
When does Liquidity matter?*

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This paper studies the role of liquidity in the world's largest over-the-counter market (OTC), the foreign exchange (FX) market. We are the first to systematically disentangle FX liquidity from volatility showing that both relate to FX premia in distinct ways. Our results are derived from a comprehensive trade and quotes dataset covering a broad cross-section of currency pairs. We provide compelling evidence that FX liquidity is only priced conditional on volatility being high and derive a new pricing factor. Incorporating this new pricing factor into a conditional asset pricing framework distinguishing between good and bad states of the world significantly improves the fit. Our findings are consistent with the sensitivity of OTC markets to volatility swings and market participants' loss aversion.

J.E.L. classification: G12, G15, F31

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Extended Abstract

1. Introduction

The foreign exchange (FX) market is arguably the backbone of international trade and global investing. Therefore, a better understanding of FX liquidity is important for at least three reasons. First, with an average daily trading volume of \$5.4 trillion (see [BIS, 2016](#)) the FX market is the world's largest financial market. Second, the FX market plays a crucial role in guaranteeing efficiency and no-arbitrage conditions in many other markets, including bonds, stocks and derivatives (e.g. [Pasquariello, 2014](#)). Third, due to its over-the-counter (OTC) nature the FX market is characterised by limited transparency, heterogeneity of market participants and fragmentation leading to unprecedented price and liquidity patterns.¹ This paper sheds new light on how to disentangle the asset pricing implications of FX liquidity from volatility. To do this, we extend the methodology in [Karnaukh et al. \(2015\)](#) to analyse a novel, comprehensive dataset that has three main advantages: First, it is representative of the *global* FX market rather than a specific segment (e.g. inter-dealer) or source (e.g. customers' trades of a given bank). Second, it includes aggregate market order flow data that allows us to compute accurate price impact measures of liquidity. The order flow represents the net of buy volume by price takers minus the sell volume by market maker FX transactions. Third, it provides *hourly* order-flow time series, which is the finest time granularity that has ever been studied for the *global* FX market. In this framework, we address two key questions, which are as follows: Is it possible to disentangle the asset pricing implications of liquidity from volatility? Does a novel conditional liquidity risk factor improve the fit of a general two factor asset pricing model? Answering these questions is important for both regulators and academics, since an appropriate OTC market design hinges on a better understanding of how liquidity and volatility shocks propagate to asset prices. Due to the OTC-nature of the FX market answering these questions is non-trivial and needs to take into account the distinctive characteristics of its two-tier market structure. The existing literature has mostly focused on the contemporaneous correlation between order flow and exchange rate returns (e.g. [Evans and Lyons, 2002](#), [Berger et al., 2008](#), [Banti et al., 2012](#)). Prior empirical research shows that FX liquidity helps to explain currency excess returns (e.g. [Christiansen et al., 2011](#), [Banti et al., 2012](#), [Mancini et al., 2013](#)). However, none of these studies investigates the importance of a low frequency liquidity measure (see [Karnaukh et al., 2015](#)) from a conditional asset pricing point of view that distinguishes between 'good' and 'bad' states of the world. Thus, the asset pricing implications of FX liquidity are an important issue that calls for further research. Our work provides novel insights into the role of liquidity in determining FX asset prices.

In recent years, structural changes of the FX market, such as the rise of electronic and

¹The FX market microstructure is explained in detail in [Lyons \(2006\)](#), [King et al. \(2012\)](#). More recent developments of the FX markets are discussed, for example, in [Rime and Schrimpf \(2013\)](#), [Moore et al. \(2016\)](#).

(high-frequency) automated trading, have exacerbated market fragmentation and asymmetric information across market participants (BIS, 2018). Together with its OTC nature, all these issues can create adverse selection, illiquidity and other frictions, such as search costs and bargaining power, especially in distressed times, for example, during the financial crisis of 2008 (Duffie, 2012). Consequently, regulators have implemented global regulatory reforms, for increasing transparency and market quality, such as the Dodd–Frank Act (USA, 2010), EMIR (Europe, 2012), and MiFID II (Europe, 2014). Shedding light on the direct asset pricing implications of FX liquidity would support these regulations that have direct implications on financial stability, price effectiveness and fairness. Furthermore, our study hopes to be relevant to global investors for understanding the distinct asset pricing implications of FX liquidity and volatility.

