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Price response functions and spread impact in foreign exchange markets

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Abstract To be done

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1 Introduction

The foreign exchange market is the most volatile, liquid and largest of all financial markets in the world [30,33,40]. Its importance in the world economy is prominent. It affects employment, inflation, international capital flows, among others [26]. The foreign exchange market is a decentralized market without common trading floor [26,33,11]

The term "pip" (Price Increment Point) is commonly used in the foreign exchange market in place of the word 'tick'. Pips arise as a matter of convention. A pip refers to the incremental value in the fifth non-zero digit position from the left. Note that it is not related to the position of the decimal point. For example, one pip in a USD/JPY value of 113.57 would be 0.01, while one pip for EUR/USD of 1.0434 would be 0.0001 [31,26].

The foreign exchange market has attracted a lot of attention in the last 20 years. Electronic trading has changed an opaque market to a fairly transparent with transactions costs that are a fraction of their former level. The large amount of data that is now available to the public make possible different kinds of analysis to this data. A lot of research is currently carry out in different directions [7,9,41,26,14,23,33,40,18,11,25,28,15,32,30].

In Ref. [31], McGroarty et al. found that smaller volumes cause larger bid-ask spreads for technical reasons to do with measurement, whereas in Refs. [22,23], Hau et al. claim that larger bid-ask spreads caused smaller volumes due to trader behavior.

In Ref. [7], Burnside et al. found the spreads to be between two and four times larger for emerging market currencies than for developed country currencies. In Ref. [25], Huang et al. found that bid-ask spreads increase when the foreign exchange market volatility increases, and decrease when the dealer competition increases. In Ref. [14], Ding et al. found the Electronic Broking Services (EBS) reduces spreads significantly, but dealers with information advantage tend to quote relatively wider spreads. In Ref. [13], King analyzed the foreign exchange futures market and found that the number of transactions is negatively related with bid-ask spread, whereas volatility in general is positively related. In Ref. [40], Serbinenko et al. focus in the three major market characteristics, namely efficiency, liquidity and volatility, finding that the market is efficient in a weak form.

Due to the lack of available data in the past, very few studies exist on price response functions in the foreign exchange market. Even if there are several papers about foreign exchange markets, we did not found large information about price response functions in this market. In Ref. [32], Melvin et al. simulate their proposed model for different region foreign exchange markets to analyze the impact of a one-standard-deviation shock using impulse response functions. The general pattern of response was a fairly steep drop over the first couple of days followed by a few days of gradual decline until the response is not statistically different from zero. In Ref. [30], Mancini et al. model the price impact and return reversal to analyze liquidity. Their model predicts that more liquid assets should exhibit narrower spreads and lower price impact.

Here, we want to discuss, based on a series of detailed empirical results obtained on trade by trade data, that the price response functions behave qualitatively the same in foreign exchange markets compared with correlated financial markets. We consider different time scales and currency pairs to compute the price response. To facilitate the reproduction of our results, the source code for the data analysis is available in Ref. (Poner referencia).

We delve into the price response function computation in foreign exchange markets. We perform a empirical study in different time scales and different years. We show the similarity between the price response functions in foreign exchange markets and correlated financial markets. Finally, we shed light on the spread impact in the response functions for currency pairs.

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The paper is organized as follows: in Sect. 2 we present our data set of foreign exchange pairs and briefly describe the physical and trade time. We define the time scale we will use in Sect. 3, and compute the price response functions for the majors pairs in Sect. 4. In Sect. 5 we show how the spread impact the values of the response functions. Our conclusions follows in Sect. 6.

2 Data set

In this study, we analyze foreign exchange pairs from the foreign exchange market. In the foreign exchange market, the trading day begins in the markets of Australia and Asia. Then the markets of Europe open and finishes late in the afternoon in New York [26]. The markets does not formally closes during the week. Thus, using the New York time as reference, the market opens on Sunday at 19h00 and closes on Friday at 17h00.

