

Price response functions and spread impact in foreign exchange markets

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Abstract Due to the lack of foreign exchange data, an analysis considering large intervals of time was not possible. Due to the large interest in foreign exchange market now is possible to access tick data for different years. We analyzed price response functions in the foreign exchange market for different years and different time scales. The price response functions show an increase to a maximum followed by a slowly decrease in trade time scale and in physical time scale for all the analyzed years. Further, we use a pip spread definition to group different foreign exchange pairs to analyze the impact in the price response functions. We found that large pip spreads have stronger impact. The results of this paper were also seen in price responses functions in correlated financial markets.

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1 Introduction

The foreign exchange market is the most volatile, liquid and largest of all financial markets in the world [31, 34, 39, 43]. Its importance in the world economy is prominent. It affects employment, inflation, international capital flows, among others [27]. The foreign exchange market is a decentralized market without common trading floor [11, 27, 34, 39]

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 124.21 would be 0.01, while one pip for EUR/USD of 1.1025 would be 0.0001 [12, 27, 32, 39].

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, 11, 15, 16, 19, 24, 26, 27, 29, 31, 33, 34, 35, 43, 44].

In Ref. [32], McGroarty et al. found that smaller volumes cause larger bid-ask spreads for technical reasons to do with measurement, whereas in Refs. [23, 24], 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. [26], 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. [15], 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. [14], 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. [43], 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. In Ref [35], Menkhoff et al. used orders from the Russian interbank for Russian rouble/US dollar pair. They analyzed the price impact in different regions of Russia, finding that regions that are better informed, have high permanent price impact.

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. [33], 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. [31], Mancini et al. model the price impact and return reversal to analyze liq-

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uidity. 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 an 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.

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 [27, 39]. 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](https://www.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 HH-MMSSNNN), 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. 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.

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 mar-

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

ket, we systematically discarded the first ten and the last ten minutes of trading in a given week [5, 17, 22, 25, 51]. 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, 21, 46]. 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 [21, 51], 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. [51] and used in Refs. [25, 48, 49, 50] that reads

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

$\varepsilon^{(t)}(t, n) = +1$ 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. [51], 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. [51] and used in Refs. [48, 50], that depends on the classification in Eq. (1) and reads

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

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, there 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. [51], 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 executed 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 [6, 18, 27, 30, 39, 41]. 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. [25].

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 $b(t)$ [3, 8, 13, 41, 45]. The price gap between them is called the spread $s(t) = a(t) - b(t)$ [3, 4, 5, 8, 11, 17, 28, 45]. 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, 20]. Despite the foreign exchange market is often cited as the world’s largest financial market, this description fails to consider the considerable differences in trading volume and liquidity across different currency pairs [16]. 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, 14].

Due to the lack of prices information in the data, we consider a basic definition of the price given by [19, 29, 31]. The average of the best ask and the best bid is the midpoint price, which is defined as [3, 5, 11, 17, 25, 28, 41, 45]

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

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, 36, 37, 38, 42],

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

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

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

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, 22, 40, 47].

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

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

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 ($average = T$).

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 [25, 50].

4.2 Response functions on trade time scale

The price response function in trade time scale is defined as [25]

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

To compute the response functions on trade time scale, we used 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 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 due to the amount of data of the 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 signal in 2014 have approximately twice the strength

