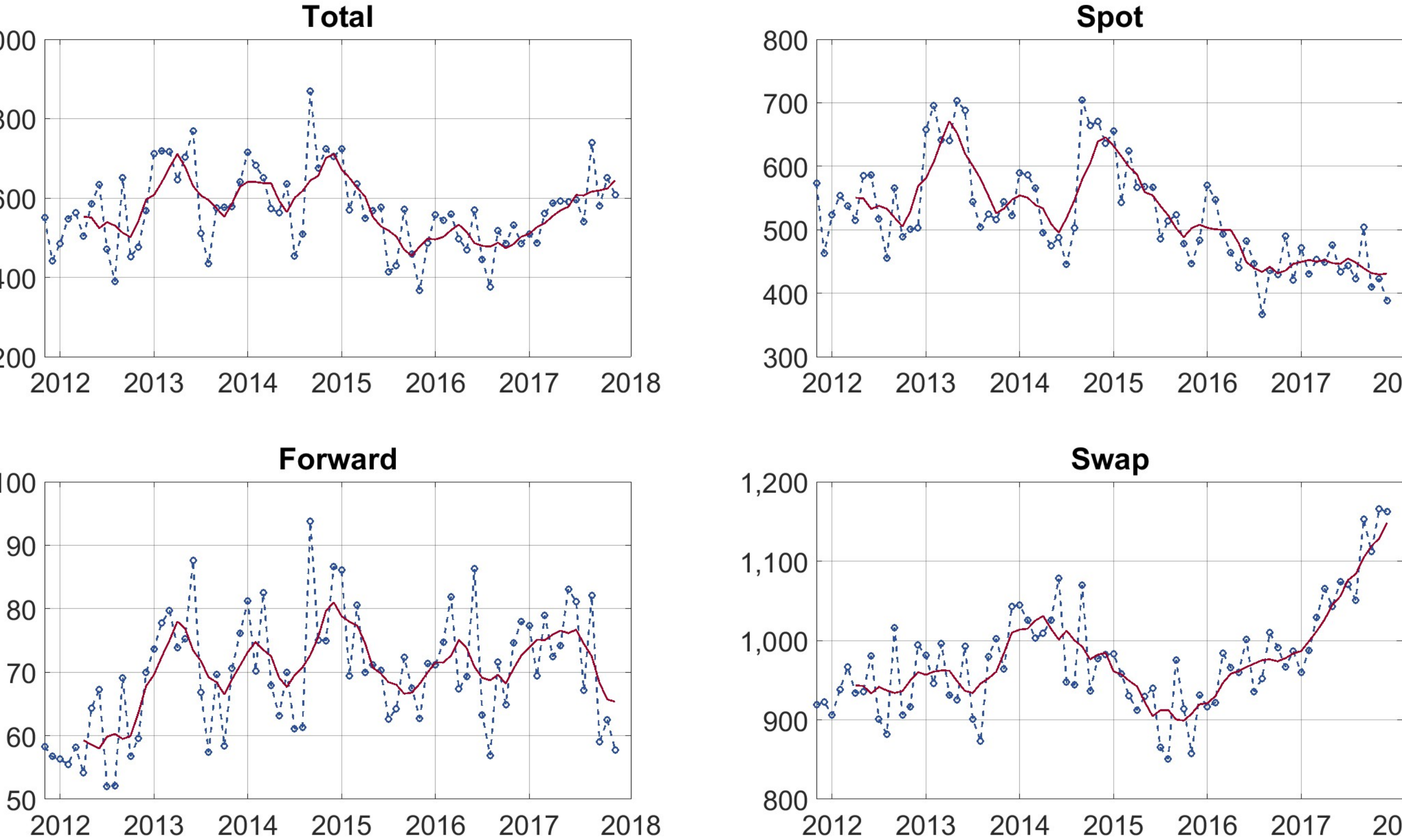
This table compares CLS spot volume data with alternative data from the Thomson Reuters Dealing platform. Panel A displays, for each currency pair available in both datasets, the pairwise time-series correlations for $v_{i,t}$, the (log) deviation of volume from its recent trend, defined as $v_{i,t} = \log(Volume_{i,t}) - \log\left(\frac{\sum_{s=1}^{21} Volume_{i,t-s}}{21}\right)$ Panel B displays the mean, median, standard deviation and the 10th, 25th, 70th and 90th percentile of the correlation in rankings. Panel C presents the out-of-sample economic performance of the currency reversal strategy. The LV R_{CS} strategy takes positions in currency pairs with abnormally low volume, with long positions in currencies which previously depreciated and short positions in currencies which previously appreciated. The HV R_{CS} strategy is the analogous strategy that takes positions in currency pairs with abnormally high volume. We report the annualized average return (mean), annualized Sharpe ratio (SR), 'theta' performance measure (Θ) proposed by Ingersoll et al. (2007) and the maximum drawdown (M DD). The values in the LMH column denote the difference between the annualized average return and Sharpe ratio between the LV R_{CS} and HV R_{CS} strategies. We test whether the individual annualized average returns (and their difference) are statistically different from zero with Newey and West (1987) adjusted t-statistics. We test whether the two Sharpe ratios are statistically different using the procedure proposed by Ledoit and Wolf (2008). Values marked with ***, **, and * are significant at the 1%, 5%, and 10% level. $\rho(LVR)_{CLS,TR}$ denotes the correlation between the LV R_{CS} returns from the two datasets. All panels are based on data from November 2011 to December 2015.

Figure 1: The Effect of an Increase in Information Asymmetry on θ_2



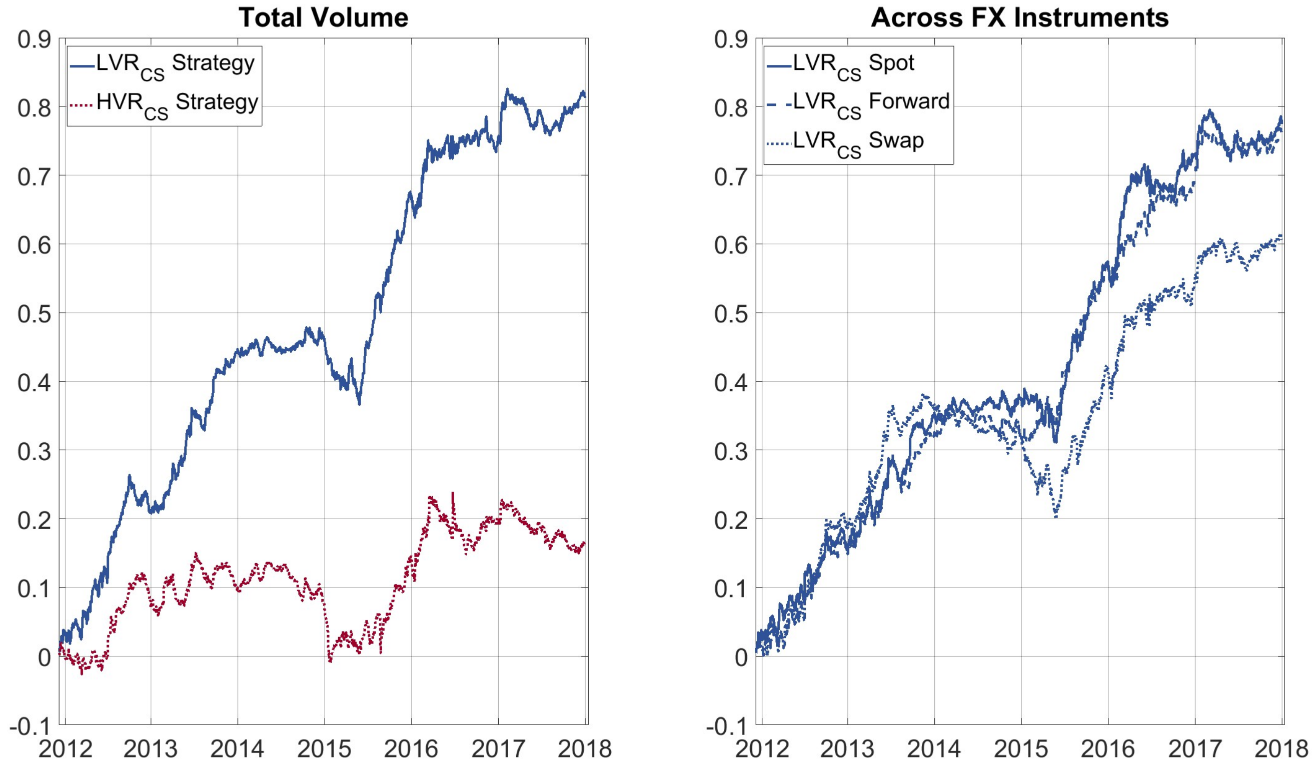
e figure displays how the coefficient θ_2 varies across different levels of information asymmetry (σ_G). The values are obtained from a numer
ulation of the model, described in Section 3.

Figure 2: Foreign Exchange Volume Over Time



e figure displays the time-series of average monthly FX volume (in $ billions) across all 31 currency pairs for the entire sample from Novem
1 to December 2017 (see Section 4 for further details on the FX volume data). The information is presented for spot, forward, swap, and t
m of spot, forward, and swap) volume. A six-month rolling moving average is overlaid on each series.

Figure 3: Cumulative Returns to the Cross-Sectional Reversal Strategies



e figure displays out-of-sample daily cumulative returns. The left-hand plot reports the cumulative returns to the LV R_{CS} and HV R_{CS} strateg culated using total (sum of spot, forward, and swap) volume. The right-hand plot reports cumulative returns to the LV R_{CS} strategy construc ng spot, forward, and swap volume.