The foreign exchange financial data was obtained from HistData.com. We used a tick-by-tick database in generic ASCII format for different years and currency pairs. The data comprises the date time stamp (YYYYMMDD HHMMSSNNN), the best bid and best ask quotes prices in the Eastern Standard Time (EST) time zone. No information about the size of each transaction is provided. Also, the identity of the participants is not given.

On physical time scale, for each exchange rate, we process the irregularly spaced raw data to construct second-by-second price and volume series, each containing 86,400 observations per day. For every second, the midpoint of best bid and ask quotes or the transaction price of deals is used to construct one-second log-returns.

To analyze the price response functions in Sect. **??**, we select the seven major currency pairs in three different years (2008, 2014 and 2019). Table 1 shows the currency pairs with their corresponding symbols.

Table 1. Analyzed currency pairs.

Currency pair	Symbol
euro/U.S dollar	EUR/USD
British pound/U.S dollar	GBP/USD
Japanese yen/U.S dollar	JPY/USD
Australian dollar/U.S dollar	AUD/USD
U.S dollar/Swiss franc	USD/CHF
U.S dollar/Canadian dollar	USD/CAD
New Zealand dollar/U.S dollar	NZD/USD

To analyze the spread impact in price response functions (Sect. 5), we select 57 currency pairs, in three different years (2011, 2015 and 2019). The selected pairs are listed in Appendix A

In order to avoid overnight effects and any artifact due to the opening and closing of the foreign exchange market, we systematically discarded the first ten and the last ten minutes of trading in a given week [5,16,21,48,24]. Therefore, we only consider trades of the same week from Sunday 19:10:00 to Friday 16:50:00 New York local time. We will refer to this interval of time as the “market time”.

3 Time scale

In Sect. 3.1 we describe the physical time scale and the trade time scale. In Sect. 3.2 and Sect. 3.3 we define the trade time scale and physical time scale respectively.

3.1 Time definition

Due to the nature of the data, they are several options to define time for analyzing data.

In general, the time series are indexed in calendar time (hours, minutes, seconds, milliseconds). Moreover, tick-by-tick data available on financial markets all over the world is time stamped up to the millisecond, but the order of magnitude of the guaranteed precision is much larger, usually one second or a few hundreds of milliseconds [4,10]. In several papers are used different time definitions (calendar time, physical time, event time, trade time, tick time) [10,20,43]. The foreign exchange market data used in the analysis only has the quotes. In consequence, we have to infer the trades during the market time. As we have tick-by-tick resolution, we can use either trade time scale or physical time scale.

The trade time scale is increased by one unit each time a transaction happens, which in our case is every time the quotes change. The advantage of this count is that limit orders far away in the order book do not increase the time by one unit. The main outcome of trade time scale is its “smoothing” of data and the aggregational normality [10].

The physical time scale is increased by one unit each time a second passes. This means that computing the responses in this scale involves sampling [20,48], which has to be done carefully when dealing for example with several stocks with different liquidity. This sampling is made in the trade signs and in the midpoint prices.

3.2 Trade time scale

We use the trade sign classification in trade time scale proposed in Ref. [48] and used in Refs. [45,46,47,24] that reads

$$\varepsilon^{(t)}(t,n) = \begin{cases} \operatorname{sgn}\left(S(t,n) - S(t,n-1)\right), & \text{if} \\ \quad S(t,n) \neq S(t,n-1) & \\ \varepsilon^{(t)}(t,n-1), & \text{otherwise} \end{cases} \tag{1}$$

$\varepsilon^{(t)}(t,n) = +1$ implies a trade triggered by a market order to buy, and a value $\varepsilon^{(t)}(t,n) = -1$ indicates a trade triggered by a market order to sell.

In the second case of Eq. (1), if two consecutive trades with the same trading direction did not exhaust all the available volume at the best quote, the trades would have the same price, and in consequence they will have the same trade sign.

With this classification we obtain trade signs for every single trade in the data set. According to Ref. [48], the average accuracy of the classification is 85% for the trade time scale.