2. Methodology & Results

Our paper proceeds in three parts. In the first part, we construct a low-frequency global liquidity measure by averaging the first principal component of nine low frequency liquidity measures across currency pairs.² To accurately estimate price impacts as a proxy for liquidity we use a novel and unique dataset from Continuous Linked Settlement Group (CLS) from September 2013 to January 2019. CLS operates the world’s largest multi-currency cash settlement system, handling over 50% of the global spot, swap and forward FX transaction volume. This dataset includes aggregate hourly buy and sell order flow for 15 USD-base currency pairs. The data has recently been introduced and made publicly accessible, thereby allowing the replicability and extensions of our study. The order flow data is matched with bid–ask quotes from Olsen, a market leading provider of high-frequency time-series data.³ This is the first paper to use an accurate low frequency measure à la Karnaukh et al. (2015) to study the asset pricing implications of liquidity. Given the definition of its constituents our measure is effectively an *illiquidity* proxy. On the methodological side, this paper extends Karnaukh et al. (2015) who focus on estimating a low frequency liquidity measure that most accurately proxies effective cost by incorporating alternative definitions of liquidity⁴ namely price impact and reversal.

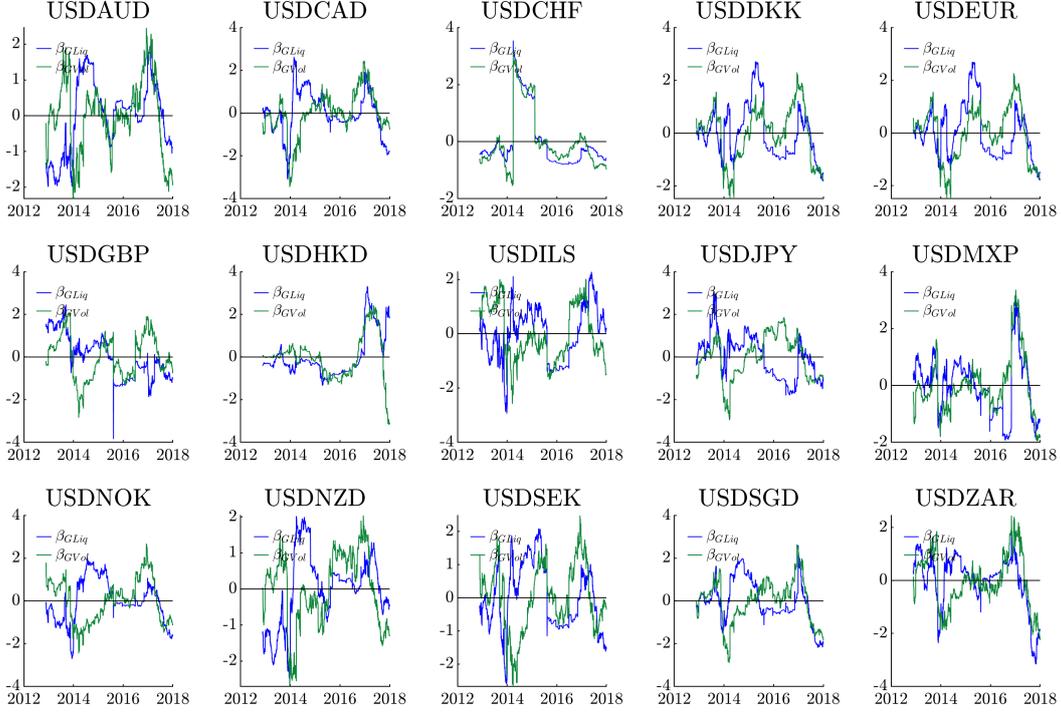
Second, to disentangle liquidity from volatility we regress currency excess returns on innovations in the global volatility factor by Menkhoff et al. (2012a) and our global liquidity

²The nine measures are the spread, price impact and reversal measures in Roll (1984), Brennan and Subrahmanyam (1996), Amihud (2002), Pástor and Stambaugh (2003), Bao et al. (2011), Corwin and Schultz (2012), Mancini et al. (2013), and Abdi and Ranaldo (2017).

³Olsen data are filtered in real time by assigning a credibility tick (ranging from 0–1), and they are directly available for all currency pairs. The number of ticks excluded from the supplied data due to credibility ≤ 0.5 depends on the number of ‘bad’ quotes, but typically ranges from 0.5%–3.0% per day.