Figure 4: A Comparison of Bid-Ask Spreads

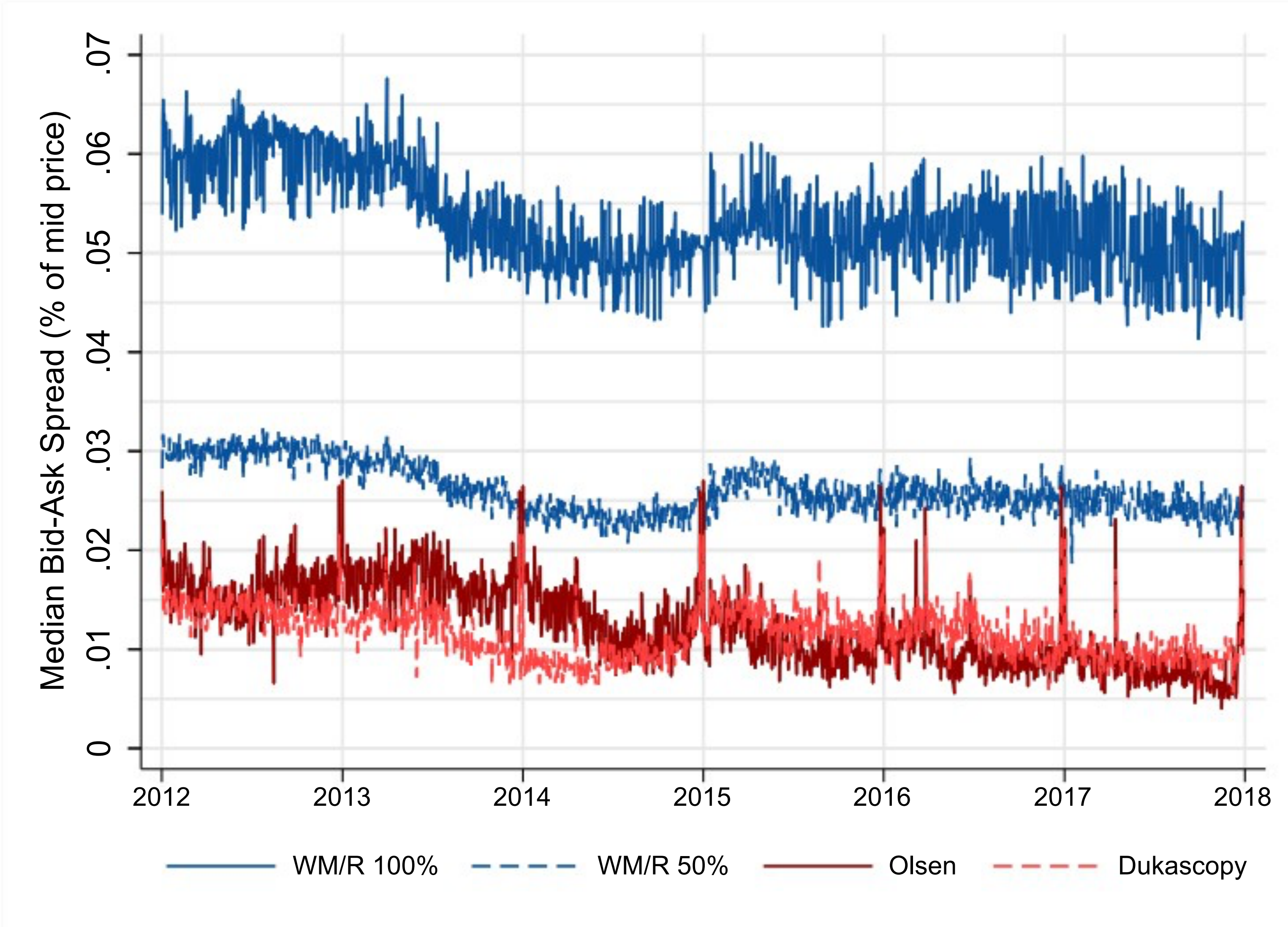
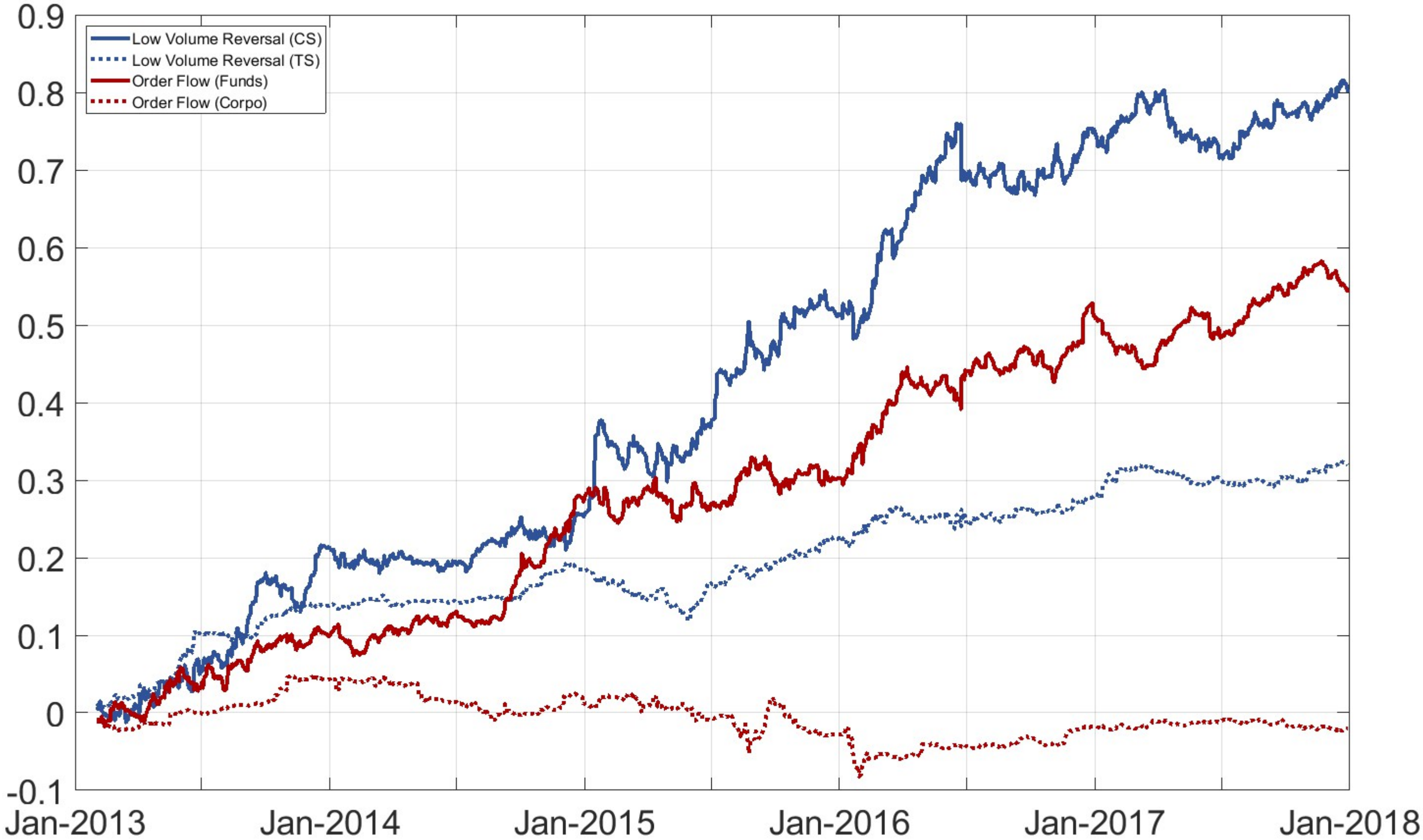


figure presents the time-series of median bid-ask spreads (as a percentage of the mid price) across all currency pairs in our sample across th a sources: WM/Reuters, Olsen Financial Technologies (Olsen), and Dukascopy Bank (Dukascopy). All series are constructed using bid- eads and exchange rates that are recorded at 4pm in London.

Figure 5: Cumulative Returns to Volume and Order Flow Strategies



e figure displays out-of-sample daily cumulative returns to volume and order flow strategies. The blue lines denotes the cumulative return LV R_{CS} and LV R_{TS} strategies calculated using total (sum of spot, forward, and swap) volume. The red lines denote cumulative return er flow strategies constructed using either "Funds" or "Corporate" order flow (see Section 6.1.1 for further details).

INTERNET APPENDIX

to

FOREIGN EXCHANGE VOLUME

Contents

Appendix A

We provide additional technical proofs for Proposition 1 and Corollary 1.

Appendix B

We explore the data in various ways including: (i) comparing CLS FX volume data with volume data from the BIS; (ii) comparing indicative bid-ask spreads in the FX spot market from various providers; (iii) documenting the daily, weekly, and monthly patters in FX volume; and (iv) exploring the factor structure of FX volume.

Appendix C

We provide additional analysis from the main panel regressions of returns on FX volume across spot, forward, and swap markets and also document the persistence of the relationship.

Appendix D

We provide a series of tests on the robustness of the FX volume trading strategy by testing: (i) alternative trading times; (ii) the impact of end-of-month effects; (iii) different construction approaches; (iv) dollar neutral portfolios; (v) different currency sub-groups; and (vi) small sample concerns.

Appendix E

We explore the relationship between FX volume and order flow and assess whether FX predictability is subsumed by order flow.

Appendix F

We discuss the theoretical determinants of volume and provide details on the variables we use to capture these determinants in our empirical analysis.

Appendix A: Theory

Proof of Proposition 1

Using (15) to compute the expectation and variance in (17a) and (17b) yields:

$$E_{It}[R_{t+1}] = \frac{\alpha(a_2 g_{t+1} - a_3 z_t) - (1+\alpha)s_t + g_t}{\alpha} \tag{A.1a}$$

$$E_{Ut}[R_{t+1}] = \frac{\alpha(a_2 E_{Ut}[g_{t+1}] - a_3(\rho_z z_{t-1} + E_{Ut}[\epsilon_t])) - (1+\alpha)s_t + g_t}{\alpha}, \tag{A.1b}$$

and

$$Var_{It}[R_{t+1}] \equiv \sigma^2_{IR} = a_0(\sigma_G + b_2\sigma_\epsilon) \tag{A.2a}$$

$$Var_{Ut}[R_{t+1}] \equiv \sigma^2_{UR} \tag{A.2b}$$

$$= a_0^2(\sigma^2_G + b_2\sigma_\epsilon) + a_2 Var_{Ut}[g_{t+1}] + a_3 Var_{Ut}[\epsilon_t] - 2a_2 a_3 Cov_{Ut}[g_{t+1}, \epsilon_t],$$

where

$$E_{Ut}[g_{t+1}] = \underbrace{\frac{\sigma^2_G}{\sigma^2_G + b^2\sigma_\epsilon}}_{\gamma} \hat{s}_t \tag{A.3a}$$

$$E_{Ut}[\epsilon_t] = \frac{\gamma - 1}{b}\hat{s}_t \tag{A.3b}$$

$$Var_{Ut}[g_{t+1}] = \gamma b^2 \sigma^2_\epsilon \tag{A.3c}$$

$$Var_{Ut}[\epsilon_t] = \gamma \sigma^2_\epsilon \tag{A.3d}$$

$$Cov_{Ut}[g_{t+1}, \epsilon_t] = \gamma b \sigma^2_\epsilon, \tag{A.3e}$$

and $\hat{s}_t \equiv g_{t+1} - b\epsilon_t$ denotes the informational content of the round t exchange rate about g_{t+1} and ϵ_t that uninformed investors infer from s_t. Replacing (A.3c)-(A.3e) in (A.2b), and rearranging yields:

$$\sigma^2_{UR} = \sigma_{IR} + (a_2 b - a_3)^2 \gamma \sigma_\epsilon. \tag{A.4}$$

Replacing (A.1a) in (17a), and (A.1b) in (17b), and rearranging yields:

$$x_{It} = \frac{\alpha(a_2 g_{t+1} - a_3 z_t) - (1+\alpha)s_t + g_t - \alpha a_2 \sigma_{GN} z_t}{\alpha\sigma^2_{IR}} \tag{A.5a}$$

$$x_{Ut} = \frac{\alpha((a_2\gamma + (1-\gamma)a_3/b)\hat{s}_t - a_3\rho_z z_{t-1}) - (1+\alpha)s_t + g_t}{\alpha\sigma^2_{UR}} \tag{A.5b}$$

Imposing market clearing,

$$\omega x_{It} + (1-\omega)x_{Ut} = 0,$$

and solving for s_t, we identify the coefficients of the equilibrium exchange rate:

$$s_t = a_0(g_{t+1} - b\epsilon_t) - a_3 z_{t-1} + a_2 g_t,$$

where $b \equiv a_1/a_0$, obtaining:

$$a_0 = \alpha a_2 \left(\frac{a_3(1-\gamma)(1-\omega)\sigma_{IR} + a_2 b(\omega\sigma_{UR} + (1-\omega)\gamma\sigma_{IR})}{(\omega\sigma^2_{UR} + (1-\omega)\sigma_{IR})b} \right) \tag{A.6a}$$

$$a_2 = \frac{1}{1+\alpha} \tag{A.6b}$$

$$a_3 = \alpha a_2 \omega \rho_z \sigma_{GN} \frac{\sigma^2_{UR}}{(1+(1-\rho_z)\alpha)(\omega\sigma^2_{UR} + (1-\omega)\sigma_{IR})} \tag{A.6c}$$

$$b = \sigma_{GN} \frac{(1+\alpha)\omega\sigma^2_{UR} + (1+(1-\rho_z)\alpha)(1-\omega)\sigma_{IR}}{(1+(1-\rho_z)\alpha)(\omega\sigma^2_{UR} + (1-\omega)\sigma_{IR})} \tag{A.6d}$$