3.3 Physical time scale

We use the trade sign definition in physical time scale proposed in Ref. [48] and used in Refs. [45,47], that depends on the classification in Eq. (1) and reads

$$\varepsilon^{(p)}(t) = \begin{cases} \mathrm{sgn}\left(\sum_{n=1}^{N(t)} \varepsilon^{(t)}(t,n)\right), & \text{If } N(t) > 0 \\ 0, & \text{If } N(t) = 0 \end{cases} \quad (2)$$

where $N(t)$ is the number of trades in a second interval. $\varepsilon^{(p)}(t) = +1$ implies that the majority of trades in second t were triggered by a market order to buy, and a value $\varepsilon^{(p)}(t) = -1$ indicates a majority of sell market orders. In this definition, they are two ways to obtain $\varepsilon^{(p)}(t) = 0$. One way is that in a particular second there are no trades, and then no trade sign. The other way is that the addition of the trade signs ($+1$ and -1) in a second be equal to zero. In this case, there is a balance of buy and sell market orders.

Market orders show opposite trade directions to limit order executed simultaneously. An executed sell limit order corresponds to a buyer-initiated market order. An executed buy limit order corresponds to a seller-initiated market order.

In this case we do not compare every single trade sign in a second, but the net trade sign obtained for every second with the definition, see Eq. (2). According to Ref. [48], this definition has an average accuracy up to 82% in the physical time scale.

4 Price response functions

In Sect. 4.1 we establish the fundamental quantities used in the price response definitions. In Sect. 4.2 we analyze the responses functions in trade time scale and in Sect. 4.3 we analyze the responses functions in physical time scale.

4.1 Key concepts

In general, three categories of currency pairs are defined: majors, crosses, and exotics. The "major" foreign exchange currency pairs are the major countries that are paired with the U.S. dollar (see Table 1). The "crosses" are those majors pairs that are not paired against the U.S. dollar. Finally, the "exotic" pairs usually consist of a major currency alongside a thinly traded currency or an emerging market economy currency. The majors are the most liquid pairs, in contrast with the exotics, who can be much more volatile.

In foreign exchange markets, orders are execute at the best available buy or sell price. Orders often fail to result in an immediate transaction, and are stored in a queue called the limit order book [38,6,17,29,26]. The order book is visible for all traders and its main purpose is to ensure that all traders have the same information on what is offered on the market. For a detailed description of the operation of the markets, we suggest to see Ref. [24].

At any given time there is a best (lowest) offer to sell with price $a(t)$, and a best (highest) bid to buy with price $b(t)$ [38,3,8,12,42]. The price gap between them is called the spread $s(t) = a(t) - b(t)$ [3,4,5,8,16,27,42,11]. Spreads are significantly positively related to price and significantly negatively related to trading volume. Companies with more liquidity tend to have lower spreads [1,2,8,19]. Despite the foreign exchange market is often cited as the world's largest financial market, this description fail to consider the considerable differences in trading volume and liquidity across different currency pairs [15]. These differences can be directly seen in the spread. Furthermore, the bid-ask spread is directly related with the transaction costs to the dealer [11,13].

Due to the lack of prices information in the data, we consider a basic definition of the price given by [18,28,30]. The average of the best ask and the best bid is the midpoint price, which is defined as [38,3,5,16,27,42,24,11]

$$m(t) = \frac{a(t) + b(t)}{2} \quad (3)$$

Price changes are typically characterized as returns. If one denotes $S(t)$ the price of an asset at time t, the return $r(t,\tau)$, at time t and time lag τ is simply the relative variation of the price from t to $t+\tau$ [3,10,34,35,36,39],

$$r^{(g)}(t,\tau) = \frac{S(t+\tau) - S(t)}{S(t)} \quad (4)$$

We define the returns via the midpoint price as

$$r(t,\tau) = \frac{m(t+\tau) - m(t)}{m(t)} \quad (5)$$

The distribution of returns is strongly non-Gaussian and its shape continuously depends on the return period τ. Small τ values have fat tails return distributions [3]. The trade signs are defined for general cases as

$$\varepsilon(t) = \mathrm{sign}\left(S(t) - m(t-\delta)\right) \quad (6)$$

where δ is a positive time increment. Hence we have

$$\varepsilon(t) = \begin{cases} +1, & \text{If } S(t) \text{ is higher than the last } m(t) \\ -1, & \text{If } S(t) \text{ is lower than the last } m(t) \end{cases} \quad (7)$$

