Dissertation

Analyzing Market Microstructure with Methods of Statistical Physics

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M. Sc. Juan Camilo Henao Londono
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An meine Familie

Hiermit versichere ich, die vorliegende Dissertation selbstständig, ohne fremde Hilfe und ohne Benutzung anderer als den angegebenen Quellen angefertigt zu haben. Alle aus frem- den Werken direkt oder indirekt übernommenen Stellen sind als solche gekennzeichnet. Die vorliegende Dissertation wurde in keinem anderen Promotionsverfahren eingereicht. Mit dieser Arbeit strebe ich die Erlangung des akademischen Grades Doktor der Naturwissenschaften (Dr. rer. nat.) an.

Ort, Datum	Juan Camilo Henao Londono

List of publications

Parts of this thesis are included in the following publications:

[1] Juan C. Henao-Londono, Sebastian M. Krause and Thomas Guhr. *Price response functions and spread impact in correlated financial markets.* The European Physical Journal B (2021) 94:78

[2] Juan C. Henao-Londono and Thomas Guhr. *Foreign exchange markets: Price response and spread impact.* Physica A: Statistical Mechanics and its Applications (2022) 126587

Author contributions

Here, I lay out my contributions to the publications mentioned above:

[1] Sebastian M. Krause and I developed the method of analysis. I had the idea to look the time shift and to analyze the spread impact. I carried out the analysis and all the authors contributed equally to analyze the results and write the paper.

[2] I developed the method of analysis and proposed the idea to analyze the bid-ask spread impact. I carried out the analysis and both authors contributed equally to analyzing the results and writing the paper.

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Abstract

Econophysics is a new interdisciplinary field, where methods and concepts of statistical physics are used to study economics and financial phenomena. In our research, market microstructure is a key concept that has gained a lot of attention due to the development of high-frequency trading. The main focus of the thesis is the application of methods from statistical physics on diverse complex systems. Particularly, we are interested in price response functions applied to correlated financial markets and foreign exchange markets. The study of price response functions is relevant to better understand the impact of trading on price changes. We extend previous works to evaluate the methods and show the impact of slight changes on the results.

We start analyzing price response functions and spread impact in correlated financial markets. Knowing that the price response measurement depends on the data set and the research focus, we center on how the details of the price response definition modify the results. We evaluate different price response implementations. Furthermore, we show the key importance of the order between trade signs and returns. Moreover, we confirm the dominating contribution of immediate price response directly after a trade and finally, we test the impact of the spread in the price response.

We then extend the price response functions analysis in the spot foreign exchange market for different years and different time scales. Furthermore, we use a price increment point (pip) bid-ask spread definition to group different foreign exchange pairs and analyze the impact of the bid-ask spread in the price response functions.

Zusammenfassung

Wirtschaftsphysik ist ein neues interdisziplinäres Gebiet, in dem Methoden und Konzepte der statistischen Physik verwendet werden, um Wirtschafts- und Finanzphänomene zu untersuchen. In unserer Untersuchung ist die Marktmikrostruktur ein Schlüsselkonzept, das aufgrund der Entwicklung des Hochfrequenzhandels viel Aufmerksamkeit erlangt hat. Dabei liegt der Schwerpunkt unserer Arbeit auf der Anwendung von Methoden der statistischen Physik auf vielfältige komplexe Systeme. Insbesondere sind wir an Preisresponsfunktionen interessiert, die auf korrelierte Finanzmärkte und Devisenmärkte angewendet werden. Die Untersuchung von Preisreponsfunktionen ist relevant, um die Auswirkungen des Handels auf Preisänderungen besser zu verstehen. Hierbei werden frühere Arbeiten erweitert, um ihre Methoden zu evaluieren und wir zeigen die Auswirkungen von geringfügigen Änderungen auf die Ergebnisse auf.

Zu Beginn werden Preisresponsfunktionen und Spreadauswirkungen in korrelierten Finanzmärkten analysiert. Basierend auf den Erkenntnissen, dass die Preisresponsmessung von einem bestimmten Datensatz sowie dem Forschungsschwerpunkt abhängen, wird der Fokus darauf gelegt, wie unterschiedliche Details in der Preisresponsedefinition die Ergebnisse variieren. Des Weiteren werden verschiedene Preisreaktionsimplementierungen evaluiert und die zentrale Bedeutung der Reihenfolge zwischen Handelsvorzeichen und Renditen aufgezeigt. Zudem kann der dominierende Beitrag der unmittelbaren Preisreaktion direkt nach einem Trade bestätigt und der Einfluss des Spreads auf die Preisrespons getestet werden.