Replacing (A.6b), (A.6c), and (A.6d), in (A.4) and rearranging yields:

$$\sigma^2_{UR} = \sigma_{IR} + \gamma\sigma_\epsilon a^2 \sigma_{GN}, \tag{A.7}$$

since, as one can verify,

$$b = a_3 + a_2\sigma_{GN}. \tag{A.8}$$

Also, replacing (A.6b), (A.6c), and (A.6d) into (A.6a), shows that, because of (A.7), the equilibrium is pinned down by a system of two simultaneous, non-linear equations in a_0 and b, respectively given by:

$$a_0 = h_1(a_0,b) \equiv \alpha a_2 \left(\frac{a_3(1-\gamma)(1-\omega)\sigma_{IR} + a_2 b\left(\omega\sigma_{UR} + (1-\omega)\gamma\sigma_{IR}\right)}{\left(\omega\sigma^2_{UR} + (1-\omega)\sigma_{IR}\right) b} \right) \qquad \text{(A.9a)}$$

$$b = h_2(a_0,b) \equiv \sigma_{GN} \frac{(1+\alpha)\omega\sigma^2_{UR} + (1+(1-\rho_z)\alpha)(1-\omega)\sigma_{IR}}{(1+(1-\rho_z)\alpha)(\omega\sigma^2_{UR} + (1-\omega)\sigma_{IR})}, \qquad \text{(A.9b)}$$

with $h_1(\cdot)$ and $h_2(\cdot)$ continuous functions. Note that for $\rho_z \geq 0$,

$$a_0 \in [0,\alpha/(1+\alpha)^2],\ b \in \left[(1+\alpha)\sigma_{GN},\ (1+\alpha)\sigma_{GN}\frac{1+(1-(1-\omega)\rho_z)\alpha}{1+(1-\rho_z)\alpha}\right], \qquad \text{(A.10)}$$

which, for a_0 follows from (A.8):

$$a_0 = \frac{\alpha a_2\left(\left(a_3 + a_2\frac{\sigma_{GN}}{b}\right)\alpha\sigma_{UR} + (1-\omega)\left(a_3 + \gamma a_2\frac{\sigma_{GN}}{b}\right)\sigma_{IR}\right)}{\omega\sigma^2_{UR} + (1-\omega)\sigma_{IR}} < \frac{\alpha}{(1+\alpha)^2}. \qquad \text{(A.11)}$$

Then, let

$$H : [0,\alpha/(1+\alpha)^2] \times \left[(1+\alpha)\sigma_{GN},\ (1+\alpha)\sigma_{GN}\frac{1+(1-(1-\omega)\rho_z)\alpha}{1+(1-\rho_z)\alpha}\right] \rightarrow [0,\alpha/(1+\alpha)^2] \times \left[(1+\alpha)\sigma_{GN},\ (1+\alpha)\sigma_{GN}\frac{1+(1-(1-\omega)\rho_z)\alpha}{1+(1-\rho_z)\alpha}\right]$$

be defined by the component functions $h_1(\cdot),h_2(\cdot)$. As H is continuous and maps a compact set on itself, Brouwer's theorem ensures the existence of a fixed point (a^*_0, b_*), implying equilibrium existence. 2

Proof of Corollary 1

To simplify notation, we make the following substitution: $R_{t+1} = x$, $R_t = y$, and $(\alpha a_2 - (1+\alpha)a_0)(\hat{s}_t - \hat{s}_{t-1}) + (1+\alpha)a_3(z_{t-1} - z_{t-2}) = z$, and start by computing the regression of R_{t+1} on past return and (the informational content of) signed volume. As (x, y, z) is a normally distributed random vector, centered on zero with variance covariance matrix

$$\Sigma = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \end{pmatrix}, \qquad \text{(A.12}$$

where $\Sigma_{11} = \mathrm{Var}[x]$, $\Sigma_{12} = (\mathrm{Cov}[x, y], \mathrm{Cov}[x, z])$, and

$$\Sigma_{22} = \begin{pmatrix} \mathrm{Var}[y] & \mathrm{Cov}[y, z] \\ \mathrm{Cov}[y, z] & \mathrm{Var}[z] \end{pmatrix}, \tag{A.13}$$

due to the projection theorem we have

$$E[x|y, z] = \beta_{xy}\, y + \beta_{xz}\, z, \tag{A.14}$$

where

$$\beta_{xy} = (\Sigma_{12}\Sigma^{-1}_{22})_1 \tag{A.15a}$$

$$\beta_{xz} = (\Sigma_{12}\Sigma^{-1}_{22})_2. \tag{A.15b}$$

Computing the elements of the matrices (A.12) and (A.13):

$$\sigma^2_x = \frac{1}{\alpha^2}\Big((\alpha a_2 - (1+\alpha)a_0)^2\sigma^2_G + \sigma_{IR} + (\alpha a_3 - (1+\alpha)a_1)^2\sigma^2_\epsilon + (1+(1-\rho_z)\alpha)^2 a_3\sigma_\epsilon/(1-\rho_z) \Big) \tag{A.16a}$$

$$\sigma^2_z = (\alpha a_2 - (1+\alpha)a_0)^2(\sigma^2_G + b^2\sigma_\epsilon) + ((\alpha a_2 - (1+\alpha)a_0)b + (1+\alpha)a_3)^2\sigma^2_\epsilon + (1+\alpha)^2(1-\rho_z)^2 a_3\sigma_\epsilon/(1-\rho_z) \tag{A.16b}$$

$$\sigma_{xy} = \frac{1}{\alpha^2}\Big((\alpha a_2 - (1+\alpha)a_0)a_0\sigma^2_G + (\alpha a_3 - (1+\alpha)a_1)a_0 b\sigma_\epsilon - (1+(1-\rho_z)\alpha)(\alpha a_3 - (1+\alpha)a_1 - (1+(1-\rho_z)\alpha)\rho_z a_3/(1-\rho^2_z))a_3\sigma_\epsilon \Big) \tag{A.16c}$$

$$\sigma_{xz} = \frac{1}{\alpha}\Big((\alpha a_2 - (1+\alpha)a_0)^2\sigma^2_G + (\alpha a_3 - (1+\alpha)a_1)(\alpha a_2 - (1+\alpha)a_0)b\sigma_\epsilon + (1+(1-\rho_z)\alpha)\big(((\alpha a_2 - (1+\alpha)a_0)b + (1+\alpha)a_3)a_3\sigma^2_\epsilon + (1+\alpha)(\rho_z - 1)\rho_z a_3\sigma_\epsilon/(1-\rho_z) \big) \Big) \tag{A.16d}$$

$$\sigma_{yz} = \frac{1}{\alpha}\Big(-(\alpha a_2 - (1+\alpha)a_0)^2\sigma^2_G + (\alpha a_2 - (1+\alpha)a_0)a_0\sigma_G \tag{A.16e}$$

$$+ (\alpha a_2 - (1+\alpha)a_0)a_0 b^2\sigma^2_\epsilon - (\alpha a_3 - (1+\alpha)a_1)((\alpha a_2 - (1+\alpha)a_0)b + (1+\alpha)a_3)\sigma_\epsilon$$

$$+ (1 + (1-\rho_z)\alpha)(1+\alpha)(\rho_z - 1)a^2_3\sigma_\epsilon/(1-\rho_z)\Big)$$

where, because of stationarity, $\sigma^2_x = \sigma_y$.

The expression for the regression of R_{t+1} on R_t an V_t, and its first order linear approximation are as follows (see Llorente et al. (2002b)):

$$E[R_{t+1}|R_t, |\hat{s}_t - \hat{s}_{t-1}|] = \beta_{xy} R_t - \beta_{xz} |z| \tanh((\Sigma^{-1}_{22})_{yz} |z| R_t)$$

$$\approx -(\theta_1 + \theta_2|z|^2)R_t, \tag{A.17}$$

where

$$z = (\alpha a_2 - (1+\alpha)a_0)(\hat{s}_t - \hat{s}_{t-1}) + (1+\alpha)a_3(z_{t-1} - z_{t-2}),$$

and

$$\theta_1 = -\beta_{xy} \tag{A.18a}$$

$$\theta_2 = \beta_{xz}(\Sigma^{-1}_{22})_{yz}. \tag{A.18b}$$

2

Appendix B: Exploring the Data

Table B.1: Comparison Between CLS and BIS FX Volume Data

	April 2013			April 2016		
Pair	CLS ($ billions)	CLS (%)	BIS(%)	CLS ($ billions)	CLS (%)	BIS(%)
EURUSD	490.45	29.89	28.57	455.84	30.61	28.38
USDJPY	290.17	17.69	21.67	285.94	19.20	21.82
GBPUSD	188.69	11.50	10.46	165.08	11.08	11.38
AUDUSD	151.62	9.24	8.05	100.11	6.72	6.35
USDCHF	87.50	5.33	4.07	79.56	5.34	4.36
USDCAD	76.16	4.64	4.42	81.53	5.47	5.28
EURJPY	40.85	2.49	3.27	16.11	1.08	1.91
USDMXN	34.64	2.11	2.83	25.68	1.72	2.18
EURGBP	34.59	2.11	2.26	30.45	2.04	2.42
NZDUSD	34.02	2.07	1.81	31.28	2.10	1.89
USDSEK	27.00	1.65	1.22	32.36	2.17	1.60
USDSGD	26.20	1.60	1.44	30.00	2.01	1.96
USDNOK	25.37	1.55	1.08	19.78	1.33	1.16
EURCHF	24.14	1.47	1.57	15.43	1.04	1.07
USDZAR	23.19	1.41	1.13	17.59	1.18	0.97
USDHKD	22.46	1.37	1.53	26.19	1.76	1.86
USDKRW	18.18	1.11	1.33	15.79	1.06	1.89
EURSEK	9.29	0.57	0.62	10.76	0.72	0.87
AUDJPY	8.56	0.52	1.02	5.67	0.38	0.75
EURNOK	8.30	0.51	0.44	9.51	0.64	0.68
EURAUD	5.99	0.37	0.46	4.58	0.31	0.39
EURDKK	4.44	0.27	0.29	3.87	0.26	0.31
EURCAD	3.19	0.19	0.33	3.59	0.24	0.34
CADJPY	0.79	0.05	0.13	1.12	0.08	0.17

The table presents summary statistics for CLS volume data in April of 2013 and 2016. For each year, we report the average daily volume settled by CLS across currency pairs (column 1), the volume as a percentage of the total volume (column 2), and the equivalent percentage share reported by the Bank for International Settlements (BIS) in their 2013 and 2016 Triennial Surveys of Central Banks.

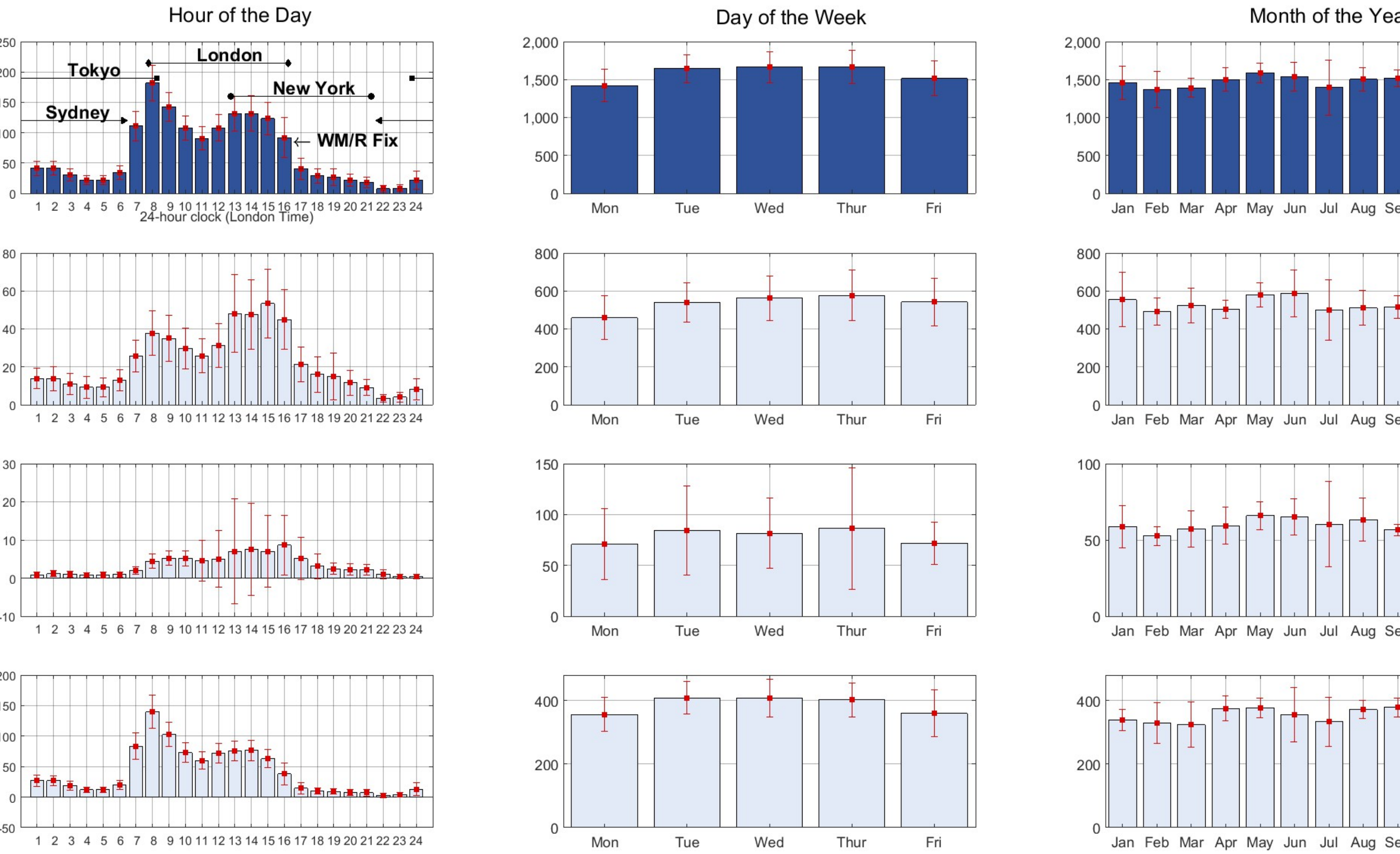
Table B.2: A Comparison of Bid-Ask Spreads Across Data Providers