$\varepsilon(t) = +1$ indicates that the trade was triggered by a market order to buy and a trade triggered by a market order to sell yields $\varepsilon(t) = -1$ [3,5,21,37,44].

The main objective of this work is to analyze the price response functions. In general we define the price response functions in a foreign exchange market as

$$R_{ii}^{(scale)}(\tau) = \left\langle r_i^{(scale)}(t-1,\tau)\,\varepsilon_i^{(scale)}(t) \right\rangle_{average} \tag{8}$$

where the index i correspond to currency pairs in the market, $r_i^{(scale)}$ is the return of the pair i in a time lag τ in the corresponding scale and $\varepsilon_i^{(scale)}$ is the trade sign of the pair i in the corresponding scale. The superscript *scale* refers to the time scale used, whether physical time scale ($scale = p$) or trade time scale ($scale = t$). Finally, The subscript *average* refers to the way to average the price response, whether relative to the physical time scale ($average = P$) or relative to the trade time scale ($average = T$).

4.2 Response functions on trade time scale

The price response function in trade time scale is defined as

$$R_{ii}^{(t)}(\tau) = \left\langle r_i^{(p)}(t-1,\tau)\,\varepsilon_i^{(t)}(t,n) \right\rangle_T \tag{9}$$

where the superscript t refers to the trade time scale.

To compute the response functions on trade time scale, we used all the trade signs during a week in market time.

4.3 Response functions on physical time scale

One important detail to compute the market response in physical time scale is to define how the averaging of the function will be made, because the response functions highly differ when we include or exclude $\varepsilon_j^{(p)}(t) = 0$ [48]. The cross-responses including $\varepsilon_j^{(p)}(t) = 0$ are weaker than the excluding ones due to the omission of direct influence of the lack of trades. However, either including or excluding $\varepsilon_j^{p}(t) = 0$ does not change the trend of price reversion versus the time lag, but it does affect the response function strength [47]. For a deeper analysis of the influence of the term $\varepsilon_j^{(p)}(t) = 0$, we suggest to check Refs. [47, 48]. We will only take in account the cross-response function excluding $\varepsilon_j^{p}(t) = 0$.

We define the price response functions in physical time scale, using the trade signs and the returns in physical time scale. The price response function on physical time scale is defined as

$$R_{ii}^{(p)}(\tau) = \left\langle r_i^{(p)}(t-1,\tau)\,\varepsilon_i^{(p)}(t) \right\rangle_P \tag{10}$$

where the superscript p refers to the physical time scale.

5 Spread impact in price response functions

As we showed in Sect. 1, due to the difference in the position of the decimal points between foreign exchange rates,