⁴This alternative view was first formalised by Glosten and Milgrom (1985) and Kyle (1985) who put forward the idea that order flow price impacts are lower the more liquid an asset is as well as the lower the information asymmetry is across market participants.

Figure 1: Global Liquidity and Volatility Betas



Note: Regression coefficients have been scaled to have zero mean and unit variance.

factor. Figure 1 illustrates that both global volatility betas (β_{GVol}) and global liquidity betas (β_{GLiq}) exhibit substantial time-variation lending themselves to be analysed in an asset pricing framework. To accomplish this, we perform a dependent double sorting exercise that controls non-parametrically for the effect of volatility by first sorting on β_{GVol} and then conditionally on β_{GLiq} . All regression coefficients are estimated over a 252 days rolling window. To construct currency excess returns we follow the methodology in [Lustig and Verdelhan \(2007\)](#) and [Lustig et al. \(2011\)](#) and calculate the log *excess* return rx of buying a foreign currency in the forward market and selling it in the spot market next period as

$$rx_{t+1} = f_{t,t+1} - s_{t+1}. \quad (1)$$

Here, $f_{t,t+1}$ denotes the log-forward rate and s_t the log-spot rate, in units of the foreign currency per USD.⁵ Liquidity strategies are formed by taking long positions in high liquidity

⁵Daily forward bid-ask points are obtained from Bloomberg. Forward rates can be expressed as the forward discount/premium (or forward points) plus the spot rate. Therefore, the simple (outright) forward bid-ask rates are $F_t^b = S_t + P_t^b$ and $F_t^a = S_t + P_t^a$, respectively, where P_t^b and P_t^a denote the bid-ask values of forward

beta currencies and short positions in low liquidity beta currencies across the subsets of low ($Q_2 - Q_1$, LVO), and high ($Q_4 - Q_3$, HVO) volatility beta currencies. In Figure 2 we report summary statistics for the six characteristic portfolios formed from the conditional double sort. Three results stand out. First, the majority of portfolio returns are not statistically significant except for Q_3 that is the high volatility and low liquidity beta portfolio. Second, the turnover of the portfolios is high. On average, each portfolio exhibits over 55% turnover each day, and thus no single currency pair dominates any of the portfolios. Third, the return spread between high and low liquidity currency pairs is economically and statistically only significant conditional on volatility being high. This asymmetric liquidity premium squares well with OTC markets' sensitivity to volatility swings and market participants' loss aversion.

Our result can be rationalised as follows: currencies that provide a hedge against unexpected innovations in *liquidity* should trade at a discount and therefore earn higher expected returns, whereas the opposite is true for currencies with a low or even negative *liquidity* beta. Hence, our liquidity risk factor HVO is effectively short the low liquidity beta and long the high liquidity beta currency pairs.

Figure 2: 2x2 Conditional Double Sort

	Low Liquidity		High Liquidity		(High - Low) Liqu.	
Low Volatility	Q_1	mean -3.16%	Q_2	mean -1.90%	$Q_2 - Q_1$ LVO	mean 1.25%
	Sharpe -0.42	t-stat _{mean} 1.04	Sharpe -0.21	t-stat _{mean} 0.49	Sharpe 0.17	t-stat _{mean} 0.41
High Volatility	Q_3	mean -5.83%	Q_4	mean -0.86%	$Q_4 - Q_3$ HVO	mean 4.97%
	Sharpe -0.86	t-stat _{mean} 1.96	Sharpe -0.15	t-stat _{mean} 0.35	Sharpe 0.88	t-stat _{mean} 2.07

Note: This table summarises the performance of the four characteristic portfolios (Q_1 to Q_4) that emerge from the conditional double sorting. *Liqu.* stands for *Liquidity*.

points, respectively, and S_t is the mid-quote, defined as $S_t \equiv \frac{(S_t^a + S_t^b)}{2}$. Our results are robust to using spot bid (S_t^b) and ask (S_t^a) quotes instead of the mid-quote for calculating forward rates.