	Bid-Ask Spreads		Ratio of Bid-Ask Spreads		
Pair	WM/R	Olsen	$\frac{\text{Olsen}}{\text{WM/R}}$	$\frac{\text{Olsen}}{\text{Bank}}$	$\frac{\text{Olsen}}{\text{Dukas}}$
AUDJPY	7.75	1.16	0.15	1.02	1.01
AUDNZD	10.45	1.96	0.19	0.75	0.93
AUDUSD	4.58	0.94	0.20	1.05	0.92
CADJPY	5.91	1.36	0.23	-	1.17
EURAUD	6.95	1.01	0.15	-	0.91
EURCAD	5.40	1.15	0.21	-	0.96
EURCHF	3.33	0.90	0.27	0.64	0.98
EURDKK	0.54	0.94	1.76	1.73	2.59
EURGBP	5.55	0.96	0.17	1.10	0.99
EURJPY	5.35	0.73	0.14	0.95	1.67
EURNOK	4.91	2.50	0.51	0.84	.1.35
EURSEK	3.36	1.97	0.58	0.73	1.14
EURUSD	2.43	0.45	0.18	0.95	2.44
GBPAUD	7.60	1.29	0.17	-	0.87
GBPCAD	6.10	1.36	0.22	-	0.77
GBPCHF	8.86	1.45	0.16	-	0.98
GBPJPY	6.20	0.98	0.16	0.84	1.17
GBPUSD	3.08	0.60	0.19	0.89	1.23
NZDUSD	5.88	1.41	0.24	0.78	0.98
USDCAD	3.01	0.68	0.23	0.78	0.94
USDCHF	5.94	0.89	0.15	0.69	0.86
USDDKK	2.92	0.90	0.31	1.24	1.40
USDHKD	0.64	0.58	0.90	2.98	1.95
USDJPY	2.96	0.51	0.17	0.92	1.78
USDMXN	2.00	1.49	0.74	1.39	0.78
USDNOK	7.24	2.37	0.33	0.88	1.14
USDSEK	5.81	1.90	0.33	0.79	1.03
USDSGD	4.87	1.74	0.36	1.10	1.07
USDZAR	9.09	3.65	0.40	1.17	0.98
Average	5.13	1.30	0.22	0.95	1.01

The table presents summary statistics of foreign exchange bid-ask spreads from four data providers: WM/Reuters, Olsen Financial Technologies (Olsen), Dukascopy Bank (Dukas), and an anonymous dealer bank (Bank). The first two columns report the time series median bid-ask spreads (as percentage of the mid-price, i.e. $\frac{p_{ask}-p_{bid}}{0.5*(p_{bid}+p_{ask})}$) scaled by 10,000. These values are based on prices recorded at 4pm in London.

The third column displays the ratio between the median bid-ask spread from Olsen and WM/R, the fourth column displays the ratio between the median bid-ask spreads from Olsen and Bank, while the fifth column displays the ratio between the median daily bid-ask spreads from Olsen and Dukas.

Figure B.1: Foreign Exchange Volume at Hourly, Daily and Monthly Frequency



e figure displays the average volume (in $ billions) across each hour (in London), day, and month. The top row reflects total (sum of s
ward, and swap) volume. Rows 2-4 represent spot, forward, and swap volume, respectively. In all plots, volume is aggregated across the
rency pairs in the sample. One standard-deviation bounds are reported for each value.

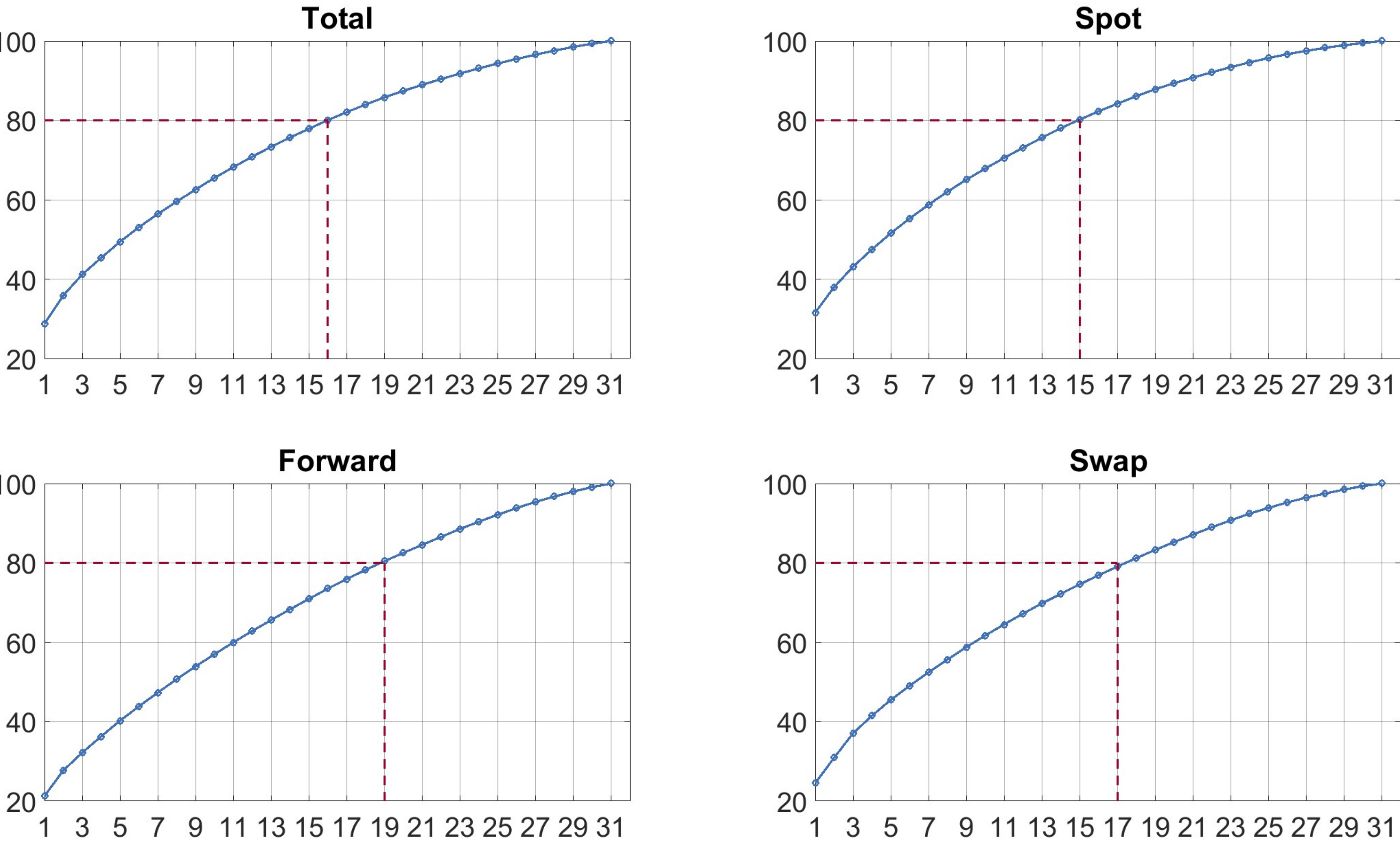
B.1: The Factor Structure of FX Volume

We take a purely statistical approach and explore the factor structure in FX volume. It is well known there is strong commonality in the cross-sectional variation of asset returns, order flow, volatility, and liquidity, which implies that one or very few common factors drive the variation in many financial variables (see, e.g. Hasbrouck and Seppi, 2001; Kelly, Lustig, and Van Nieuwerburgh, 2016). In the FX market, currency excess returns possess a strong factor structure (Lustig, Roussanov, and Verdelhan, 2011; Verdelhan, 2018) and a growing literature has documented commonality in FX liquidity measures, based on bid-ask spreads and order flow (Banti, Phylaktis, and Sarno, 2012; Mancini, Ranaldo, and Wrampelmeyer, 2013).

The results from a factor decomposition of FX volume are reported graphically in Figure B.2. The figure plots the cumulative variance (on the vertical axis) explained by the principal components, estimated separately for total volume and each of the three FX instruments. As is custom in the literature, we standardize the data so that each volume series has zero mean and unit variance. For total volume, the first principal component explains around 30% of the variation in volume across currency pairs. These results point to the importance of a systematic factor, but its role is smaller than recorded, for example, by Mancini, Ranaldo, and Wrampelmeyer (2013), who find the first principal component explains 70-90% of the variation in return reversals, bid-ask spreads, effective costs, and price dispersion across currencies during the global financial crisis. Our result is similar, however, to Karnaukh, Ranaldo, and Söderlind (2015), who document that a common component in liquidity can explain around 30% of the variation in individual currency-pair liquidity over long samples. Overall, around 15 principal components are required to explain 80% of the variation in total FX volume. The results are similar for the three FX instruments, suggesting that volume is not, in general, driven by just a few common factors and thus currency-specific factors are likely to be particularly important determinants of FX volume.

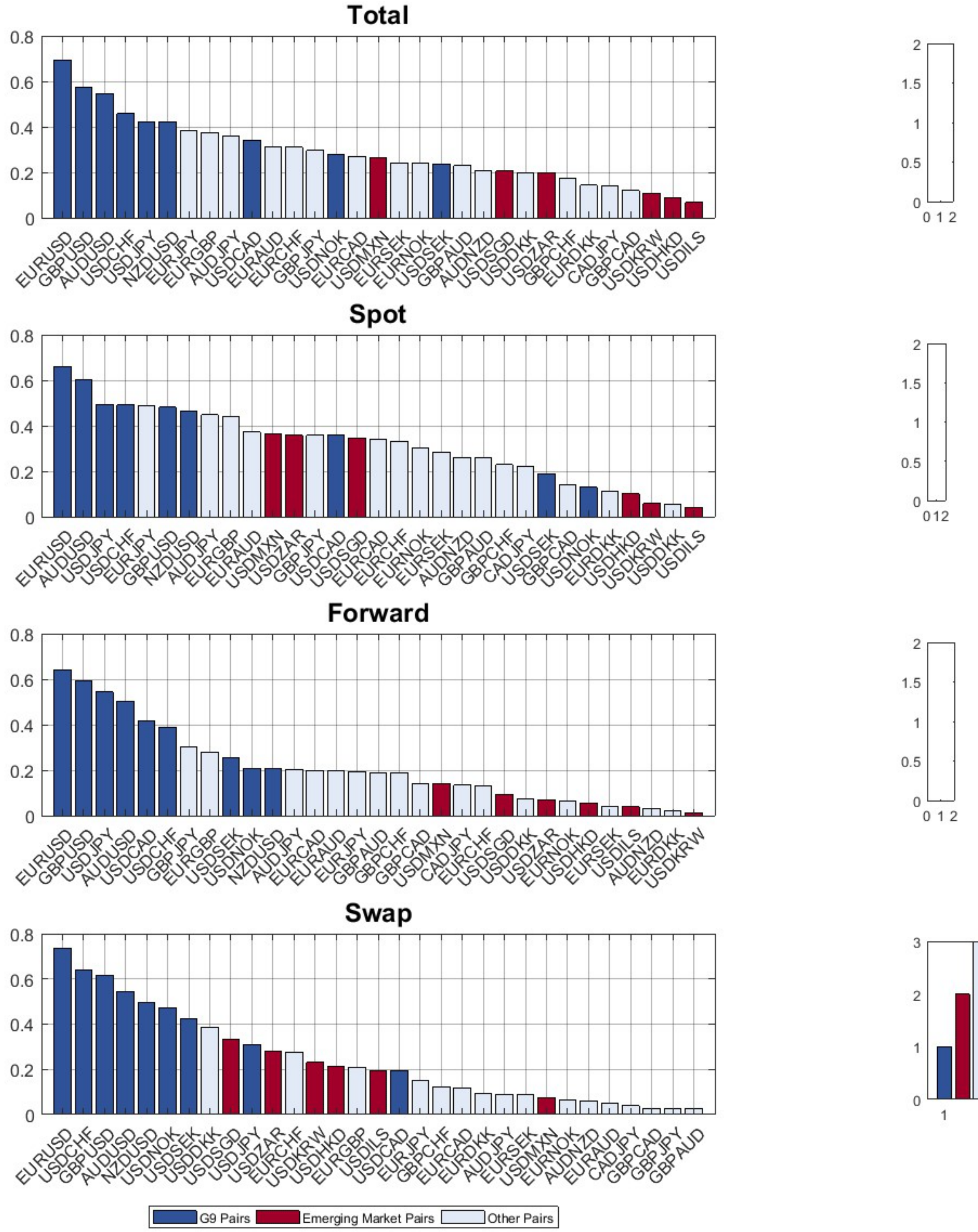
In Figure B.3 we show the R-square from regressing volume on the first principal component for each currency pair. The highest R-squares are associated with the most traded currency pairs, which is interesting since volume is standardized prior to running the PCA, and so while the result is intuitive, it is not mechanically driven.

