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Price response functions and spread impact in foreign exchange markets

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Abstract In spite of the considerable interest, a thorough statistical analysis of foreign exchange markets was hampered by limited access to data. This changed, and nowadays such data analyses are possible down to the level of ticks and over long time scales. We analyze price response functions in the foreign exchange market for different years and different time scales. Such response functions provide quantitative information on the deviation from Markovian behavior. The price response functions show an increase to a maximum followed by a slow decrease as the time lag grows, in trade time scale and in physical time scale, for all analyzed years. Furthermore, we use a price increment point (pip) spread definition to group different foreign exchange pairs and analyze the impact of the spread in the price response functions. We found that large pip spreads have stronger impact on the response. This is similar to what has been found in stock markets.

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1 Introduction

A major objective of data driven research on complex systems is the identification of generic or universal statistical behavior. The tremendous success of thermodynamics and statistical mechanics serves as an inspiration when continuing this quest in complex systems beyond traditional physics. Particularly interesting are large complex systems which consists of similar, yet clearly distinguishable complex subsystems. The degree of universality found in one particular subsystem can then be assessed if the type of universality is seen in another subsystem. Useful information on the impact or lack thereof of specific system features on this universality may then be inferred.

Here, we carry out such a study for finance, because a tremendous amount of data is available [1]. Markets may be viewed as macroscopic complex systems with an internal microscopic structure that is to a large extent accessible by large scale data analysis [2]. Stock markets and foreign exchange markets are clearly distinct, but share many common features. In previous analyses, we studied response functions in stock markets to shed light on non-Markovian behavior. Here, we extend that to the foreign exchange markets. To our surprise, we did not find such an investigation in the literature. Hence, we believe that this study is a rewarding effort. It helps to examine the behavior of the functions applied to the foreign exchange market and it is suitable to compare the similarities and differences to other markets.

The foreign exchange market is the most volatile, liquid and largest of all financial markets [3,4,5,6], and it has a paramount importance for the world economy. It affects employment, inflation, international capital flows, among others [7]. The foreign exchange market is a decentralized market without a common trading floor [4,5,7,8]

The term pip (Price Increment Point) is commonly used in the foreign exchange market instead of tick. The precise definition of a pip is a matter of convention. Usually, it refers to the incremental value in the fifth non-zero digit position from the left. It is not related to the position of the decimal point. For example, one pip in the exchange rate USD/JPY of 124.21 would be 0.01, while one pip for EUR/USD of 1.1021 would be 0.0001 [5,7,9,10].

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 one 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 data analysis. Intense research is currently carried out in different directions [3,4,6,7,8,11,12,13,14,15,16,17,18,19,20,21].

McGroarty et al. [10] found that smaller volumes cause larger bid-ask spreads for technical reasons related to the measurement, whereas Hau et al. [16,22] claim that larger bid-ask spreads caused smaller volumes due to the traders' behavior.

Burnside et al. [14] found the spreads to be between two and four times larger for emerging market curren-

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cies than for developed country currencies. According to Huang and Masulis [17], bid-ask spreads increase when the foreign exchange market volatility increases, and decrease when the competition between the dealers increases. Ding and Hiltrop [12] showed that the Electronic Broking Services (EBS) reduces spreads significantly, but dealers with information advantage tend to quote relatively wider spreads. King [23] analyzed the foreign exchange futures market and observed that the number of transactions is negatively related with bid-ask spread, whereas volatility in general is positively related. Serbinenko and Rachev [6] focus on the three major market characteristics, namely efficiency, liquidity and volatility, and found that the market is efficient in a weak form. Menkhoff and Schmeling [20] used orders from the Russian interbank for Russian rouble/US dollar rate. They analyzed the price impact in different regions of Russia, and found that regions that are centers of political and financial decision making have high permanent price impact.

The price response functions measure price changes resulting from execution of market orders. Specifically, they measure how a buy or sell order at time t influences on average the price at a later time $t+\tau$. It was shown in different works [24,25,26,27,28,29,30,31,32] that the price response functions increase to a maximum and then slowly decrease as the time lag grows.

Little is known about price response functions in the foreign exchange markets: [3,19,33]. Melvin and Melvin [19] simulate their proposed model for different foreign exchange markets region 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. Mancini et al. [3] 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.

To the best of our knowledge, no large-scale data analysis of response functions for foreign exchange market has been carried out. Response functions are important observables as they give information on non-Markovian behavior. It is the purpose of the present study to close this gap. Based on a series of detailed empirical results obtained on trade by trade data, we show that the price response functions in the foreign exchange markets behave qualitatively similar as the ones in correlated stocks markets. We consider different time scales, years and currency pairs to compute the price response functions. Finally, we shed light on the spread impact in the response functions for foreign exchange pairs. We use a pip spread definition to group different foreign exchange pairs and show that large pip spreads have stronger impact on the response.To facilitate the reproduction of our results, the source code for the data analysis is available in Ref. [34].