Abschließend wird die Analyse der Preisresponsfunktionen im Devisenmarkt für verschiedene Jahre und verschiedene Zeitskalen erweitert. Dabei wird eine Bid-Ask-Spread-Definition für Preiserhöhungspunkte (Pip) verwendet, um verschiedene Devisenpaare zu gruppieren und die Auswirkungen des Bid-Ask-Spreads in den Preisresponsfunktionen zu analysieren.

Contents

1. Introduction

1.1. Econophysics

Econophysics is a recently created branch of physics that combines economics and physics [3]. In econophysics, the goal of physicists is to try to explain economic and financial phenomena with physical methods. Although econophysics was established in recent decades, the interest of physicists and mathematicians in economic problems has a long history [3, 4].
In the past, several famous physicists tried to solve economics related problems and even had a huge impact among economists. One of the most historically relevant situation was the influence of Sir Isaac Newton in the work of Adam Smith, particularly in his book "An inquiry into the nature and causes of the wealth of nations". Newton is remembered as the founding figure of calculus, mechanics and optics. Although he directly did not contribute in formulating the economic theory we know today, he spurred many influential economists to their discoveries. It is remarkable that his work as Master of the Royal Mint [5], was not the one who inspired the economists, but his methods used in physics that motivated that inspiration. Furthermore, Newton's investor experience with the South Sea Bubble in 1720 and the large losses he obtained [3] remind us how the universal laws that govern the mathematics and natural sciences are much more ordered than the rather chaotic laws that govern the social sciences. In Newton's words:

> "I can calculate the movement of the stars, but no the madness of men"

The relation between Smith's and Newton's work is not coincidence. In addition to his books "The theory of moral sentiments" and "An inquiry into the nature and causes of the wealth of nations", Adam Smith also wrote "History of astronomy" [6]. His large understanding of the theories developed by Newton helped him build his description of human beings in its moral, social, political and economic aspects [7]. It seems clear that a deep comprehension of natural science and physical theory, leads to the inclusion of these ideas to the work of Smith, or at least as an inspiration to his work [8, 9]. In contrast, contemporary physical concepts and ideas are so specialized and hard to understand for non-physicists, that it is difficult to find concrete and fruitful models inspired by them. Smith was the first to try to write a set of rules for free-market economics. To create these laws, he learned from experience and human interaction. He did not try to create a model from scratch, but to get the fundamental ideas from discussions with many of the great thinkers of his time. It was not his intention to create an ideal word in his head unrelated to reality to develop his ideas, but to take into account the reality and from there create a description of economics. It is reasonable to argue that the general laws of economics of Adam Smith were highly influenced by the success of Newton discovering the natural laws of motion [10]. In his work, they are a series of connections between laws, axioms and conclusions as elaborated or taken up from Newton's "Philosphiæ Naturalis Principia Mathematica" structure [7]. It is important to clarify that Smith was not just transposing Newton's system from natural to social science [11]. He always took the social world as it was, or as he perceived it [8, 9]. Smith was very prudent and careful about the use of mathematics. In his own words "the use of those sciences, either to the individual or the public, is not very obvious" [12]. Furthermore, he famously declared "I have no great faith in political arithmetic" [13]. His methods in economics, with the exception of some simple arithmetical operations such as averages, are not mathematical at all [11].

It seems clear that Newton had a deep impact on the development of classic and modern economics, but not for a direct implementation of his physical theories. This can be seen for example from how his method of reasoning influenced Smith's way of thinking to write the Wealth of Nations. It is imperative to understand that it is not in Newton's laws but in his methods that economists tried to obtain inspiration.

Newton was not the only one who had relation with economics. Carl Friederich Gauss updated the Göttingen University widow's fund [14]. Nicolas Copernicus formulated the quantity theory of money, where he mainly worked around the concept of inflation and currencies [15]. Daniel Bernoulli offered a solution to the Saint Petersburg paradox as the basis of the economic theory of risk aversion, risk premium and utility [5, 16]. Edmund Halley was a pioneer on vital statistics and mortality tables [5]. Louis Bachelier's [5, 17] work of random walks and Albert Einstein's work of Brownian motion [5, 18], are both considered important models for financial markets. Benoît Mandelbrot developed several approaches for modelling financial fluctuations [19], and obtained evidence that the cotton prices had fat-tailed distributions [20]. Fisher Black and Myron Scholes used the geometric Brownian motion for determining the price of a stock option [21]. They won the 1997 Nobel memorial prize in Economic sciences [4] together with Robert Merton [22] for their theory of option pricing. Black-Scholes formula is just the solution of the heat equation, with a peculiar boundary condition [3].