Figure B.2: Cumulative Variation in FX Volume Explained by Principal Components



e figure displays the cumulative variance explained by principal components. Principal component analysis is performed on daily (log) volu ndardized to have zero mean and unit standard deviation. The analysis is performed using spot, forward, swap, and total (sum of spot, forw swap) volume. The number of principal components required to explain 80% of the variation in volume is denoted by the dashed line.

F



The figure displays the R^2 from regressing daily standardized log volume series on the first principal component. The principal component analysis is performed on daily (log) volume, standardized to have zero mean and unit standard-deviation. The first plot reflects total volume (sum of spot, forward, and swap volume), while the second, third, and fourth plots reflect spot, forward, and swap volume, respectively.

ppendix C: The Dynamic Relationships Between Volume and Returns

Table C.1: Foreign Exchange Volume (V^2) and Currency Excess Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
				Volume		Bid-Ask Spread		Volatility			
		All Pairs		High	Low	High	Low	High	Low	USD	EUR
$Return_t$	-0.005	-0.072***	-0.072***	-0.094***	-0.049**	-0.054**	-0.097***	-0.061**	-0.103***	-0.117***	-0.169***
	(0.022)	(0.018)	(0.018)	(0.021)	(0.022)	(0.023)	(0.018)	(0.025)	(0.021)	(0.029)	(0.022)
$\bar{V}^2_t$	-0.006	-0.002	-0.002	-0.003	-0.000	0.008	-0.023	0.038*	-0.037***	-0.005	-0.022
	(0.013)	(0.012)	(0.012)	(0.024)	(0.013)	(0.015)	(0.015)	(0.020)	(0.013)	(0.024)	(0.019)
$\bar{V}^2_t * Return_t$		0.043***	0.043***	0.061***	0.020*	0.024**	0.059***	0.032**	0.051***	0.075***	0.058***
		(0.010)	(0.011)	(0.005)	(0.012)	(0.012)	(0.004)	(0.016)	(0.009)	(0.021)	(0.006)
Controls	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj-R^2	0.0195	0.0230	0.0233	0.0247	0.0331	0.0351	0.0262	0.0378	0.0355	0.0270	0.1039
Nobs	46199	46199	46199	22380	23819	22379	23820	22379	23820	23820	13428

e table presents coefficient estimates and associated double-clustered standard errors (reported in parentheses) for the following fixed-effec el regression:

$$r_{i,t+1} = \alpha_i + \tau_t + \beta_1 r_{i,t} + \beta_2 \left(r_{i,t}\bar{V}^2_{i,t} \right) + \beta_3 \bar{V}^2_{i,t} + \gamma' x_{i,t} + \epsilon_{i,t+1},$$

ere α_i and τ_t denote currency-pair and time fixed effects, $r_{i,t}$ is the log currency excess return for currency pair i at time t, $\bar{V}_{i,t}$ is total volu m of spot, forward and swap) scaled by its average over the previous 21 days, $x_{i,t}$ is a vector of controls relative to pair i and $\epsilon_{i,t+1}$ is the mo or term. The values reported in columns (1) to (3) are based on all 31 currency pairs in our sample while in columns (4) to (9) currency pairs t based on median Volume (columns 4 and 5), median Bid-Ask spread (columns 6 and 7) and median Volatility (8 and 9). The values repo olumns (10) and (11) are calculated for samples including only USD and EUR-base pairs. Coefficients marked with ***, **, and * are signific he 1%, 5%, and 10% level.

Table C.2: Foreign Exchange Volume and Currency Excess Returns [Spot]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
				Volume		Bid-Ask Spread		Volatility			
	All Pairs			High	Low	High	Low	High	Low	USD	EUR
						Panel A: Spot					
$Return_t$	-0.005	-0.039***	-0.039***	-0.049***	-0.041***	-0.047***	-0.041***	-0.044**	-0.053***	-0.043***	-0.118***
	(0.022)	(0.015)	(0.015)	(0.018)	(0.015)	(0.016)	(0.015)	(0.017)	(0.014)	(0.016)	(0.019)
$Volume_t$	-0.007	-0.003	-0.002	-0.086**	0.005	0.040	-0.007	0.036	-0.005	-0.010	-0.047
	(0.011)	(0.011)	(0.011)	(0.036)	(0.011)	(0.035)	(0.012)	(0.042)	(0.011)	(0.012)	(0.050)
$Return_t * Volume_t$		0.169***	0.170***	0.226***	0.128***	0.150**	0.197***	0.149**	0.195***	0.140***	0.247***
		(0.057)	(0.057)	(0.065)	(0.046)	(0.059)	(0.056)	(0.062)	(0.057)	(0.053)	(0.065)
Controls	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj-R^2	0.02	0.02	0.02	0.03	0.04	0.04	0.02	0.04	0.04	0.03	0.10
Nobs	46,201	46,201	46,201	22,380	23,821	22,380	23,821	22,380	23,821	23,821	13,428

e table presents coefficient estimates and associated double-clustered standard errors (reported in parentheses) for the following fixed el regression:

$$r_{i,t+1} = \alpha_i + \tau_t + \beta_1 r_{i,t} + \beta_2 \left(r_{i,t} v_{i,t} \right) + \beta_3 v_{i,t} + \gamma' x_{i,t} + \epsilon_{i,t+1},$$

ere α_i and τ_t denote currency-pair and time fixed effects, $r_{i,t}$ is the log currency excess return for currency pair i at time t, $v_{i,t}$ is the (log) iation of spot volume from its recent trend, defined as $v_{i,t} = \log(Volume_{i,t}) - \log\left(\frac{\sum_{s=1}^{21} Volume_{i,t-s}}{21}\right)$, $x_{i,t}$ is a vector of controls relative to pai d $\epsilon_{i,t+1}$ is the model error term. The values reported in columns (1) to (3) are based on all 31 currency pairs in our sample while in column to (9) currency pairs are split based on median Volume (columns 4 and 5), median Bid-Ask spread (columns 6 and 7) and median Volatilit 9). The values reported in columns (10) and (11) are calculated for samples including only USD and EUR-base pairs. Coefficients marked **, and * are significant at the 1%, 5%, and 10% level.

Table C.3: Foreign Exchange Volume and Currency Excess Returns [Forward]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
				Volume		Bid-Ask Spread		Volatility			
		All Pairs		High	Low	High	Low	High	Low	USD	EUR
$Return_t$	-0.005	-0.009	-0.009	-0.011	-0.019	-0.021	-0.007	-0.019	-0.016	-0.023	-0.069***
	(0.022)	(0.019)	(0.019)	(0.020)	(0.018)	(0.020)	(0.018)	(0.020)	(0.021)	(0.018)	(0.019)
$Volume_t$	-0.007	-0.004	-0.004	-0.025	-0.000	0.009	-0.009	0.020	-0.012	-0.006	-0.006
	(0.008)	(0.009)	(0.009)	(0.019)	(0.009)	(0.018)	(0.009)	(0.021)	(0.009)	(0.010)	(0.016)
$Return_t * Volume_t$		0.065**	0.065**	0.105**	0.049**	0.052**	0.091**	0.052*	0.083**	0.038	0.124*
		(0.029)	(0.030)	(0.053)	(0.023)	(0.025)	(0.044)	(0.029)	(0.040)	(0.023)	(0.064)
Controls	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj-R^2	0.02	0.02	0.02	0.02	0.03	0.04	0.02	0.04	0.03	0.03	0.10
Nobs	46,200	46,200	46,200	22,380	23,820	22,380	23,820	22,380	23,820	23,820	13,428

e table presents coefficient estimates and associated double-clustered standard errors (reported in parentheses) for the following fixed-effec
el regression:

$$r_{i,t+1} = \alpha_i + \tau_t + \beta_1 r_{i,t} + \beta_2 \left(r_{i,t} v_{i,t} \right) + \beta_3 v_{i,t} + \gamma' x_{i,t} + \epsilon_{i,t+1},$$

ere α_i and τ_t denote currency-pair and time fixed effects, $r_{i,t}$ is the log currency excess return for currency pair i at time t, $v_{i,t}$ is the (log) (
iation of forward volume from its recent trend, defined as $v_{i,t} = \log(Volume_{i,t}) - \log \frac{\sum_{s=1}^{1} Volume_{i,t-s}}{21}$, $x_{i,t}$ is a vector of controls relative

pair i and $\epsilon_{i,t+1}$ is the model error term. The values reported in columns (1) to (3) are based on all 31 currency pairs in our sample whil
umns (4) to (9) currency pairs are split based on median Volume (columns 4 and 5), median Bid-Ask spread (columns 6 and 7) and med
atility (8 and 9). The values reported in columns (10) and (11) are calculated for samples including only USD and EUR-base pairs. Coeffici
rked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table C.4: Foreign Exchange Volume and Currency Excess Returns [Swap]