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 scale. We define the time scale to be used 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 follow in Sect. 6.

2 Data set

In the foreign exchange market, the trading day begins in Australia and Asia. Then the markets in Europe open and finally the markets in America [5,7]. As the market close time in New York overlaps the market open time in Australia and Asia, the markets do not formally close 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 use 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 the 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. 4, 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 46 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 discard the first ten and the last ten minutes of trading in a given week [28,30,32,35,36]. 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 and the physical time scales, 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 labeled 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 [37,38]. In several papers are used different time definitions (calendar time, physical time, event time, trade time, tick time) [38,39,40]. 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 increases 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 [38].

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 [32,39], 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. [32] and used in Refs. [30,31,41,42] that reads

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

Here, $\varepsilon^{(\mathrm{t})}(t,n) = +1$ 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 do not exhaust all the available volume at the best quote, the trades would have the same price, and they will thus have the same trade sign.

With this classification we obtain trade signs for every single trade in the data set. According to Ref. [32], 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. [32] and used in Refs. [31,41], that depends on the classification in Eq. (1) and reads

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

where $N(t)$ is the number of trades in an interval of one second. Here, $\varepsilon^{(\mathrm{p})}(t) = +1$ implies that the majority of trades in second t are triggered by a market order to buy, and a value $\varepsilon^{(\mathrm{p})}(t) = -1$ indicates a majority of sell market orders. In this definition, they are two ways to obtain $\varepsilon^{(\mathrm{p})}(t) = 0$. First, there are not trades in a particular second and thus no trade sign. Second, the sum of the trade signs in a given second amounts to zero, indicating an exact balance of buy and sell market orders.

Market orders show opposite trade directions as compared to limit orders 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. [32], 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 most frequently traded currencies that are paired with the U.S. dollar (see Table 1). The "crosses" are those majors pairs paired between them and that exclude 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 [5,7,43,44,45,46]. 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. [30].

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 $b(t)$ [27,46,47,48,49]. The price gap between them is called the spread $s(t) = a(t) - b(t)$ [8,27,28,35,37,47,49,50]. Spreads are significantly positively related to price and significantly negatively related to trading volume. Companies with more liquidity tend to have lower spreads [24,47,51,52]. 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 [11]. These differences can be directly seen in the spread. Furthermore, the bid-ask spread is directly related with the transaction costs to the dealer [8,23].

As there is no price information in the data, we consider a basic definition of the price given by [3,15,18]. The average of the best ask and the best bid is the midpoint price, which is defined as [8,27,28,30,35,46,49,50]

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

Price changes are typically characterized as returns. If one denotes $S(t)$ the price of an asset at time t, the return $r^{(g)}(t, \tau)$, at time t and time lag τ is simply the relative variation of the price from t to $t + \tau$ [27,38,53,54,55,56],

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

We define the returns via the midpoint price as

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

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 [27]. The trade signs are defined for general cases as

$$\varepsilon(t) = \text{sign}(S(t) - m(t - \delta)), \tag{6}$$

where δ is a positive time increment. Hence we have

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

Here, $\varepsilon(t) = +1$ indicates that the trade was triggered by a market order to buy and a trade triggered by a market order to sell yields $\varepsilon(t) = -1$ [27,28,36,57,58].

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

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

where the index i correspond to currency pairs in the market, $r_i^{(\text{scale})}$ is the return of the pair i in a time lag τ in the corresponding scale and $\varepsilon_i^{(\text{scale})}$ 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 $= T$).

For correlated financial markets, the price response function increase to a maximum and then slowly decrease. This result is observed empirically in trade time scale and in physical time scale [30,31].

4.2 Response functions on trade time scale

The price response function in trade time scale is defined as [?]

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

To compute the response functions on trade time scale, we use both, the trade signs and the returns during a week in market time.

The results of Fig. 1 show the price response functions of the seven foreign exchange major pairs used in the analysis (see Table 1) for three different years. For all the years it can be seen the same behavior observed in financial correlated markets. The response functions increase to a maximum and then slowly decrease. For our selected pairs, a time lag of $\tau = 10^3 s$ is enough to see an increase to a maximum followed by a decrease. Thus, the trend in the price response functions is eventually reversed. The response signal is much more noisier in the year 2008 for the first seconds in the time lag. This behavior is because of the smaller amount of data of the corresponding year. In general, more data was recorded in recent years than in past years. In the three years analyzed, the more liquid currency pairs have a smaller response in comparison with the non-liquid pairs. The strength of the response function vary from one year to the other. In 2008 the strength of the signal is one order of magnitude stronger than the response in 2014, but the signals in 2014 have approximately twice the strength the signals of 2019. This behavior can be explained by the fact that in recent times algorithm trading has been used intensively. Thus, many more trades were carried out in the last years, which means, the impact of each trade is reduced, and then the response functions tend to decrease compared with previous years.