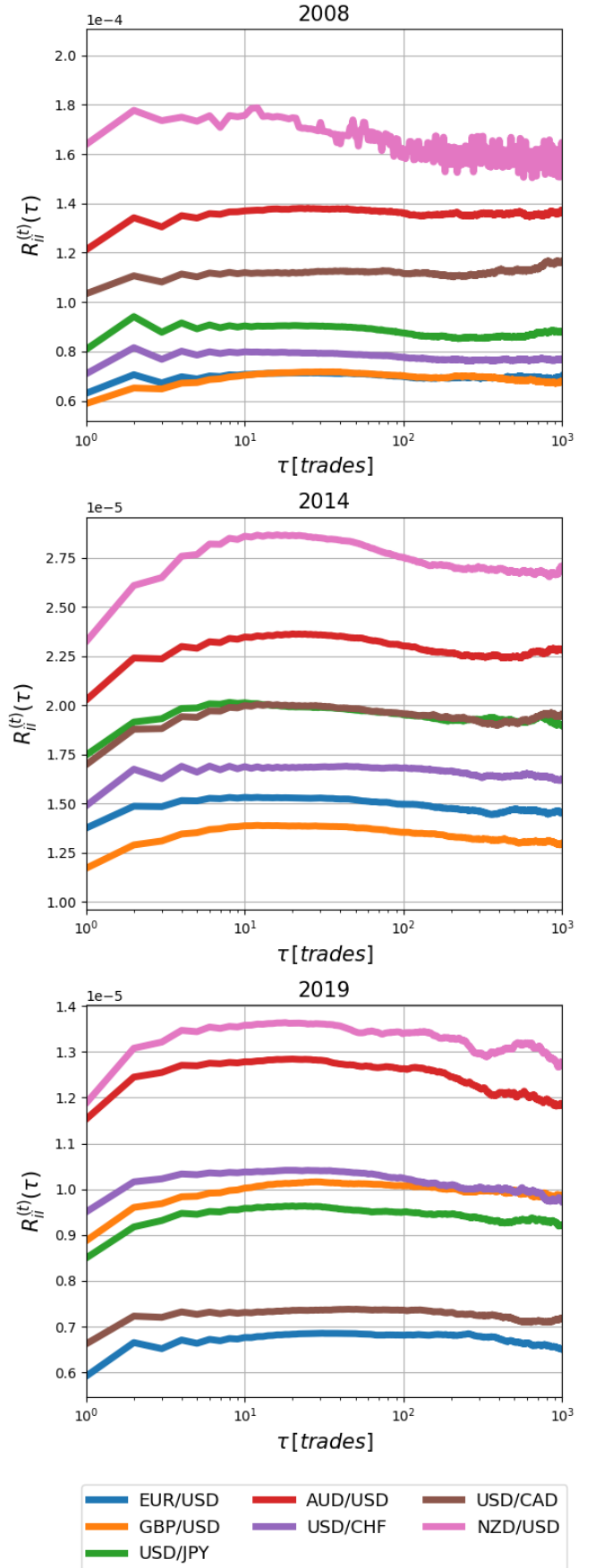


Figure 1. Price response functions $R_{ii}^{(t)}(\tau)$ versus time lag τ on a logarithmic scale in trade time scale for the years 2008 (top), 2014 (middle) and 2019 (bottom).

the signal 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 $\varepsilon_j^{(p)}(t) = 0$ [51]. The price 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 [50]. For a deeper analysis of the influence of the term $\varepsilon_j^{(p)}(t) = 0$, we suggest to check Refs. [50, 51]. We will only take in account the price response functions 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 [25]

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

The results showed in Fig. 2 are the price response functions in physical time scale for three different years. The results show 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.

The price response functions on physical time scale are smoother than the responses in 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 in trade time scale, the strength of the signal of the response functions in 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.

In 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.