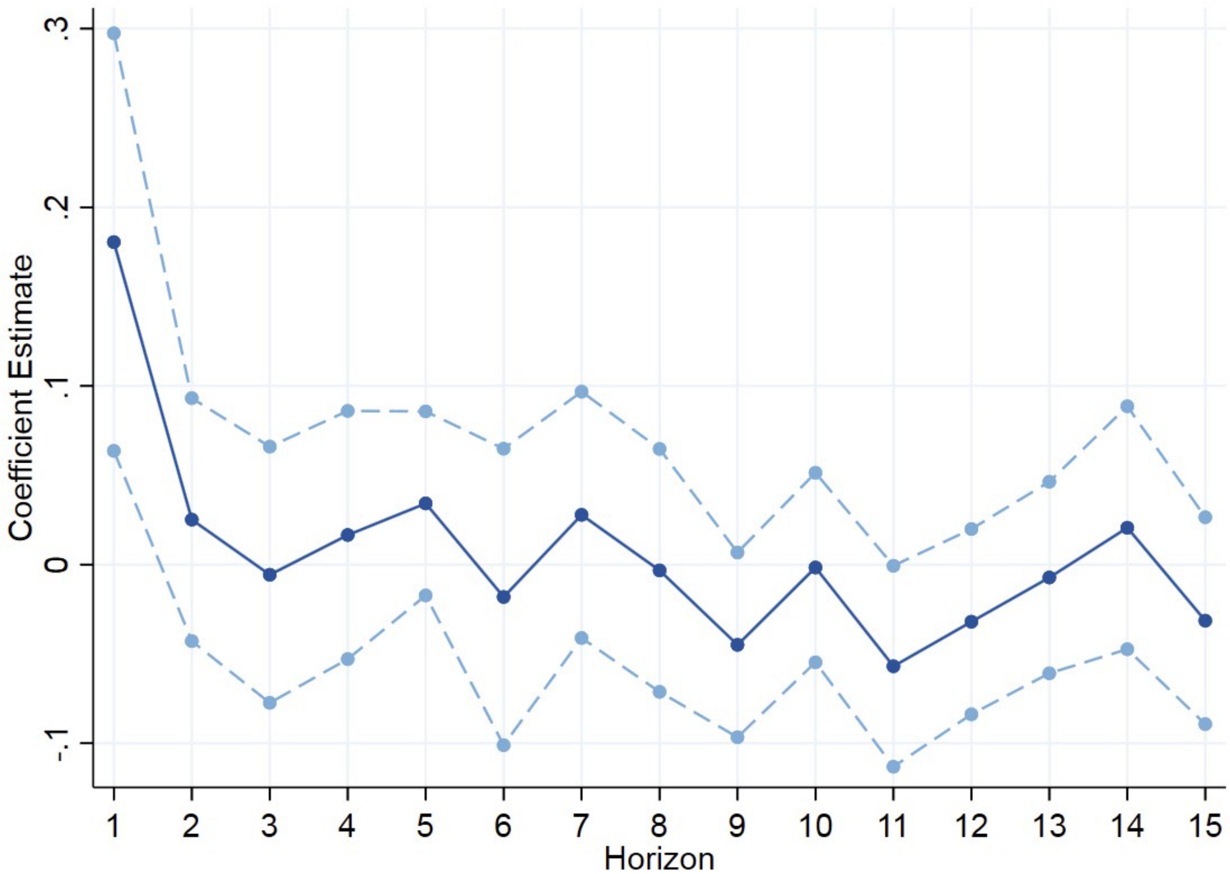
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
				Volume		Bid-Ask Spread		Volatility			
		All Pairs		High	Low	High	Low	High	Low	USD	EUR
$Return_t$	-0.005	-0.003	-0.003	0.001	-0.015	-0.015	0.001	-0.013	-0.011	-0.021	-0.050
	(0.022)	(0.021)	(0.021)	(0.026)	(0.018)	(0.020)	(0.024)	(0.020)	(0.027)	(0.018)	(0.033)
$Volume_t$	-0.012	-0.012	-0.012	0.008	-0.014	-0.016	-0.006	0.015	-0.023**	-0.009	-0.009
	(0.012)	(0.012)	(0.012)	(0.029)	(0.012)	(0.024)	(0.010)	(0.028)	(0.010)	(0.011)	(0.024)
$Return_t * Volume_t$		0.012	0.012	0.030	0.010	0.011	0.057	0.013	0.015	0.020	0.038
		(0.023)	(0.023)	(0.077)	(0.022)	(0.023)	(0.064)	(0.024)	(0.039)	(0.051)	(0.057)
Controls	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj-R^2	0.02	0.02	0.02	0.02	0.03	0.03	0.02	0.04	0.03	0.03	0.09
Nobs	46,200	46,200	46,200	22,380	23,820	22,379	23,821	22,379	23,821	23,821	13,428

e table presents coefficient estimates and associated double-clustered standard errors (reported in parentheses) for the following fixed
el regression:

$$r_{i,t+1} = \alpha_i + \tau_t + \beta_1 r_{i,t} + \beta_2 \left(r_{i,t} v_{i,t} \right) + \beta_3 v_{i,t} + \gamma' x_{i,t} + \epsilon_{i,t+1},$$

ere α_i and τ_t denote currency-pair and time fixed effects, $r_{i,t}$ is the log currency excess return for currency pair i at time t, $v_{i,t}$ is the (log)
iation of swap volume from its recent trend, defined as $v_{i,t} = \log(Volume_{i,t}) - \log\left(\frac{\sum_{s=1}^{21} Volume_{i,t-s}}{21}\right)$, $x_{i,t}$ is a vector of controls relative to pa
d $\epsilon_{i,t+1}$ is the model error term. The values reported in columns (1) to (3) are based on all 31 currency pairs in our sample while in column
to (9) currency pairs are split based on median Volume (columns 4 and 5), median Bid-Ask spread (columns 6 and 7) and median Volatilit
9). The values reported in columns (10) and (11) are calculated for samples including only USD and EUR-base pairs. Coefficients marked
**, and * are significant at the 1%, 5%, and 10% level.

Figure C.1: Persistence of the β_2 Coefficient



The table presents coefficient estimates (blue solid lines) and 95% confidence intervals (dashed lines) of the β_2 coefficient for the following fixed-effects panel regression:

$$r_{i,t+h} = \alpha_i + \tau_t + \beta_1 r_{i,t} + \beta_2 \left(r_{i,t} v_{i,t} \right) + \beta_3 v_{i,t} + \gamma' x_{i,t} + \epsilon_{i,t+1}, \quad h = 1,2,\ldots,15.$$

where α_i and τ_t denote currency-pair and time fixed effects, $r_{i,t+h}$ is the log currency excess return for currency pair i at time t + h, $v_{i,t}$ is the (log) deviation of total volume (sum of spot, forward and swap) from its recent trend, defineds $v_{i,t} = \log(Volume_{i,t}) - \log\left(\frac{\sum_{s=1}^{21} Volume_{i,t-s}}{21}\right)$, $x_{i,t}$ is a vector of controls relative to pair i and $\epsilon_{i,t+1}$ is the model error term.

Appendix D: Robustness of the LV R Trading Strategy

D.1: Alternative trading times

Our results reflect bid-ask spreads recorded at 4pm in London, which is a highly liquid point during the day when both European and American markets are trading. Investors trading outside this period would likely face higher bid-ask spreads, making the strategy less appealing during those hours. We explore this possibility by forming the LV R_{CS} strategy each hour, conditioning on information over the previous 24 hours. Results are reported in Figure D.1. Gross returns are high across the entire day: the return is always above 10% and rises to over 20% on five occasions.

But the effect of transaction costs is substantial and becomes strikingly apparent when bid-ask spreads are at their widest. To see the effect of bid-ask spreads, we plot the median spread each hour (white boxes, right-hand-side axis). Notably, after-cost returns fall most during Sydney opening hours, which is because the bid-ask spreads during those hours are between 200% and 300% higher than those observed during London trading hours. We conclude that while bid-ask spreads do not eliminate the large gross returns, they do place constraints on when the strategy can be successfully implemented.

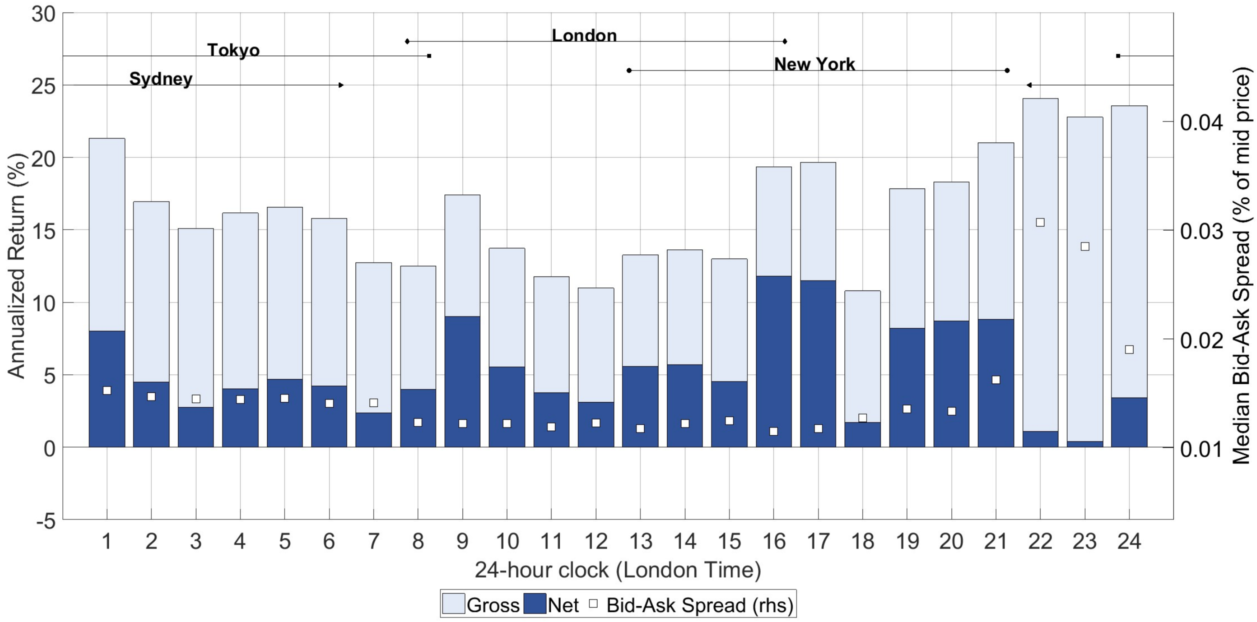
D.2: Alternative trading costs

We examine the performance of the LV R_{CS} strategy after incorporating either WM/Reuters (25% scale) or Dukascopy indicative spreads. The results are reported in Table D.1. The results are qualitatively identical across the spreads from WM/Reuters and Dukascopy the are also similar to those reported in Table 5 in the main body of the paper: the returns for the strategy, constructed using either total, spot, or forward volume, remain high and statistically significant. Across these markets the Sharpe ratios range from 0.70 to 0.97. Consistent with the results in Table 5, the strategy does not generate statistically meaningful performance when constructed using swap volume.

D.3: The WM/R fixing and FX regulation

Melvin and Prins (2015) show that hedging activity of international fund managers spikes at the 4pm fix on the last business day of each month. This intense trading activity generates a return reversal

Figure D.1: The LV R_{CS} Strategy Across Formation Hours



The figure presents the gross and net returns to the LV R_{CS} strategy when implemented at different times of the trading day (London time). The height of each bar reflects the average daily gross return to the strategy, while the inner bars reflect the net return to the strategy after incorporating bid-ask spreads (left-hand-size axis). The white squares reflect the median bid-ask spread (as a percentage of the mid price) at each hour of the day (right-hand-side axis).

in the three hours immediately following the fix. We explore if this affects our results using a two-sample t -test to determine whether the difference between returns realized at the end-of-the month are statistically different from the average returns on all other days. We obtain an insignificant t -statistic of 0.40. Du, Tepper, and Verdelhan (2018) also highlight regulatory driven end-of-quarter effects in FX rates, although we do not find the LV R_{CS} returns are statistically any different on those days (t -stat of 0.21). Finally, we rule out day-of-the-week effects. To this end, we regress the demeaned returns of the LV R_{CS} strategy on five day-of-week dummies and test the null hypothesis that the coefficient estimates are jointly equal to zero. We obtain an F -statistic of 1.19, which indicates that the null hypothesis cannot be rejected.

D.4: Alternative Detrending

In our main analysis, we define unexpected volume as the (log) deviation in volume from its previous one month trend. We investigate if this approach has a material impact on the returns to the LV R_{CS}

strategy. In Panel A of Table D.2, we compare the returns of the LV R_{CS} strategy constructed using a 21 trading day window with alternative measures using 63, 126, and 252 trading days. We find the returns and Sharpe ratios remain comparably high (returns between 15.2% and 16.0% per annum and Sharpe ratios between 1.5 and 1.6). Moreover, the returns to the LV R_{CS} strategy are always statistically higher (in terms of the average return and Sharpe ratio) than the HV R_{CS} strategy. We also standardize volume by its rolling standard deviation, calculated over the same period as the trend. The results, reported in Panel B of Table A.4, are largely comparable with Panel A. The results become slightly stronger in the case of the 21-day and 63-day standardizations and moderately weaker in the 126-day and 252-day cases. Across all specifications, however, the returns to the LV R_{CS} strategy are always high and statistically much larger than observed for the HV R_{CS} strategy.

D.5: Dollar neutral

We examine the LV R_{CS} returns when considering only the 16 U.S. dollar pairs in a dollar-neutral strategy. The results are reported in Table D.3. The LV R_{CS} strategy generates high Sharpe ratios when conditioning on either spot or forward volume of 1.66 and 1.70, respectively. When conditioning on total volume the returns are slightly lower than in the main sample, although the Sharpe ratio is still high (1.46) and the returns remain statistically larger than observed for the HV R_{CS} strategy. Once again, the weakest overall performance is documented when conditioning on swap volume alone.