4.3 Response functions on physical time scale

One important detail to compute the price response function on 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 $\varepsilon_j^{(\text{p})}(t) = 0$ [32]. The price responses including $\varepsilon_j^{(\text{p})}(t) = 0$ are weaker than the excluding ones due to the omission of direct influence of the lack of trades. However, either including or excluding $\varepsilon_j^{(\text{p})}(t) = 0$ does not change the trend of price reversion versus the time lag, but it does affect the response function strength [31]. For a deeper analysis of the

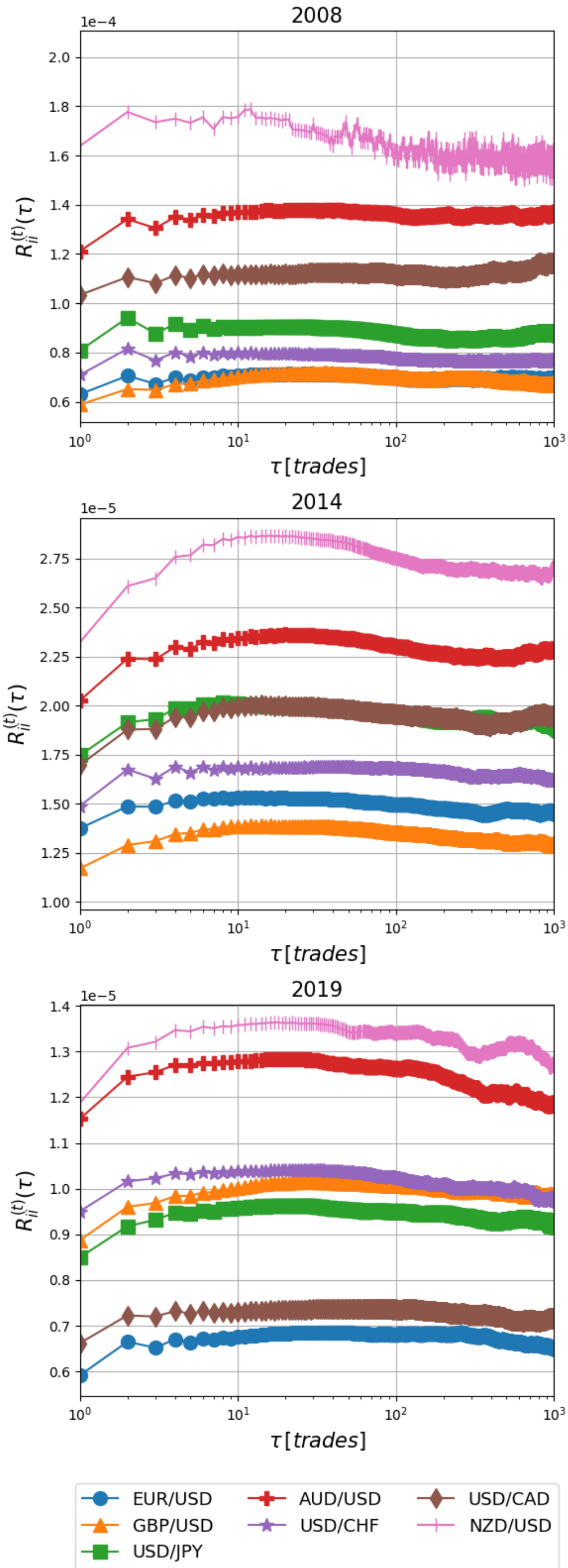

Figure 1. Price response functions $R_{ii}^{(\mathrm{t})}(\tau)$ versus time lag τ on a logarithmic scale in trade time scale for the years 2008 (top), 2014 (middle) and 2019 (bottom).

influence of the term $\varepsilon_j^{(\mathrm{p})}(t) = 0$ in price response functions, we suggest to review Refs. [31,32]. We will only take into account the price response functions excluding $\varepsilon_j^{\mathrm{p}}(t) = 0$.

We define the price response functions on 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 [?]

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

The results shown in Fig. 2 are the price response functions on physical time scale for three different years. The results show approximately the same behavior observed in currency exchange pairs in trade time scale, and in correlated financial markets, where we can see that an increase to a maximum is followed by a decrease. Thus again, the trend in the price responses is eventually reversed. An exception occurs in the year 2008, where the response at short time lags seems to decrease, to then start to slightly increase, and finally it decrease again.