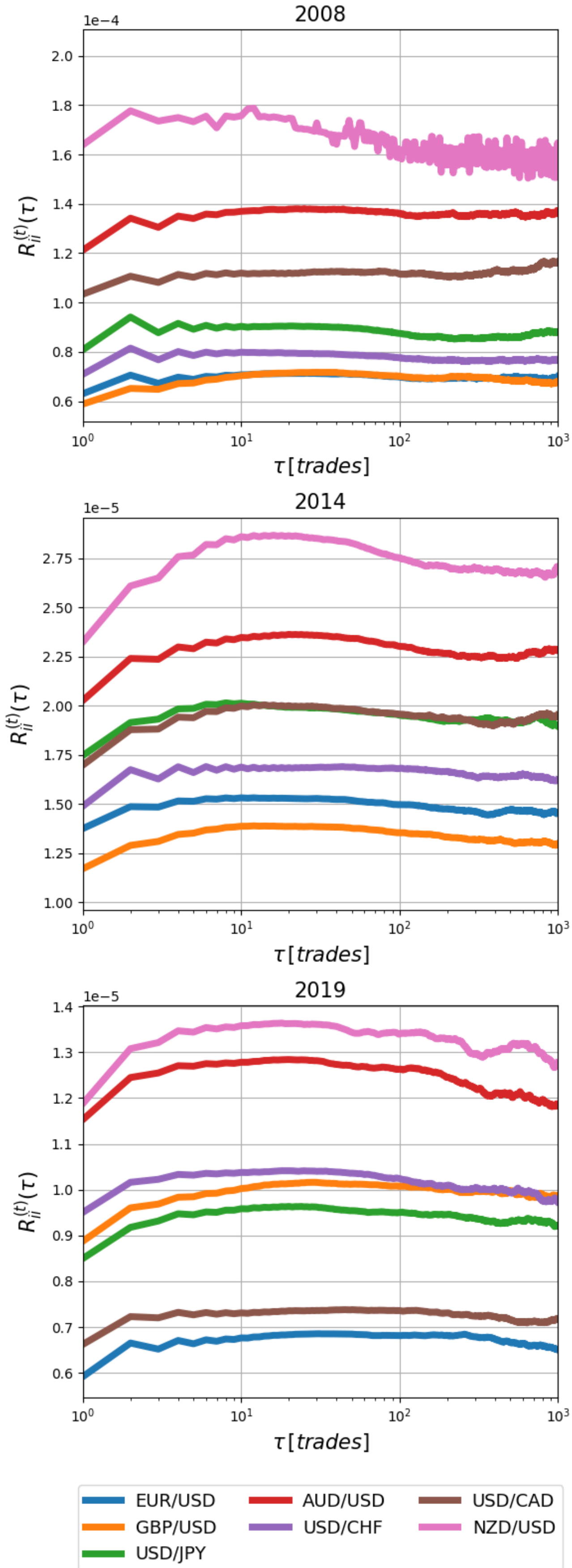

Figure 1. Price response functions $R_{ij}^{(t)}(\tau)$ versus time lag τ on a logarithmic scale in trade time scale for the years 2008 (top), 2014 (middle) and 2019 (bottom).