D.6: Currency sub-groups

We investigate if the returns to the LV R_{CS} strategy are driven by only a few currency pairs by running the analysis on subsets of the 31 currency pairs in our sample. Results are reported in Table D.4. We consider three groups: (i) EUR and GBP base pairs (13 currency pairs); (ii) all pairs excluding emerging market and non-floating pairs (24 currency pairs); and (iii) the G9 pairs plus the most liquid EUR crosses (14 currency pairs). In each case the returns to the LV R_{CS} strategy remain large, ranging from 15% to 17% and are highly statistically significant in each case. The Sharpe ratios also remain high and statistically larger than those observed for the HV R_{CS} strategy.

Table D.1: Cross-Sectional Portfolios with Alternative t-costs

Panel A: WM/R 25%

	Total			Spot		
	LV R_{CS}	HV R_{CS}	LMH	LV R_{CS}	HVR_{CS}	LMH
mean (%)	10.28**	-2.69	12.98***	7.70*	-1.54	9.24**
SR	0.93	-0.22	1.16***	0.70	-0.12	0.83**
Θ (%)	8.47	-4.89		5.91	-3.80	
MDD	15.42	35.78		16.40	32.47	

	Forward			Swap		
	LV R_{CS}	HV R_{CS}	LMH	LV R_{CS}	HVR_{CS}	LMH
mean (%)	9.59**	-3.00	12.60***	3.55	-0.81	4.37
SR	0.86	-0.26	1.12***	0.32	-0.07	0.39
Θ (%)	7.73	-5.00		1.67	-2.69	
MDD	12.67	34.44		29.28	23.91	

Panel B: Dukascopy

	Total			Spot		
	LV R_{CS}	HV R_{CS}	LMH	LV R_{CS}	HVR_{CS}	LMH
mean (%)	10.66**	-2.45	13.12***	7.95*	-1.28	9.22**
SR	0.97	-0.20	1.17***	0.73	-0.10	0.83**
Θ (%)	8.85	-4.65		6.16	-3.54	
MDD	14.83	34.71		15.90	31.63	

	Forward			Swap		
	LV R_{CS}	HV R_{CS}	LMH	LV R_{CS}	HVR_{CS}	LMH
mean (%)	9.93**	-2.72	12.65***	4.01	-0.49	4.50
SR	0.89	-0.24	1.12***	0.36	-0.04	0.40
Θ (%)	8.07	-4.71		2.13	-2.37	
MDD	12.23	33.60		28.26	22.61	

The table presents the out-of-sample after transaction cost economic performance of currency reversal strategies. In Panel A we adjust using a 25% scaling of the WM/R bid-ask spread. In Panel B we use the raw Dukascopy bid-ask spreads. The LV R_{CS} strategy takes positions in currency pairs with abnormally low volume, with long positions in currencies which previously depreciated and short positions in currencies which previously appreciated. The HV R_{CS} strategy is the analogous strategy that takes positions in currency pairs with abnormally high volume. Results are reported separately for spot, forward, swap, and total (sum of spot, forward, and swap) volume. We report the annualized average return (mean), annualized Sharpe ratio (SR), 'theta' performance measure (Θ) proposed by Ingersoll et al. (2007) and the maximum drawdown (M DD). The values in the LMH column denote the difference between the annualized average return and Sharpe ratio between the LV R_{CS} and HV R_{CS} strategies. We test whether the individual annualized average returns (and their difference) are statistically different from zero with Newey and West (1987) adjusted t-statistics. We test whether the two Sharpe ratios are statistically different using the procedure proposed by Ledoit and Wolf (2008). Values marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table D.2: Alternative Measures of Unexpected Volume

	21 Days			63 Days			126 Days			252 Days		
Panel A: Without Standardization												
	LV R_{CS}	HV R_{CS}	LMH	LV R_{CS}	HV R_{CS}	LMH	LV R_{CS}	HV R_{CS}	LMH	LV R_{CS}	HV R_{CS}	LMH
ean (%)	17.61***	3.95	13.66***	15.18***	2.92	12.26***	15.54***	2.29	13.25***	16.02***	1.01	15.01***
R	1.70	0.34	1.36***	1.49	0.25	1.24***	1.57	0.19	1.38***	1.60	0.08	1.52***
(%)	16.01	1.97		13.62	0.91		14.09	0.16		14.53	-1.14	
DD	9.02	19.06		9.61	20.38		8.00	23.77		8.16	23.27	
Panel B: With Standardization												
	21 Days			63 Days			126 Days			252 Days		
	LV R_{CS}	HV R_{CS}	LMH	LV R_{CS}	HV R_{CS}	LMH	LV R_{CS}	HV R_{CS}	LMH	LV R_{CS}	HV R_{CS}	LMH
ean (%)	18.50***	3.76	14.74***	16.04***	4.40	11.64***	14.60***	0.19	14.41***	14.38***	-1.14	15.53***
R	1.75	0.32	1.43***	1.54	0.38	1.17***	1.43	0.02	1.42***	1.43	-0.09	1.52***
(%)	16.83	1.76		14.42	2.38		13.05	-1.99		12.86	-3.33	
DD	7.95	15.62		9.59	20.07		8.60	28.41		10.16	25.40	

table presents the out-of-sample economic performance of currency reversal strategies. The LV R_{CS} strategy takes positions in currency p
 abnormally low volume, with long positions in currencies which previously depreciated and short positions in currencies which previo
reciated. The HV R_{CS} strategy is the analogous strategy that(takes positions i)currency pairs with abnormally high prior volume. In Pan
we measure unexpected volume as $v_{i,t} = \log(V olume_{i,t}) - \log \frac{\sum_{s=1}^{21} V olume_{i,t-s}}{N}$, allowing N to take values ranging from 63 to 252 days.
nel B, we also standardized the measure of abnormal volume by the standard deviation observed over the same window. Results are repo
arately for spot, forward, swap, and total (sum of spot, forward, and swap) volume. We report the annualized average return (mean), annual
rpe ratio (SR), 'theta' performance measure (Θ) proposed by Ingersoll et al. (2007) and the maximum drawdown (M DD). The values in
H column denote the difference between the annualized average return and Sharpe ratio between the LV R_{CS} and HV R_{CS} strategies. We
ether the individual annualized average returns (and their difference) are statistically different from zero with Newey and West (1987) adjuste
istics. We test whether the two Sharpe ratios are statistically different using the procedure proposed by Ledoit and Wolf (2008). Val
rked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table D.3: Dollar Neutral Portfolios

	Total			Spot		
	LV R_{CS}	HV R_{CS}	LMH	LV R_{CS}	HV R_{CS}	LMH
mean (%)	12.23***	0.60	11.63**	14.04***	-1.48	15.52***
SR	1.46	0.06	1.40***	1.66	-0.14	1.80***
Θ (%)	11.17	-1.09		12.98	-3.20	
MDD	6.94	25.20		7.95	21.81	
	Forward			**Swap**		
	LV R_{CS}	HV R_{CS}	LMH	LV R_{CS}	HV R_{CS}	LMH
mean (%)	14.55***	7.55*	7.01	10.72***	3.52	7.20
SR	1.70	0.74	0.96*	1.21	0.34	0.87*
Θ (%)	13.45	5.97		9.55	1.93	
MDD	4.97	12.96		8.69	20.21	

The table presents the out-of-sample economic performance of currency reversal strategies constructed such that the portfolio has zero net cost (dollar neutral). The LV R_{CS} strategy takes positions in currency pairs with abnormally low volume, with long positions in currencies which previously depreciated and short positions in currencies which previously appreciated. The HV R_{CS} strategy is the analogous strategy that takes positions in currency pairs with abnormally high volume. Results are reported separately for spot, forward, swap, and total (sum of spot, forward, and swap) volume. We report the annualized average return (mean), annualized Sharpe ratio (SR), 'theta' performance measure (Θ) proposed by Ingersoll et al. (2007) and the maximum drawdown (M DD). The values in the LMH column denote the difference between the annualized average return and Sharpe ratio between the LV R_{CS} and HV R_{CS} strategies. We test whether the individual annualized average returns (and their difference) are statistically different from zero with Newey and West (1987) adjusted t-statistics. We test whether the two Sharpe ratios are statistically different using the procedure proposed by Ledoit and Wolf (2008). Values marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table D.4: Subsamples of Currency Pairs

	EUR and GBP Pairs (13)			Ex EM and Fixed (24)		
	LV R_{CS}	HV R_{CS}	LMH	LV R_{CS}	HV R_{CS}	LMH
mean (%)	15.05***	7.59	7.46	16.19***	4.57	11.62**
SR	1.42	0.60	0.82*	1.43	0.34	1.09***
Θ (%)	13.37	5.21		14.27	1.88	
MDD	14.54	18.88		16.96	25.05	

	Liquid pairs (14)		
	LV R_{CS}	HV R_{CS}	LMH
mean (%)	16.86***	7.42	9.44
SR	1.25	0.50	0.75*
Θ (%)	14.15	4.20	
MDD	9.75	29.12	

The table presents the out-of-sample economic performance of currency reversal strategies using different subsamples of the 31 currency pairs available. We consider: only EUR and GBP pairs (13 currency pairs in total); excluding emerging market and fixed exchange rate pairs (24 currency pairs in total); and only liquid pairs including the G9 pairs and main EUR pairs (14 currency pairs). The LV R_{CS} strategy takes positions in currency pairs with abnormally low volume, with long positions in currencies which previously depreciated and short positions in currencies which previously appreciated. The HV R_{CS} strategy is the analogous strategy that takes positions in currency pairs with abnormally high volume. Results are reported for total (sum of spot, forward, and swap) volume. We report the annualized average return (mean), annualized Sharpe ratio (SR), 'theta' performance measure (Θ) proposed by Ingersoll et al. (2007) and the maximum drawdown (M DD). The values in the LMH column denote the difference between the annualized average return and Sharpe ratio between the LV R_{CS} and HV R_{CS} strategies. We test whether the individual annualized average returns (and their difference) are statistically different from zero with Newey and West (1987) adjusted t-statistics. We test whether the two Sharpe ratios are statistically different using the procedure proposed by Ledoit and Wolf (2008). Values marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

D.7: Bootstrap procedure

While the LV R_{CS} strategy generates substantial returns in our sample, a possible concern is that the sample itself is relatively short and, given the returns are positively skewed, may lead to an overstatement of the statistical significance of the strategy's returns. We address this concern by adopting a bootstrap procedure, similar to Goyal and Welch (2008) and Mark (1995), to generate p-values for each measure of investment performance previously considered. We show the strategy's performance is consistent with a clear rejection of the null hypotheses that the average returns, Sharpe ratios, and theta values are statistically no different from zero.

We generate data under the null hypothesis that neither past volume nor past returns have any predictive ability, and that instead the data are generated according to the following system:

$$r_{i,t+1} = \alpha_i + \varepsilon_{i,t+1} \tag{37}$$

$$v_{i,j,t+1} = \mu_{i,j} + \rho_{i,j} v_{i,j,t} + \eta_{i,j,t+1} \tag{38}$$

where $r_{i,t}$ is the log excess return for currency pair i at time t, $v_{i,j,t}$ is the dollar trading volume for currency pair i at time t for instrument j (j={total, spot, forward, swap}), α_i and $\mu_{i,j}$ are intercepts and $\eta_{i,j,t+1}$ and $\varepsilon_{i,t+1}$ are error terms. We begin by estimating the system via OLS equation-by-equation for each currency pair, and obtain a vector of residuals $\{\hat{E}_t = (\epsilon_t, \eta_{j=total,t}, \eta_{j=spot,t}, \eta_{j=orf,t}, \eta_{j=swap,t})'\}^T_{t=1}$ where $\epsilon_t = (\epsilon_{1,t}, \epsilon_{2,t}, ..., \epsilon_{31,t})$, and $\eta_{j,t} = (\eta_{1,j,t}, \eta_{2,j,t}, ..., \eta_{31,j,t})$. In order to generate a series of disturbances for our bootstrapped sample, we randomly draw with replacement T + 100 times from the residuals $\hat{E}_t$, yielding a bootstrapped series of residuals $\{\hat{E}^b_t\}^{T+100}_{t=1}$.[35] We draw from the residuals in tandem to preserve the contemporaneous correlation between the disturbances in the original sample across instruments and currency pairs.