The price response functions on physical time scale are smoother than the responses on trade time scale. As we reduce from trade data all the returns and trade signs in one second to one data point on physical time scale, and as this sampling gives the same weight to every data point, the curves look smoother.

Compared with the response functions on trade time scale, the strength of the signal of the response functions on physical time scale are similar in magnitude in the corresponding years. Thus, the strength of the signal in 2008 for trade time scale is similar to the strength of the signal in 2008 for physical time scale, and so on. This behavior is different to the one presented in correlated financial markets, where the results differ about a factor of two depending on the time scale.

On physical time scale, we can see that the liquid pairs have a smaller price response compared with non-liquid pairs. Therefore, the price response of a foreign exchange pair with large activity is smaller to the small impact of each trade. Also, the older the response, the stronger the signal. We consider the same argument of algorithm trading to explain why the signals in recent years are weaker than in older years.

5 Spread impact in price response functions

To analyze the spread impact in price response functions, we use 47 foreign exchange pairs from three different years (Appendix A). As we showed in Sect. 1, due to the difference in the position of the decimal points in the price between foreign exchange pairs, to compare them 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 the one for the EUR/USD is 10000.

The pip bid-ask spread is defined as [10]

$$s_{\mathrm{pip}} = (a(t) - b(t)) \cdot \text{scaling factor}. \qquad (11)$$

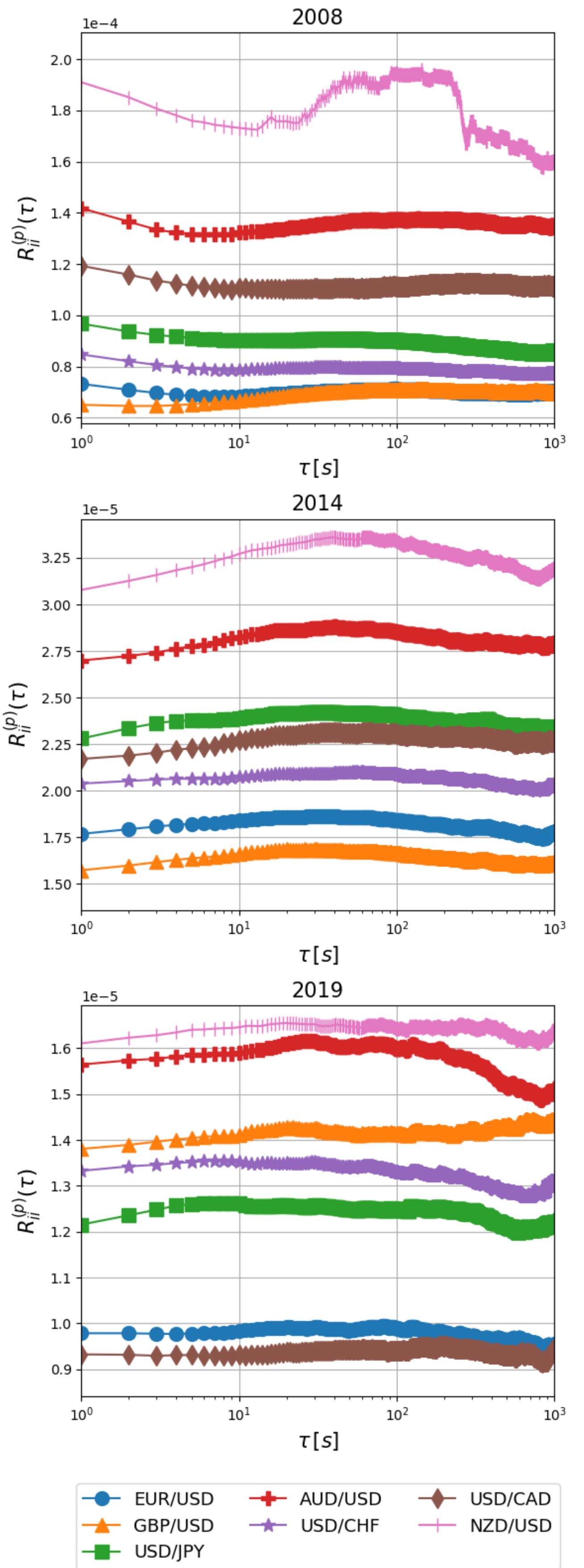

Figure 2. Price response functions $R_{ii}^{(\mathrm{p})}(\tau)$ excluding $\varepsilon_i^{(\mathrm{p})}(t) = 0$ versus time lag τ on a logarithmic scale in physical time scale for the years 2008 (top), 2014 (middle) and 2019 (bottom).