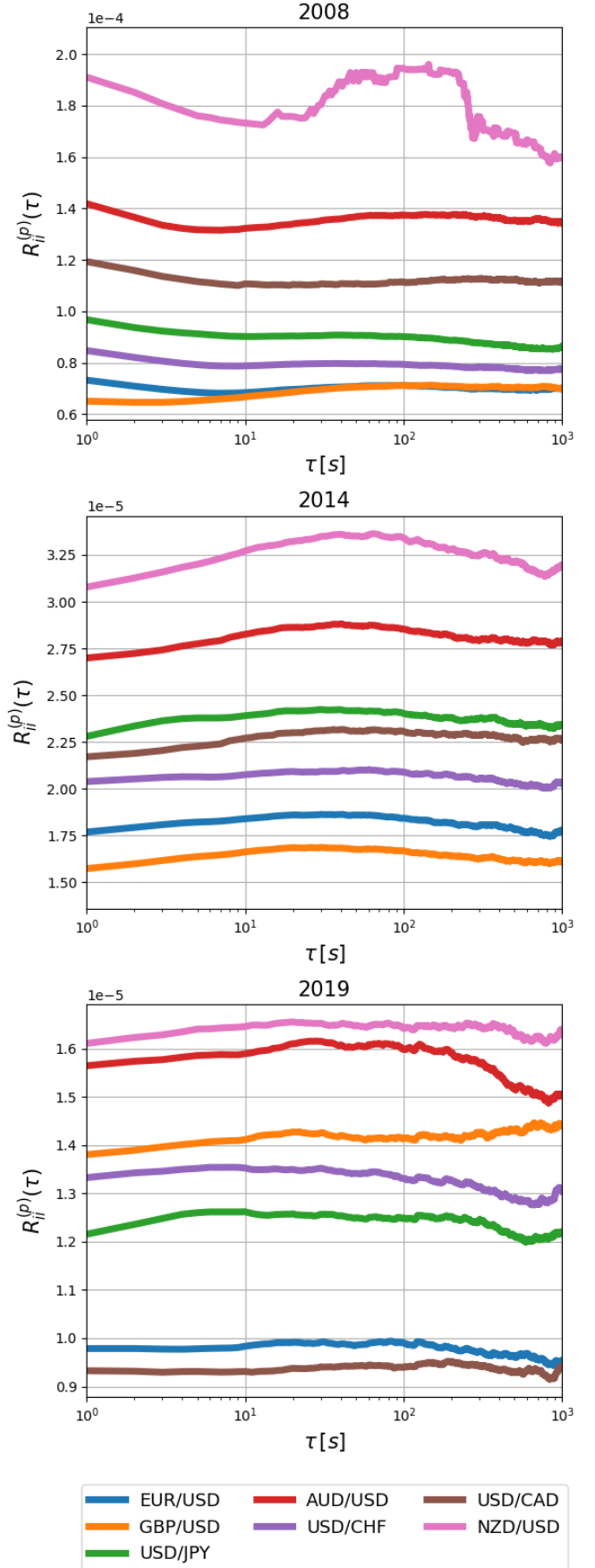


Figure 2. Price response functions $R_{ii}^{(p)}(\tau)$ excluding $\varepsilon_i^{(p)}(t) = 0$ versus time lag τ on a logarithmic scale in physical time scale for the years 2008 (top), 2014 (middle) and 2019 (bottom).

5 Spread impact in price response functions

To analyze the spread impact in price response functions, we used 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 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 that for the EUR/USD is 10000.

The pip bid-ask spread is defined as [32]:

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

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.

We used three intervals to select the stocks groups ($s_{pip} < 0.6$, $0.6 \leq s_{pip} < 7$ and $7 \leq s_{pip} < 40$). 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 averaged the price response functions of each group.

In Fig. 3 we show the average response functions for three 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 could expect the increase-maximum-decrease behavior. In all the figures with the average response on trade time scale, we can see that the curves keep their shape and follow an increase, reach a maximum and then start to slowly decrease. 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 the group 1 and 2 the response decrease almost immediately. For the group 3, it starts to decrease, but then it starts to grow and stabilize at the end of the time lag.

In the three plots, the foreign exchange market seems to have a global influence over all the pairs in the corre-

sponding years. A similar behavior can be seen in correlated financial markets [25].

6 Conclusion

We analyzed price response functions in foreign exchange markets for different years and different time scales. We set out the trade time scale and physical time scale to compute the price response functions for the seven major foreign exchange pairs for three different years. Due to the characteristics of the used data, we had to classify and sampling values to obtain the corresponding quantities in different time scale.

The price response functions were analyzed according to the time scales. We used trade signs and returns in trade time scale to define the price response function. On trade time scale, the signal is noisier. We also define the price response function using the trade signs and returns in physical time scale. In this case, the signal is smoother. For both time scales we observe that the signal for all the pairs increase to a maximum and then start to slowly decrease. This behavior is also reported in correlated financial markets. This results show the price response functions conserve their behavior in different years and in different markets. As the response functions can not grow indefinitely with the time lag, they increase to a peak, to then decrease. 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, in recent years the quantity of trades has grown, and in consequence, the impact in the response has decreased.