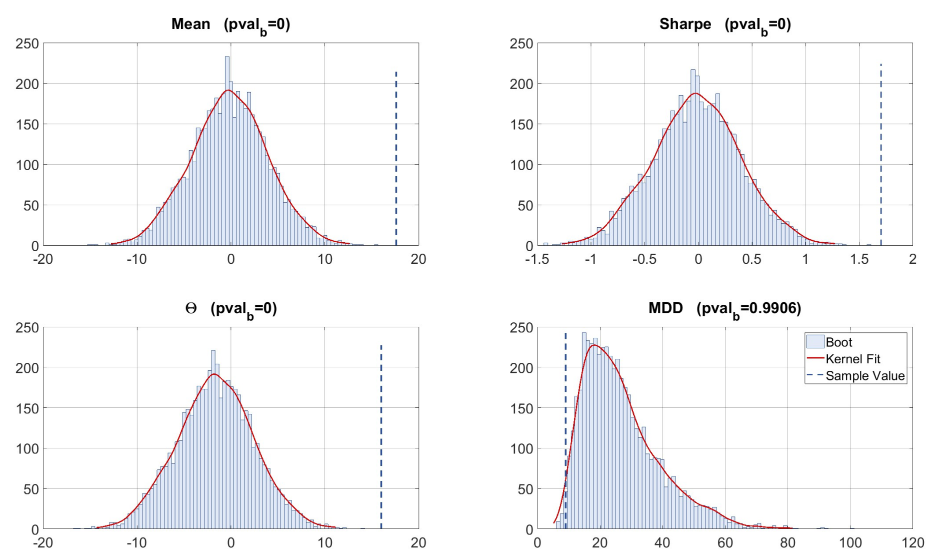
Using $\{\hat{E}^b_t\}^{T+100}_{t=1}$ and setting the initial observations equal to the unconditional means of the respective series, we build a bootstrapped sample of T + 100 observations, $\{r^b_t, v^b_{j=total,t}, v^b_{j=spot,t}, v^b_{j=orf,t}, v^b_{j=swap,t}\}_{t=1}$ where $r^b_t = (r^b_{1,t}, r_{2,t}, \ldots, r_{31,t})$, and $v^b_{j,t} = (v^b_{1,j,t}, v^b_{2,j,t}, \ldots, v^b_{31,j,t})$ are the vectors containing the bootstrapped values across the 31 currency pairs in our sample. For each bootstrap sample we perform the cross-sectional portfolio exercise described in Section 6. We repeat

[35] We drop the first 100 observations to randomize the initial observations and thus consider a bootstrapped sample of T observations that matches the original sample length.

this process 5,000 times, providing an empirical distribution of the performance measures used in Table 6, including the average annualized return, Sharpe Ratio, the 'theta' performance fee (Θ) measure of Ingersoll et al. (2007), and maximum drawdown, all under the null hypothesis of no predictability. For each performance measure, the bootstrapped p-value is calculated using the proportion of the bootstrap values greater than the ones computed using the original sample.

Figure D.2 reports the result for the reversal strategy that conditions on low volume. The vertical dashed line in each sub-figure denotes the value we record in Table 6. In each case, the realized investment performance of the strategy is found to be substantially different from the expected value under the null of no predictability. In only 0.02% of simulations is a higher average return, Sharpe ratio or Θ observed. Furthermore, in almost 99% of the simulations, the maximum drawdown of the strategy was higher than the one we documented in our sample. Overall, we view these findings as consistent with our earlier conclusion that the returns are highly statistically significant and suggestive of a dynamic relationship between FX volume and currency excess returns.

Figure D.2: Bootstrapped Economic Performance



The figure compares the economic performance of the LV R_{CS} strategy computed from 5,000 bootstrapped samples generated under the null of no predictability (light blue histogram), with the one computed from the original sample (vertical dashed line). All results are based on total volume (sum of spot, forward, and swap volume). The upper-left plot displays the annualized average return, the upper-right plot displays the annualized Sharpe Ratio, the lower-left plot displays the 'theta' (Θ) performance measure of Ingersoll et al. (2007), and the lower-right plot displays the maximum drawdown (mdd). The bootstrapped p-values ($pval_b$) are reported in parenthesis in each title.

Appendix E: Volume and Order Flow

Table E.1: Correlations Between Volume and Order Flow

		Order Flow			
	(1)	(2)	(3)	(4)	(5)
	Volume	BuySide	Funds	Non Bank	Corporate
AUDJPY	0.78	-0.01	-0.11	-0.00	0.02
AUDNZD	0.92	-0.07	0.01	0.05	0.01
AUDUSD	0.79	-0.01	0.03	-0.09	0.04
CADJPY	0.94	0.02	0.01	-0.02	0.08
EURAUD	0.92	0.02	-0.01	-0.02	-0.03
EURCAD	0.90	0.04	-0.01	-0.04	-0.15
EURCHF	0.95	-0.06	-0.05	-0.04	0.02
EURDKK	0.87	-0.00	0.01	-0.07	0.03
EURGBP	0.81	-0.01	-0.04	0.01	-0.03
EURJPY	0.92	-0.08	0.02	-0.03	-0.06
EURNOK	0.91	0.08	0.00	0.05	-0.03
EURSEK	0.89	-0.04	-0.01	0.07	-0.12
EURUSD	0.84	-0.02	-0.03	0.00	-0.06
GBPAUD	0.91	-0.07	-0.01	0.04	-0.09
GBPCAD	0.89	0.05	0.01	0.02	0.09
GBPCHF	0.86	-0.05	0.04	-0.07	0.03
GBPJPY	0.89	0.22	-0.00	0.04	0.04
GBPUSD	0.85	0.01	0.04	-0.09	-0.09
NZDUSD	0.90	0.03	0.02	-0.07	-0.00
USDCAD	0.88	-0.14	0.06	0.05	-0.04
USDCHF	0.73	-0.01	0.07	0.04	0.11
USDDKK	0.57	0.27	0.17	0.08	0.04
USDHKD	0.93	-0.04	0.04	0.08	0.12
USDILS	0.94	0.01	-0.08	0.01	0.01
USDJPY	0.90	-0.10	-0.01	-0.06	0.06
USDKRW	0.56	0.03	-0.09	-0.04	0.01
USDMXN	0.94	-0.04	-0.09	0.03	-0.01
USDNOK	0.74	0.06	0.08	0.01	0.03
USDSEK	0.81	0.13	0.12	0.07	0.06
USDSGD	0.95	0.03	0.02	0.02	0.01
USDZAR	0.87	-0.04	-0.01	0.02	0.02
Average	0.887	-0.003	0.013	0.011	0.010

Column (1) displays the correlations between daily spot volume from the CLS volume dataset and the "synthetic" spot volume from the CLS order flow dataset (computed as the sum of buy and sell volume). Columns (2) to (5) display the correlations between daily spot volume from the CLS volume dataset and spot order flow from the four customer segments in the CLS order flow dataset: "corporates", "funds", "banks" and "non-bank". Corporates includes any non-financial organizations, funds include pension funds, sovereign wealth funds, and hedge funds, while non-bank financial includes brokers and insurance companies.

Table E.2: Controlling for Order Flow

$Return_t$	-0.036**	-0.036**	-0.035**	-0.036**
	(0.016)	(0.016)	(0.016)	(0.016)
$Spot\ Volume_t$	0.009	0.010	0.007	0.003
	(0.011)	(0.011)	(0.011)	(0.011)
$Return_t * Spot\ Volume_t$	0.181***	0.181***	0.180***	0.180***
	(0.058)	(0.058)	(0.058)	(0.058)
OrderFlow : BuySide	0.011			
	(0.009)			
OrderFlow : Funds		0.031*		
		(0.019)		
OrderFlow : NonBankFinancial			-0.054	
			(0.082)	
OrderFlow : Corporate				-0.072
				(0.084)
Controls	YES	YES	YES	YES
adj-R^2	0.03	0.03	0.03	0.03
Nobs	40,536	40,536	40,536	40,536

The table presents coefficient estimates and associated p-values (reported in parentheses) for the following fixed-effects panel regression:

$$r_{i,t+1} = \alpha_i + \tau_t + \beta_1 r_{i,t} + \beta_2 \left(r_{i,t} v_{i,t} \right) + \beta_3 v_{i,t} + \beta_4 OF_{i,t} + \gamma' x_{i,t} + \epsilon_{i,t+1},$$

where α_i and τ_t denote currency-pair and time fixed effects, $r_{i,t}$ is the log currency excess return for currency pair i at time t, $v_{i,t}$ is the (log) deviation of spot volume from its recent trend, defined as $v_{i,t} = \log(Volume_{i,t}) - \log\left(\frac{\sum_{s=1}^{21} Volume_{i,t-s}}{21}\right)$, $OrderFlow_{i,t}$ is order flow; $x_{i,t}$ is a vector of controls relative to pair i and $\epsilon_{i,t+1}$ is the model error term. p-values are based on double-clustered standard errors. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Appendix F: Variables Theoretically Related to Volume

Volatility. Theoretical arguments for this relationship are based on the mixture of distributions hypothesis (e.g. Clark, 1973; Ranaldo and Santucci De Magistris, 2019), models of asymmetric information (Admati and Pfleiderer, 1988; Collin-Dufresne and Fos, 2016), and differences in opinion models (Harris and Raviv, 1993; Guo and Zhou, 2018). We consider various measures of volatility, as proxied by FX realized volatility at the currency-pair level (constructed using absolute returns), and broad market-wide measures of volatility including the VIX and VXY.[36]

Macroeconomic News. In the FX market, volume and volatility are both known to increase following macroeconomic data announcements, even when the announcement is consistent with expectations (see, e.g. Andersen et al., 2003; Chaboud, Chernenko, and Wright, 2008; Fischer and Ranaldo, 2011). We therefore include proxies for the arrival of new information based on the total number of U.S. macroeconomic data announcements taking place during the day, and a measure of the total relevance of those economic announcements, since more news announcements do not necessarily reflect more information if the economic relevance is low.

Liquidity. Volume should also be closely related to liquidity for which there are various potential definitions and measures. Demsetz (1968) argues that transaction volumes should decrease as the bid-ask spread widens, since a higher transaction cost discourages trade. A similar conclusion is reached in some models of asymmetric information (Kyle, 1985; Collin-Dufresne and Fos, 2016), in which higher levels of volume are associated with higher variability in uninformed order flow and lower price impact (e.g. smaller Kyle's lambda) or narrower spreads if informed traders place trades strategically. However, in other models of adverse selection in which orders arrive sequentially, dealers face losses from intermediating informed trades, and thus spreads widen when informed trading increases, which coincides with higher levels of volume (Glosten and Milgrom, 1985; Easley and O'Hara, 1992). The relationship between volume and liquidity is thus uncertain and prior empirical work in FX markets is limited. We proxy for liquidity using (i) the bid-ask spread, a currency-pair specific measure of

[36]The CBOE Volatility Index (VIX) is constructed from the implied volatility on options on the S&P 500. The VXY is an analogous index for currency markets created by J.P. Morgan. The index broadly measures implied volatility in a basket of G7 currencies.

trading costs and thus an important aspect of FX liquidity; (ii) absolute order flow, which proxies for the variance in order flow; and (iii) the TED spread, a measure of interbank credit risk that is common across currency pairs, defined as the difference between the 3-month LIBOR rate and the 3-month Treasury rate.

Asset Returns. Differences in money market, bond, and equity return differentials should influence FX volume via the hedging and portfolio rebalancing of global investors (Hau and Rey, 2006; Curcuru et al., 2014; Cenedese et al., 2016). Specifically, international investors, wishing to maintain a given set of portfolio weights, need to adjust portfolio holdings at regular intervals and transact in currency markets, either when converting the proceeds of sales or when purchasing new securities. We include the return differentials of short-term interest rates, 10-year bond returns, and aggregate equity returns (for each currency pair) in absolute value, since it is their absolute size that should generate trading activity, regardless of the sign.