With the s_{pip} we can group the foreign exchange pairs and check how the average strength of the price response functions on trade time scale and physical time scale behave. For each pair we compute the pip bid-ask spread in every trade along the market time. Then we average the spread during the trade weeks in the different years. With this value we group the foreign exchange pairs.

Depending on the year, we identify different number of groups according with the pip spread s_{pip}. For the years 2011 and 2015, we use two intervals to select the foreign exchange pairs groups ($s_{\mathrm{pip}} < 10$ and $10 \leq s_{\mathrm{pip}}$). We use three intervals in the year 2019 to select the foreign exchange pairs groups ($s_{\mathrm{pip}} < 4$, $4 \leq s_{\mathrm{pip}} < 10$ and $10 \leq s_{\mathrm{pip}}$). The detailed information of the foreign exchange pairs, spread and the groups can be seen in Appendix A. With the groups of the stocks defined, we average the price response functions of each group.

In Fig. 3 we show the average response functions for the corresponding groups in three different years. From year to year the groups can vary depending on the pip spread. The average price response function for the pairs with smaller pip spreads (more liquid) have in average the weakest signal in the figure for all the years and both time scales. On the other hand, the average price responses for the pairs with larger pip spread (less liquid) have in average the strongest signal for all the years in both time scales.

From Sect. 4 we expect the increase-maximum-decrease behavior. This behavior can be seen in the figures of the year 2015 for both time scales and in the figure of the year 2019 in trade time scale. In these figures the average price response functions follow an increase, reach a maximum and then start to slowly decrease. For the other figures, on average, the response functions start to decrease from the beginning.

The response in trade time scale seems to be noisier, with large changes in the first time steps. This aggregate noise can be related with the crosses and exotics pairs, who tend to fluctuate more.

For the years 2015 and 2019 in physical time scale, the increase-maximum-decrease behavior is not that well defined as in Sect. 4 or as in the average response in trade time scale. However, some groups tend to behave in the expected way. The groups that do not follow the trend, seem to have a instantaneous high response that slowly decrease with time. This behavior is mostly noticeable in the year 2019.

For the year 2011 in physical time scale, the increase-maximum-decrease shape is not present. For both groups the response decrease almost immediately.

In the three plots, the foreign exchange market seems to have a global influence over all the pairs in the corresponding years. A similar behavior can be seen in correlated financial markets [30].

6 Conclusion

Price response functions provide quantitative information on the deviation from Markovian behavior. They measure