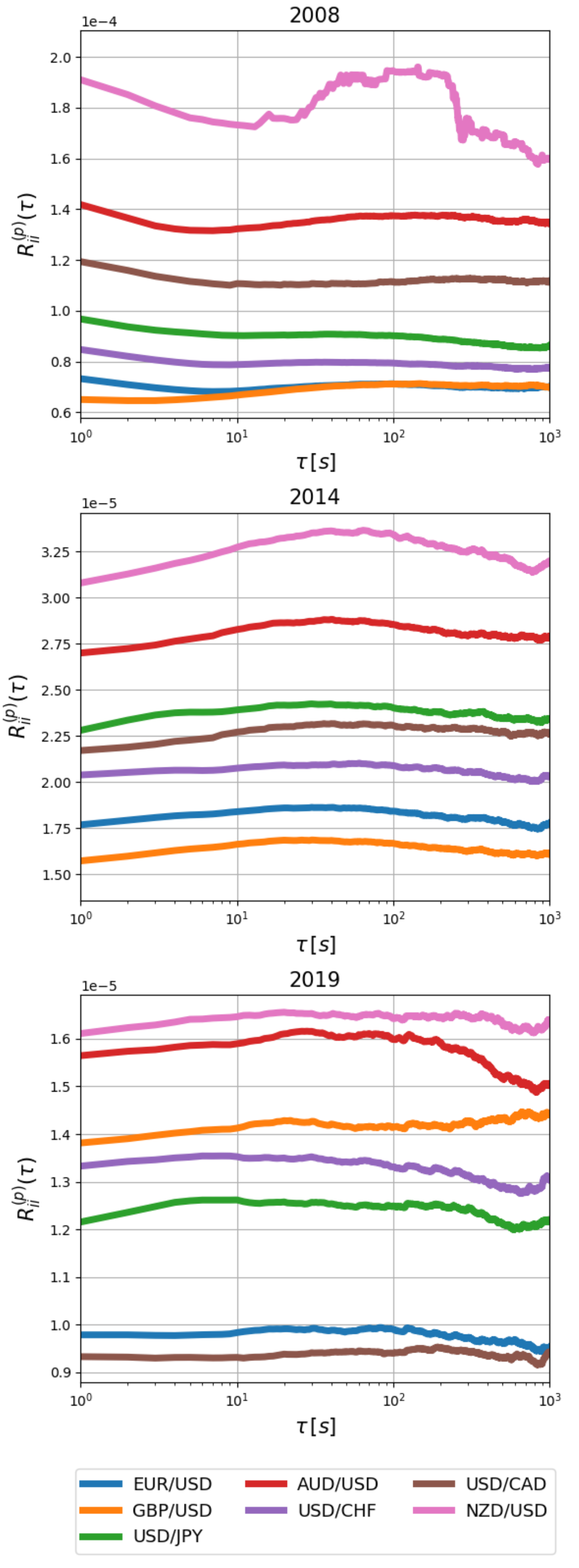

Figure 2. Price response functions $R_{ij}^{(p)}(\tau)$ excluding $\varepsilon_i^{(p)}(t) = 0$ versus time lag τ on a logarithmic scale in physical time scale for the years 2008 (top), 2014 (middle) and 2019 (bottom).

we need to introduce a "scaling factor" with the purpose of bringing the pip to the left of the decimal point. For example, the scaling factor for the USD/JPY is 100 and that for the EUR/USD is 10000.

The pip bid-ask spread is defined as [31]:

$$\text{pip}_{spread} = (a(t) - b(t)) \cdot \text{scaling factor} \qquad (11)$$

6 Conclusion

7 Author contribution statement

TG proposed the research. JCHL developed the method of analysis. The idea to analyze the spread impact was due to JCHL. JCHL carried out the analiysis. All the authors contributed equally to analyze the results and write the paper.

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Appendix A Foreign exchange pairs used to analyze the spread impact

References

1. Hee-Joon Ahn, Jun Cai, Yasushi Hamao, and Richard Y.K Ho. The components of the bid–ask spread in a limit-order market: evidence from the tokyo stock exchange. *Journal of Empirical Finance*, 9(4):399 – 430, 2002.
2. Yakov Amihud and Haim Mendelson. The effects of beta, bid-ask spread, residual risk, and size on stock returns. *The Journal of Finance*, 44(2):479–486, 1989.
3. Jean-Philippe Bouchaud. The subtle nature of financial random walks. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 15(2):026104, 2005.
4. Jean-Philippe Bouchaud, J. Doyne Farmer, and Fabrizio Lillo. How markets slowly digest changes in supply and demand. 2008.
5. Jean-Philippe Bouchaud, Yuval Gefen, Marc Potters, and Matthieu Wyart. Fluctuations and response in financial markets: the subtle nature of "random" price changes. *Quantitative Finance*, 4(2):176–190, Apr 2004.
6. Jean-Philippe Bouchaud, Marc Mézard, and Marc Potters. Statistical properties of stock order books: empirical results and models. *Quantitative Finance*, 2(4):251–256, Aug 2002.
7. Craig Burnside, Martin Eichenbaum, and Sergio Rebelo. The returns to currency speculation in emerging markets. Working Paper 12916, National Bureau of Economic Research, February 2007.
8. Carolyn Callahan, Charles Lee, and Teri Yohn. Accounting information and bid-ask spread. *Accounting Horizons*, 11:50–60, 01 1997.