Third, we test if our new pricing factor generates a non-trivial Jensen's alpha (i.e. is not spanned by common pricing factors) as well as if it can improve the fit of a general asset pricing model with a 'level' and 'slope' factor. Our choice of basic pricing factors is guided by [Verdelhan \(2017\)](#) who demonstrates that the correlation structure of bilateral exchange rates can be summarised by a small number of principal components. Principal components are difficult to interpret, however the author identifies two common risk factors, namely, dollar and carry that are constructed from portfolios of currencies. These two factors are priced in currency markets and are highly correlated with the first two principal components, explaining a substantial share of variation in currency risk. In [Table 1](#) we provide compelling evidence that the conditional liquidity premium (HVO) is not spanned by any of the common FX risk factors (e.g. dollar, carry, momentum or value) documented in the international finance literature. What is more, the way how we derive HVO ensures that it is almost orthogonal to the global volatility risk factor in [Menkhoff et al. \(2012a\)](#). In fact, HVO generates a Jensen's alpha of 4.7% p.a. on average as well as an annualised return and Sharpe ratio of 4.97% and 0.88, respectively. When incorporating HVO into a conditional two factor asset pricing model we compare two specifications:

$$rx_{i,t} = \alpha_t + \beta_{1,t}DOL + \beta_{2,t}CAR_{HML} + \epsilon \quad (2)$$

$$rx_{i,t} = \alpha_t + \beta_{1,t}DOL + \beta_{2,t}CAR_{HML} + \gamma_t HVO + \epsilon, \quad (3)$$

where DOL is the dollar factor ([Verdelhan, 2017](#)) and CAR is the carry factor ([Lustig et al., 2011](#)) and $rx_{i,t}$ the excess return of every USD-base currency pair i at time t . Given the asymmetric effect of liquidity conditional on high ('bad') and low ('good') volatility states it is intuitive to compare the two asset pricing models across 'bad' and 'good' states of the world. In our baseline specification we proxy market states by innovations in the CBOE Volatility Index (VIX) being below and above their median deviation, respectively. [Figure 3](#) illustrates that a simple two factor model is essentially lacking a third component, that is, liquidity conditional on market states. Our findings provide compelling evidence that incorporating HVO into a conditional asset pricing framework improves the fit and therefore successfully alleviates the omitted variable bias. Our results are similar when we classify 'good' and 'bad' states based on the median return on HVO but not for other candidate conditioning variables such as β_{GLiq} or β_{GVol} . This counterfactual buttresses our main result that liquidity matters dependent on volatility and is therefore a conditional pricing factor. For further robustness we implement transaction costs at monthly rebalancing using accurate quoted bid-ask rates for both forward contracts and spot transactions.⁶ All our findings remain qualitatively unchanged.

⁶Transaction costs in FX spot and future markets are studied, for example, in [Bollerslev and Melvin \(1994\)](#), [Huang and Masulis \(1999\)](#), [Christiansen et al. \(2011\)](#), [Gilmore and Hayashi \(2011\)](#), and [Mancini et al. \(2013\)](#).

Table 1: Exposure to Common Risk Factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Jensen's α	**0.050 [2.067]	**0.047 [1.978]	**0.047 [1.975]	*0.042 [1.813]	**0.049 [2.038]	**0.050 [2.115]	**0.047 [1.962]	**0.046 [2.033]
DOL		***-0.089 [2.922]	0.104 [0.706]	***-0.698 [7.521]	*-0.280 [1.868]	***0.548 [2.825]	-0.034 [0.249]	*0.341 [1.799]
RER_{HML}			-0.092 [1.351]					
RER				***0.513 [7.020]				***0.663 [9.150]
MOM_{HML}					0.093 [1.329]			
CAR_{HML}						***-0.281 [3.293]		***-0.536 [6.269]
VOL_{HML}							-0.027 [0.421]	
\bar{R}^2 in %		0.82	0.90	6.51	0.95	2.00	0.76	10.52
IR	0.06	0.05	0.05	0.05	0.06	0.06	0.05	0.05
#Obs	1386	1386	1386	1386	1386	1386	1386	1386