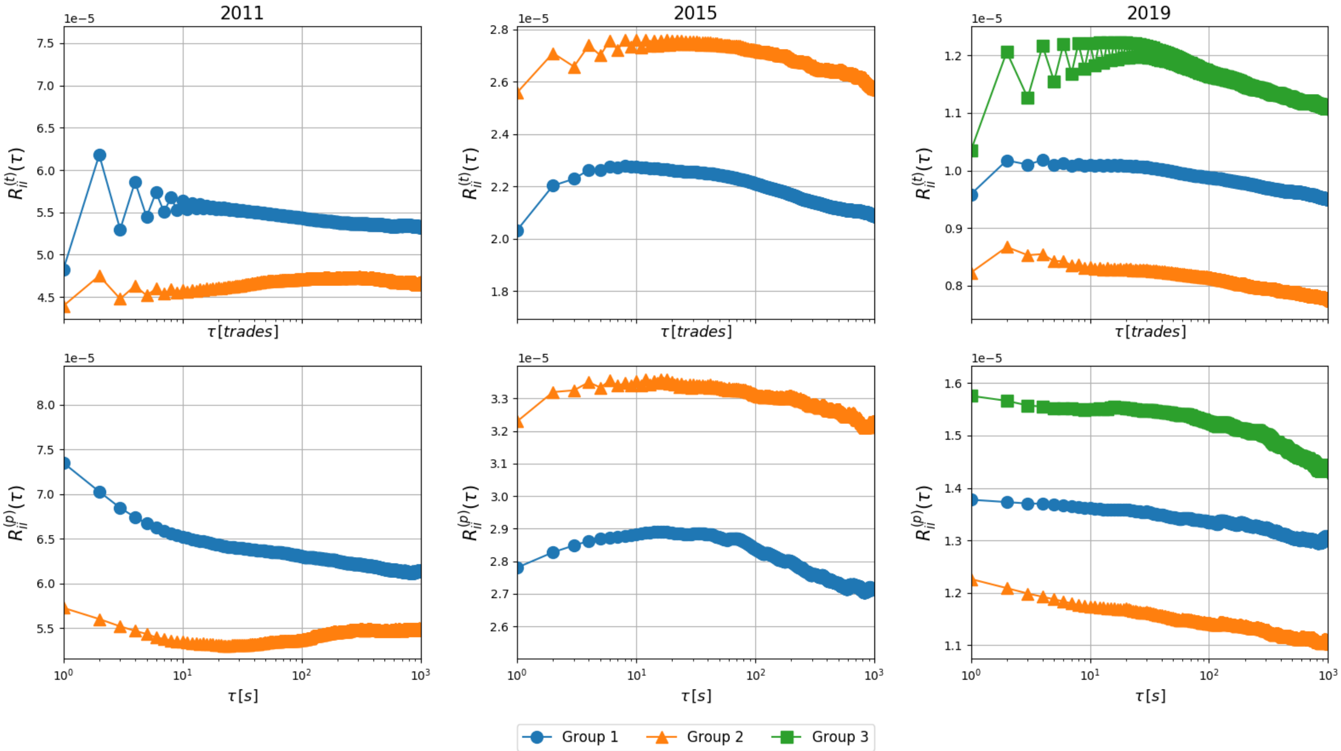

Figure 3. Average price response functions $R_{ii}^{(t)}(\tau)$ versus time lag τ on a logarithmic scale in trade time scale (Top) and $R_{ii}^{(p)}(\tau)$ excluding $\varepsilon_i^{(p)}(t) = 0$ versus time lag τ on a logarithmic scale in physical time scale (Bottom) for 47 foreign exchange pairs divided in representative groups in three different years (2011, 2015 and 2019).

price changes resulting from execution of market orders. We used these functions in a large-scale data analysis for foreign exchange markets. Such a study was, to the best of our knowledge, never done before.

We analyzed price response functions in foreign exchange markets for different years and different time scales. We used trade time scale and physical time scale to compute the price response functions for the seven major foreign exchange pairs for three different years. These major pairs are highly relevant in the dynamics of the market.

The price response functions were analyzed according to the time scales. On trade time scale, the signals were noisier. For both time scales we observe that the signal for all the pairs increase to a maximum and then start to slowly decrease. However, for the year 2008 the shape of the signals is not well defined as in the other years. The increase-decrease behavior observed in the foreign exchange market was also reported in correlated financial markets [30,31]. These results show that the price response functions conserve their behavior in different years and in different markets.

In both scales, the more liquid pairs have a smaller price response function compared with the non-liquid pairs. As the liquid pairs have more trades during the market time, the impact of each trade is reduced. Comparing between years and scales, the price response signal is stronger in past year than in recent years. As algorithm trading has gain great relevance, the quantity of trades has grown in recent years, and in consequence, the impact in the response has decreased.

Finally, we checked the pip spread impact in price response functions for three different years. We used 46 foreign exchange pairs and grouped them depending on the conditions of the corresponding year analyzed. We employ the year average pip spread of every pair for each year. For all the year and time scales, the price response function signals were stronger for the groups of pairs with larger pip spreads and weaker for the group of pairs with smaller spreads. For the average of the price response functions, it was only possible to see the increase-maximum-decrease behavior in the year 2015 in both scales, and in the year 2019 in trade time scale. This suggest there is a lot of noise in the cross and exotic pairs due to the lack of trading compared with the majors. A general average price response behavior for each year and time scale was spotted for the groups, suggesting a market effect on the foreign exchange pairs in each year.

Comparing the response functions in stock and currency exchange markets from a more general viewpoint, we find a remarkable similarity. It triggers the conclusion that the order book mechanism generates in a rather robust fashion the observed universal features in these two similar, yet different subsystems within the financial system.

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 analysis. All the authors contributed equally to analyzing the results and writing the paper.

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Appendix A Foreign exchange pairs used to analyze the spread impact

We analyzed the spread impact in the price response functions for 47 foreign exchange pairs in the foreign exchange market for the years 2011, 2015 and 2019. In Table 2, we listed the pairs in their corresponding pip spread groups.