9. Alain P. Chaboud, Benjamin Chiquoine, Erik Hjalmarsson, and Clara Vega. Rise of the machines: Algorithmic trading in the foreign exchange market. *The Journal of Finance*, 69(5):2045–2084, 2014.
10. Anirban Chakraborti, Ioane Toke, Marco Patriarca, and Frédéric Abergel. Econophysics: Empirical facts and agent-based models. *arXiv.org, Quantitative Finance Papers*, 09 2009.
11. Jeng-Hong Chen. Teaching the bid-ask spread and triangular arbitrage for the foreign exchange market. *American Journal of Business Education (AJBE)*, 11:55–62, 10 2018.
12. Kee H Chung, Bonnie F [Van Ness], and Robert A [Van Ness]. Limit orders and the bid–ask spread. *Journal of Financial Economics*, 53(2):255 – 287, 1999.
13. David K. Ding. The determinants of bid-ask spreads in the foreign exchange futures market: A microstructure analysis. *Journal of Futures Markets*, 19(3):307–324, 1999.
14. Liang Ding and Jonas Hiltrop. The electronic trading systems and bid-ask spreads in the foreign exchange market. *Journal of International Financial Markets, Institutions and Money*, 20(4):323 – 345, 2010.
15. Martin D.D. Evans and Dagfinn Rime. Microstructure of foreign exchange markets. *Available at SSRN 3345289*, 2019.
16. J. Doyne Farmer, László Gillemot, Fabrizio Lillo, Szabolcs Mike, and Anindya Sen. What really causes large price changes? *Quantitative Finance*, 4(4):383–397, 2004.
17. J. Doyne Farmer, Paolo Patelli, and Ilija I. Zovko. The predictive power of zero intelligence in financial markets, 2003.
18. James Glattfelder, Alexandre Dupuis, and Richard Olsen. Patterns in high-frequency fx data: Discovery of 12 empirical scaling laws. *arXiv.org, Quantitative Finance Papers*, 11, 01 2008.
19. Lawrence R Glosten and Lawrence E Harris. Estimating the components of the bid/ask spread. *Journal of Financial Economics*, 21(1):123 – 142, 1988.
20. Jim E. Griffin and Roel C. A. Oomen. Sampling returns for realized variance calculations: Tick time or transaction time? *Econometric Reviews*, 27(1-3):230–253, 2008.
21. Stephan Grimm and Thomas Guhr. How spread changes affect the order book: comparing the price responses of order deletions and placements to trades. *The European Physical Journal B*, 92:1–11, 2018.
22. Harald Hau, William Killeen, and Michael Moore. The euro as an international currency: explaining puzzling first evidence from the foreign exchange markets. *Journal of International Money and Finance*, 21(3):351–383, June 2002.
23. Harald Hau, William Killeen, and Michael Moore. How has the euro changed the foreign exchange market? *Economic Policy*, 17(34):149–192, April 2002.
24. Juan C. Henao-Londono, Sebastian M. Krause, and Thomas Guhr. Price response functions and spread impact in correlated financial markets.
25. Roger D. Huang and Ronald W. Masulis. Fx spreads and dealer competition across the 24-hour trading day. *Capital Markets: Market Microstructure*, 1999.
26. Michael King, Carol Osler, and Dagfinn Rime. *Foreign Exchange Market Structure, Players and Evolution.* 08 2012.
27. Sebastian Krause, Jonas Fiegen, and Thomas Guhr. Emergence of stylized facts during the opening of stock markets. *The European Physical Journal B*, 2018.
28. M. Kremer, A. P. Becker, I. Vodenska, H. E. Stanley, and R. Schäfer. Economic and political effects on currency clustering dynamics. *Quantitative Finance*, 19(5):705–716, 2019.
29. Fabrizio Lillo. *Introduction to market microstructure and heterogeneity of investors*, pages 73–89. 2019.