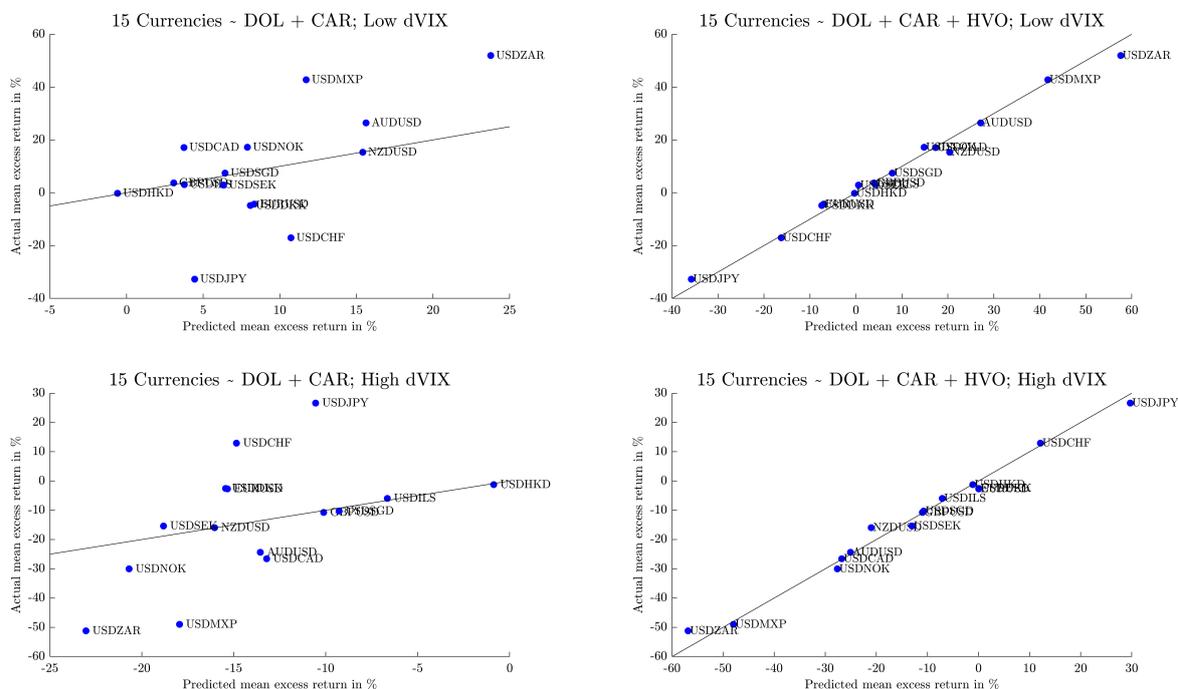
Note: In this table, we regress *gross* excess returns by HVO on daily excess returns associated with common risk factors, where DOL is based on USD currency pairs; RER/ RER_{HML} are based on the real exchange rate (cf. Menkhoff et al., 2017); MOM_{HML} is based on $f_{t-1,t}^m - s_t^m$ (cf. Asness et al., 2013); CAR_{HML} is based on the forward discount/ premium ($f_{t,t+1}^m - s_t^m$, cf. Lustig et al., 2011) and VOL_{HML} is based on the global volatility beta (β_{GVol} , cf. Menkhoff et al., 2012a). ΔVIX is the return on the VIX index and ΔCDS the change in the iTraxx Europe CDS index. The Jensen's α has been annualised ($\times 252$). The information ratio (IR) is defined as the Jensen's α divided by residual standard deviation. Significant findings at the 90%, 95% and 99% levels are represented by asterisks *, ** and ***, respectively. The numbers inside the brackets are the corresponding test statistics based on HAC errors correcting for serial correlation and small sample size (using the plug-in procedure for automatic lag selection by Newey and West (1994)).

3. Conclusion & Extensions

To summarise, two important findings emerge from our analysis: First, FX liquidity matters from an asset pricing point of view only conditional on volatility being high. Second, incorporating a conditional liquidity factor into a simple two factor asset pricing model with a 'level' and 'slope' factor significantly improves the fit.

We aim to extend this paper further along two dimensions: First, incorporating nonlinearities into the conditional asset pricing model using a logistic smooth transition regres-

Figure 3: Two versus three factor model



Note: These four figures compare asset pricing models across 'good' and 'bad' states conditioning on two and three pricing factors, respectively.

sive model. Second, developing a theoretical framework that guides the economic intuition of our empirical observations. An appropriate model will have to take into account that the source of liquidity matters for its asset pricing implications. The seminal work by Banerjee and Kremer (2010) and Vayanos and Wang (2011) will serve as a starting point for developing a framework to understand how the cross-sectional relationship between liquidity and expected returns depends both on the underlying imperfection and the sources of cross-sectional variation. Our empirical findings indicate that liquidity demanders' hedging needs and asymmetric information are prime suspects for being the driving force behind this heterogeneity. OTC markets fundamentally differ from their exchange traded counterparts as they are characterised by limited transparency, heterogeneity of participants and market fragmentation. All this will have to be taken into account modelling liquidity in the FX market.