References

1. H.E Stanley, L.A.N Amaral, D Canning, P Gopikrishnan, Y Lee, and Y Liu. Econophysics: Can physicists contribute to the science of economics? *Physica A: Statistical Mechanics and its Applications*, 269(1):156–169, 1999.
2. Dean Rickles. Econophysics and the complexity of financial markets. In Cliff Hooker, editor, *Philosophy of Complex Systems*, volume 10 of *Handbook of the Philosophy of Science*, pages 531–565. North-Holland, Amsterdam, 2011.
3. 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.
4. 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.
5. Carol Osler. *Market Microstructure, Foreign Exchange*, pages 580–614. Springer New York, New York, NY, 2011.
6. 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.
7. Michael King, Carol Osler, and Dagfinn Rime. *Foreign Exchange Market Structure, Players and Evolution.* 08 2012.
8. 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.
9. Shikuan Chen, Chih-Chung Chien, and Ming-Jen Chang. Order flow, bid-ask spread and trading density in foreign exchange markets. *Journal of Banking & Finance*, 36(2):597–612, 2012.
10. 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.
11. Martin D.D. Evans and Dagfinn Rime. Microstructure of foreign exchange markets. *Available at SSRN 3345289*, 2019.
12. 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.
13. 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.
14. 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.
15. 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.
16. Harald Hau, William Killeen, and Michael Moore. How has the euro changed the foreign exchange market? *Economic Policy*, 17(34):149–192, April 2002.
17. Roger D. Huang and Ronald W. Masulis. Fx spreads and dealer competition across the 24-hour trading day. *Capital Markets: Market Microstructure*, 1999.
18. 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.
19. 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.
20. Lukas Menkhoff and Maik Schmeling. Local information in foreign exchange markets. *Journal of International Money and Finance*, 27(8):1383 – 1406, 2008.
21. 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.
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. 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.
24. 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.
25. M Benzaquen, I Mastromatteo, Z Eisler, and J-P Bouchaud. Dissecting cross-impact on stock markets: an empirical analysis. *Journal of Statistical Mechanics: Theory and Experiment*, 2017(2):023406, Feb 2017.
26. J. P. Bouchaud, J. Kockelkoren, and M. Potters. Random walks, liquidity molasses and critical response in financial markets, 2004.
27. Jean-Philippe Bouchaud. The subtle nature of financial random walks. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 15(2):026104, 2005.

Table 2. Foreign exchange pairs used in Sect. 5.

Symbol	Pair	Category	Scaling factor	2011	2015	2019
AUD/CAD	Australian dollar/Canadian dollar	Cross	10000	G1	G1	G1
AUD/CHF	Australian dollar/Swiss franc	Cross	10000	G1	G1	G1
AUD/JPY	Australian dollar/Japanese yen	Cross	100	G1	G1	G1
AUD/NZD	Australian dollar/New Zealand dollar	Cross	10000	G2	G1	G1
AUD/USD	Australian dollar/U. S. dollar	Major	10000	G1	G1	G1
CAD/CHF	Canadian dollar/Swiss franc	Cross	10000	G1	G1	G1
CAD/JPY	Canadian dollar/Japanese yen	Cross	100	G1	G1	G1
CHF/JPY	Swiss franc/Japanese yen	Cross	100	G1	G1	G1
EUR/AUD	euro/Australian dollar	Cross	10000	G2	G1	G1
EUR/CAD	euro/Canadian dollar	Cross	10000	G1	G1	G1
EUR/CHF	euro/Swiss franc	Cross	10000	G1	G1	G1
EUR/CZK	euro/Czech koruna	Exotic	10000	G2	G2	G3
EUR/GBP	euro/British pound	Cross	10000	G1	G1	G1
EUR/HUF	euro/Hungarian forint	Exotic	100	G2	G2	G3
EUR/JPY	euro/Japanese yen	Cross	100	G1	G1	G1
EUR/NOK	euro/Norwegian krone	Exotic	10000	G2	G2	G3
EUR/NZD	euro/New Zealand dollar	Cross	10000	G2	G1	G2
EUR/PLN	euro/Polish zloty	Exotic	10000	G2	G2	G3
EUR/SEK	euro/Swedish krona	Exotic	10000	G2	G2	G3
EUR/TRY	euro/Turkish lira	Exotic	10000	G2	G2	G3
EUR/USD	euro/U. S. dollar	Major	10000	G1	G1	G1
GBP/AUD	British pound/Australian dollar	Cross	10000	G1	G1	G2
GBP/CAD	British pound/Canadian dollar	Cross	10000	G2	G1	G2
GBP/CHF	British pound/Swiss franc	Cross	10000	G2	G1	G1
GBP/JPY	British pound/Japanese yen	Cross	100	G1	G1	G1
GBP/NZD	British pound/New Zealand dollar	Cross	10000	G2	G1	G2
GBP/USD	British pound/U. S. dollar	Major	10000	G1	G1	G1
NZD/CAD	New Zealand dollar/Canadian dollar	Cross	10000	G1	G1	G2
NZD/CHF	New Zealand dollar/Swiss franc	Cross	10000	G2	G1	G1
NZD/JPY	New Zealand dollar/Japanese yen	Cross	100	G1	G1	G1
NZD/USD	New Zealand dollar/U. S. dollar	Major	10000	G1	G1	G1
SGD/JPY	Singapore dollar/Japanese yen	Exotic	100	G1	G1	G1
USD/CAD	U. S. dollar/Canadian dollar	Major	10000	G1	G1	G1
USD/CHF	U. S. dollar/Swiss franc	Major	10000	G1	G1	G1
USD/CZK	U. S. dollar/Czech koruna	Exotic	10000	G2	G2	G3
USD/DKK	U. S. dollar/Danish krone	Exotic	10000	G1	G1	G2
USD/HKD	U. S. dollar/Hong Kong dollar	Exotic	10000	G1	G1	G2
USD/HUF	U. S. dollar/Hungarian forint	Exotic	100	G2	G2	G3
USD/JPY	U. S. dollar/Japanese yen	Major	100	G1	G1	G1
USD/MXN	U. S. dollar/Mexican peso	Exotic	10000	G2	G2	G3
USD/NOK	U. S. dollar/Norwegian krone	Exotic	10000	G2	G2	G3
USD/PLN	U. S. dollar/Polish zloty	Exotic	10000	G2	G2	G3
USD/SEK	U. S. dollar/Swedish krona	Exotic	10000	G2	G2	G3
USD/SGD	U. S. dollar/Singapore dollar	Exotic	10000	G1	G1	G1
USD/TRY	U. S. dollar/Turkish lira	Exotic	10000	G2	G1	G3
USD/ZAR	U. S. dollar/South African rand	Exotic	10000	G2	G2	G3