30. Loriano Mancini, Angelo Ranaldo, and Jan Wrampelmeyer. Liquidity in the foreign exchange market: Measurement, commonality, and risk premiums. *The Journal of Finance*, 68(5):1805–1841, 2013.
31. Frank McGroarty, Owain ap Gwilym, and Stephen Thomas. Microstructure effects, bid–ask spreads and volatility in the spot foreign exchange market pre and post-emu. *Global Finance Journal*, 17(1):23 – 49, 2006.
32. Michael Melvin and Bettina Peiers Melvin. The global transmission of volatility in the foreign exchange market. *The Review of Economics and Statistics*, 85(3):670–679, 2003.
33. Lukas Menkhoff, Lucio Sarno, Maik Schmeling, and Andreas Schrimpf. Information flows in foreign exchange markets: Dissecting customer currency trades. *The Journal of Finance*, 71(2):601–634, 2016.
34. Michael C. Münnix, Rudi Schäfer, and Thomas Guhr. Compensating asynchrony effects in the calculation of financial correlations. *Physica A: Statistical Mechanics and its Applications*, 389(4):767 – 779, 2010.
35. Michael C. Münnix, Rudi Schäfer, and Thomas Guhr. Impact of the tick-size on financial returns and correlations. *Physica A: Statistical Mechanics and its Applications*, 389(21):4828 – 4843, 2010.
36. Michael C. Münnix, Rudi Schäfer, and Thomas Guhr. Statistical causes for the epps effect in microstructure noise. *International Journal of Theoretical and Applied Finance*, 14(08):1231–1246, 2011.
37. Vasiliki Plerou, Parameswaran Gopikrishnan, Xavier Gabaix, and H. Eugene Stanley. Quantifying stock-price response to demand fluctuations. *Phys. Rev. E*, 66:027104, Aug 2002.
38. Marc Potters and Jean-Philippe Bouchaud. More statistical properties of order books and price impact. 2002.
39. Thilo A. Schmitt, Desislava Chetalova, Rudi Schäfer, and Thomas Guhr. Non-stationarity in financial time series: Generic features and tail behavior. *EPL (Europhysics Letters)*, 103(5):58003, sep 2013.
40. Anna Serbinenko and Svetlozar Rachev. Intraday spot foreign exchange market. analysis of efficiency, liquidity and volatility. *Investment Management and Financial Innovations*, 6:35–45, 01 2009.
41. Syed Jawad Hussain Shahzad, Jose Areola Hernandez, Waqas Hanif, and Ghulam Mujtaba Kayani. Intraday return inefficiency and long memory in the volatilities of forex markets and the role of trading volume. *Physica A: Statistical Mechanics and its Applications*, 506:433 – 450, 2018.
42. Eric Smith, J Doyne Farmer, László Gillemot, and Supriya Krishnamurthy. Statistical theory of the continuous double auction. *Quantitative Finance*, 3(6):481–514, 2003.
43. Ioane Muni Toke. *"Market Making" in an Order Book Model and Its Impact on the Spread*, pages 49–64. Springer Milan, Milano, 2011.
44. Bence Tóth, Imon Palit, Fabrizio Lillo, and J. Doyne Farmer. Why is equity order flow so persistent? *Journal of Economic Dynamics and Control*, 51(C):218–239, 2015.

45. Shanshan Wang. Trading strategies for stock pairs regarding to the cross-impact cost, 2017.
46. Shanshan Wang and Thomas Guhr. Local fluctuations of the signed traded volumes and the dependencies of demands: a copula analysis. *Journal of Statistical Mechanics: Theory and Experiment*, 2018(3):033407, mar 2018.
47. Shanshan Wang, Rudi Schäfer, and Thomas Guhr. Average cross-responses in correlated financial markets. *The European Physical Journal B*, 89(9):207, Sep 2016.
48. Shanshan Wang, Rudi Schäfer, and Thomas Guhr. Cross-response in correlated financial markets: individual stocks. *The European Physical Journal B*, 89(4), Apr 2016.