4. Related Literature

We contribute to the international finance literature in several ways. First, our analysis is related to the broad literature on analysing the contemporaneous correlation between order

flow and exchange rate returns (e.g. [Evans, 2002](#), [Marsh and O'Rourke, 2005](#), [Berger et al., 2008](#), [Breedon and Vitale, 2010](#), [Banti et al., 2012](#)). Moreover, prior empirical research shows that FX liquidity helps to explain currency excess returns (e.g. [Christiansen et al., 2011](#), [Banti et al., 2012](#), [Mancini et al., 2013](#)). However, none of these studies attempts to disentangle FX liquidity from volatility in a conditional asset pricing framework. Furthermore, each of these studies either relies on using specific measures, such as the order flow or the bid-ask spread based on indicative quotes that are loosely correlated with high-frequency liquidity measures. Contrarily, this is the first paper to use an accurate low frequency measure of liquidity inspired by the methodology in [Karnaukh et al. \(2015\)](#). We distinguish ourselves from [Karnaukh et al. \(2015\)](#) along two dimensions: i) We augment our global liquidity measure by a second dimension namely price impact and reversal. ii) We study the direct asset pricing implications of liquidity conditional on volatility.

Second, our paper contributes to the FX asset pricing literature by building a long-short portfolio derived from a conditional double sort. This is an effective method to study the effect of liquidity on asset prices, whilst simultaneously controlling non-parametrically for the effect of volatility. In the FX asset pricing literature, [Lustig and Verdelhan \(2007\)](#) are the first to build cross-sections of currency portfolios to show that consumption growth risk explains why uncovered interest rate parity (*UIP*) fails to hold. [Lustig et al. \(2011\)](#), [Menkhoff et al. \(2012a,b\)](#) and [Asness et al. \(2013\)](#) identify common risk factors in currency markets based on the real exchange rate, global FX volatility and momentum. Other factors explaining carry trade returns include macro-variables like global imbalances (e.g. [Della Corte et al., 2016b](#)) or volatility risk premia (e.g. [Della Corte et al., 2016a](#)). We add to this literature by demonstrating that FX liquidity is priced but only conditional on volatility being high.

Bibliography

- Abdi, F. and Ranaldo, A. (2017). A simple estimation of bid-ask spreads from daily close, high, and low prices. *The Review of Financial Studies*, 30(12):4437–4480.
- Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5(1):31–56.
- Asness, C. S., Moskowitz, T. J., and Pedersen, L. H. (2013). Value and momentum everywhere. *The Journal of Finance*, 68(3):929–985.
- Banerjee, S. and Kremer, I. (2010). Disagreement and learning: Dynamic patterns of trade. *The Journal of Finance*, 65(4):1269–1302.
- Banti, C., Phylaktis, K., and Sarno, L. (2012). Global liquidity risk in the foreign exchange market. *Journal of International Money and Finance*, 31(2):267–291.
- Bao, J., Pan, J., and Wang, J. (2011). The illiquidity of corporate bonds. *The Journal of Finance*, 66(3):911–946.
- Berger, D. W., Chaboud, A. P., Chernenko, S. V., Howorka, E., and Wright, J. H. (2008). Order flow and exchange rate dynamics in electronic brokerage system data. *Journal of International Economics*, 75(1):93–109.
- BIS (2016). Triennial central bank survey - foreign exchange turnover in April 2016. *Bank for International Settlements (BIS), Triennial Survey*.
- BIS (2018). Monitoring of fastpaced electronic markets. *Bank for International Settlements (BIS), Study Group Report*.
- Bollerslev, T. and Melvin, M. (1994). Bid—ask spreads and volatility in the foreign exchange market. *Journal of International Economics*, 36(3-4):355–372.
- Breedon, F. and Vitale, P. (2010). An empirical study of portfolio-balance and information effects of order flow on exchange rates. *Journal of International Money and Finance*, 29(3):504–524.
- Brennan, M. J. and Subrahmanyam, A. (1996). Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of Financial Economics*, 41(3):441–464.
- Christiansen, C., Ranaldo, A., and Söderlind, P. (2011). The time-varying systematic risk of carry trade strategies. *Journal of Financial and Quantitative Analysis*, 46(04):1107–1125.