Finally, we checked the spread impact in price response functions for three different years. We divided 47 foreign exchange pairs in three groups depending on the year average pip spread of every pair for each year. For all the year and the 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. In all the groups in trade time scale for the three years, the increase-maximum-decrease behavior is observed. For the physical time scale, the behavior is not that well defined. 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.

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 analyze the results and write the paper.

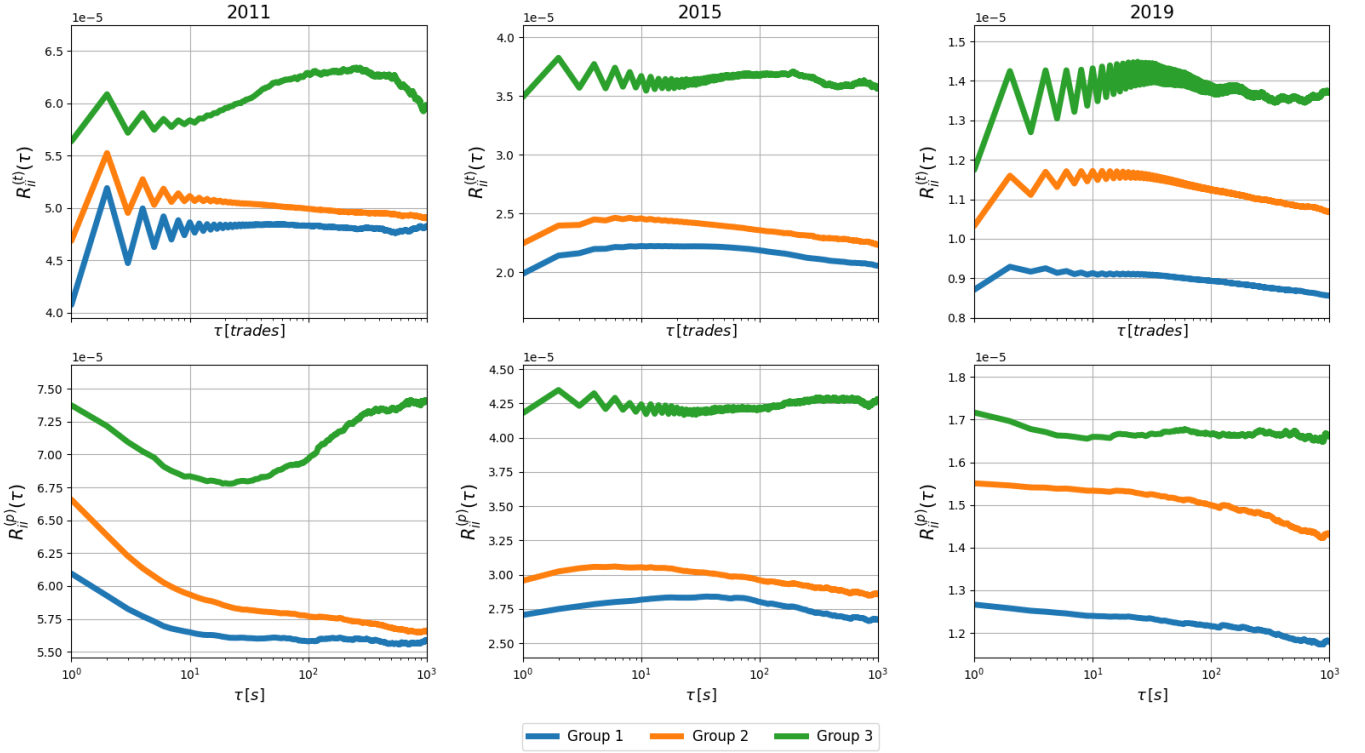


Figure 3. Average price response functions $R_{ii}^{(t)}(\tau)$ versus time lag τ on a logarithmic scale in trade time scale (Top) and $R_{ii}^{(p)}(\tau)$ excluding $\varepsilon_i^{(p)}(t) = 0$ versus time lag τ on a logarithmic scale in physical time scale (Bottom) for 47 foreign exchange pairs divided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

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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.

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

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

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