* G1 = group 1, G2 = group 2 and G3 = group 3.

28. 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.
29. Austin Gerig. A theory for market impact: How order flow affects stock price. *arXiv.org, Quantitative Finance Papers*, 04 2008.
30. Juan C. Henao-Londono, Sebastian M. Krause, and Thomas Guhr. Price response functions and spread impact in correlated financial markets, 2020.
31. Shanshan Wang, Rudi Schäfer, and Thomas Guhr. Average cross-responses in correlated financial markets. *The European Physical Journal B*, 89(9):207, Sep 2016.
32. Shanshan Wang, Rudi Schäfer, and Thomas Guhr. Cross-response in correlated financial markets: individual stocks. *The European Physical Journal B*, 89(4), Apr 2016.
33. Richard Payne. Informed trade in spot foreign exchange markets: an empirical investigation. *Journal of International Economics*, 61(2):307–329, 2003.

34. Juan Camilo Henao Londono. First release - price response functions and spread impact in foreign exchange markets code, 2021.
35. 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.
36. 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.
37. Jean-Philippe Bouchaud, J. Doyne Farmer, and Fabrizio Lillo. Chapter 2 - how markets slowly digest changes in supply and demand. In Thorsten Hens and Klaus Reiner Schenk-Hoppé, editors, *Handbook of Financial Markets: Dynamics and Evolution*, Handbooks in Finance, pages 57–160. North-Holland, San Diego, 2009.
38. Anirban Chakraborti, Ioane Toke, Marco Patriarca, and Frédéric Abergel. Econophysics: Empirical facts and agent-based models. *arXiv.org, Quantitative Finance Papers*, 09 2009.
39. 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.
40. Ioane Muni Toke. *"Market Making" in an Order Book Model and Its Impact on the Spread*, pages 49–64. Springer Milan, Milano, 2011.
41. Shanshan Wang. Trading strategies for stock pairs regarding to the cross-impact cost, 2017.
42. 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.
43. 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.
44. J. Doyne Farmer, Paolo Patelli, and Ilija I. Zovko. The predictive power of zero intelligence in financial markets, 2003.
45. Fabrizio Lillo. *Introduction to market microstructure and heterogeneity of investors*, pages 73–89. 2019.
46. Marc Potters and Jean-Philippe Bouchaud. More statistical properties of order books and price impact. 2002.
47. Carolyn Callahan, Charles Lee, and Teri Yohn. Accounting information and bid-ask spread. *Accounting Horizons*, 11:50–60, 01 1997.
48. 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.
49. Eric Smith, J Doyne Farmer, László Gillemot, and Supriya Krishnamurthy. Statistical theory of the continuous double auction. *Quantitative Finance*, 3(6):481–514, 2003.
50. Sebastian Krause, Jonas Fiegen, and Thomas Guhr. Emergence of stylized facts during the opening of stock markets. *The European Physical Journal B*, 2018.
51. 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.
52. Lawrence R Glosten and Lawrence E Harris. Estimating the components of the bid/ask spread. *Journal of Financial Economics*, 21(1):123 – 142, 1988.
53. 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.
54. 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.
55. 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.
56. 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.
57. Vasiliki Plerou, Parameswaran Gopikrishnan, Xavier Gabaix, and H. Eugene Stanley. Quantifying stock-price response to demand fluctuations. *Phys. Rev. E*, 66:027104, Aug 2002.
58. 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.