- Corwin, S. A. and Schultz, P. (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *The Journal of Finance*, 67(2):719–760.
- Della Corte, P., Ramadorai, T., and Sarno, L. (2016a). Volatility risk premia and exchange rate predictability. *Journal of Financial Economics*, 120(1):21–40.
- Della Corte, P., Riddiough, S. J., and Sarno, L. (2016b). Currency premia and global imbalances. *Review of Financial Studies*, 29(8):2161–2193.
- Duffie, D., editor (2012). *Dark Markets. Asset Pricing and Information Transmission in Over-the-Counter Markets*. Princeton University Press.
- Evans, M. D. (2002). FX trading and exchange rate dynamics. *The Journal of Finance*, 57(6):2405–2447.
- Evans, M. D. and Lyons, R. K. (2002). Order flow and exchange rate dynamics. *Journal of Political Economy*, 110(1):247–290.
- Gilmore, S. and Hayashi, F. (2011). Emerging market currency excess returns. *American Economic Journal: Macroeconomics*, 3(4):85–111.
- Glosten, L. R. and Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, 14(1):71–100.
- Huang, R. D. and Masulis, R. W. (1999). FX spreads and dealer competition across the 24-hour trading day. *Review of Financial Studies*, 12(1):61–93.
- Karnaukh, N., Ranaldo, A., and Söderlind, P. (2015). Understanding FX liquidity. *Review of Financial Studies*, 28(11):3073–3108.
- King, M. R., Osler, C., and Rime, D. (2012). *Foreign Exchange Market Structure, Players, and Evolution*. John Wiley & Sons, Inc.
- Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica*, 53(6):1315.
- Lustig, H., Roussanov, N., and Verdelhan, A. (2011). Common risk factors in currency markets. *Review of Financial Studies*, 24(11):3731–3777.
- Lustig, H. and Verdelhan, A. (2007). The cross section of foreign currency risk premia and consumption growth risk. *American Economic Review*, 97(1):89–117.
- Lyons, R. K. (2006). *The Microstructure Approach to Exchange Rates* (MIT Press). The MIT Press.
- Mancini, L., Ranaldo, A., and Wrampelmeyer, J. (2013). Liquidity in the foreign exchange market: Measurement, commonality, and risk premiums. *The Journal of Finance*, 68(5):1805–1841.

- Marsh, I. W. and O'Rourke, C. (2005). Customer order flow and exchange rate movements: Is there really information content? *SSRN Electronic Journal*.
- Menkhoff, L., Sarno, L., Schmeling, M., and Schrimpf, A. (2012a). Carry trades and global foreign exchange volatility. *The Journal of Finance*, 67(2):681–718.
- Menkhoff, L., Sarno, L., Schmeling, M., and Schrimpf, A. (2012b). Currency momentum strategies. *Journal of Financial Economics*, 106(3):660–684.
- Menkhoff, L., Sarno, L., Schmeling, M., and Schrimpf, A. (2017). Currency value. *The Review of Financial Studies*, 30(2):416–441.
- Moore, M., Schrimpf, A., and Sushko, V. (2016). Downsized FX markets: causes and implications. *BIS Quarterly Review*.
- Newey, W. K. and West, K. D. (1994). Automatic lag selection in covariance matrix estimation. *The Review of Economic Studies*, 61(4):631–653.
- Pasquariello, P. (2014). Financial market dislocations. *Review of Financial Studies*, 27(6):1868–1914.
- Pástor, L. and Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, 111(3):642–685.
- Rime, D. and Schrimpf, A. (2013). The anatomy of the global FX market through the lens of the 2013 Triennial Survey. *BIS Quarterly Review*.
- Roll, R. (1984). A simple implicit measure of the effective bid-ask spread in an efficient market. *The Journal of Finance*, 39(4):1127.
- Vayanos, D. and Wang, J. (2011). Liquidity and asset returns under asymmetric information and imperfect competition. *Review of Financial Studies*, 25(5):1339–1365.
- Verdelhan, A. (2017). The share of systematic variation in bilateral exchange rates. *The Journal of Finance*, 73(1):375–418.