In recent years, an increasing interest of physicists related to economics and finances have grown due to the large amount of available data, the evolution of the technology and the limitation of traditional approaches in economics and finances [23].

Despite the different works made by physicists related to economics, only in 1995 the word "econophysics" was coined by H. Eugene Stanley at a conference on statistical physics [24], due to the large amount of papers related to physicists trying to solve problems of financial markets.

However, econophysics is not just a word. It is a new paradigm about economic systems and financial markets treated as complex systems. These systems have internal microscopic interactions that generate their macroscopic properties. These complex systems have the particularity of non-stationarity which is also subject to systemic changes [25, 26].
We can say that the econophysics practitioners model financial and economic systems using paradigms and tools taken from theoretical and statistical physics [3, 27].
Alongside, several analogies between financial markets and physical phenomena appeared [3], e.g., turbulence [28, 29], spin systems [30], universality [31], self-organized criticality [32], earthquakes [33, 34] and so on.
One important characteristic about econophysics is that the observations can only be made on empirical data. Thus, the advancement of this branch depends inherently on the amount of available data. Another feature in econophysics is the impossibility of driving an experiment with the usual methodology. In markets we can not measure the influence of specific features on different systems. The non-stationarity does not let us repeat an experiment any number of times under the same conditions. In fact, due to the limited resources and regulatory restrictions, it is impossible to generate reactions that can be observed. And even if we could do it, a mistake in an experiment would have terrible and unpredictable consequences.
In our research we focus on the market microstructure using price response functions analysis in correlated financial markets and foreign exchange markets.

1.2. Motivation

Econophysics as an interdisciplinary research field has a broad range of applications and topics of interest. A lot of methods originally developed by physicists in order to solve problems in economics have led to a huge amount of literature showing the results and the new proposed methodologies to find the explanation of different economic phenomena.

In general, one of the most studied fields in econophysics is quantitative finance. The large amount of data available makes it really appealing for physicists, who usually have a good knowledge of statistical physics and complex systems.

According to the Efficient Market Hypothesis (EMH), all available information is included in prices. The price at all times is a consensus between rational agents and the price changes are the results of unexpected news. Thus, by definition the price changes are unpredictable. This model shows random walks in time but the observed volatility of markets is too high to be congruent with the rational pricing. On the other hand, there is a model where the agents have zero intelligence and make random decisions to buy or to sell, but the other market participants believe these actions contain some information. In this case too, the price follows a random walk for sufficiently large times. In our research our main focus is not the formation of the price, but the price response function and the market impact.

In order to better understand the impact of trading on price changes, we study response functions that takes into account the returns and the trade signs. This quantity measures how much, on average, the price moves up or down restricted to a buy or sell order at time zero to a time lag later. The response function captures a small systematic effect that relates the average price change to the sign of a trade. It is important to keep in mind that fluctuations around this small signal are large, and increase with the time lag.

To achieve this goal, we strongly based our research in works carried out in the research group Guhr by Dr. Shanshan Wang [35, 36, 37, 38, 39, 40], who was the first to look into the topic in the group. In her work, she mainly focused on cross-responses and average cross-responses in correlated financial markets, and microscopic understanding of cross-responses. In this thesis we extend some concepts that were not covered in previous research and that expand the understanding of price response functions.

First, we analyze in detail the price response function in correlated financial markets, focusing on the definition details and how the modification of these values modify the results.

Then, we apply price response functions in spot foreign exchange markets to check the behavior for different years and different time scales.

The results of these works contribute to better understanding the behavior of price response functions and their characteristics in correlated financial markets and spot foreign exchange markets.

1.3. Market microstructure and financial markets

Shares are the equal parts in which the capital of a company is divided. A share is an indivisible unit of capital, expressing the ownership relationship between a company and a shareholder. Shareholders own a percentage of the company depending on the amount of shares he possesses. Shares are issued in two moments: when companies are created and when companies want to raise funds. Shares can be taken as an investment, and receive dividends from them, or they can be traded at any time. This second possibility is the one that concerns us.

To trade the stocks they are markets where buyers and sellers meet. sellers transfer (in exchange for money) the ownership of equities to buyers. This requires these two parties to agree on a price. In a modern financial market, there is a double continuous auction. To find possible buyers and sellers in the market, agents can place different types of instructions (known as orders) to buy or to sell a given number of shares, that can be grouped into two categories: market orders and limit orders.

Market orders will go into market to execute at the best available buy or sell price, they are executed as fast as possible and only after the purchase of the stock is possible to know the exact price [41]. Limit orders allow to set a maximum purchase price for a buy order, or a minimum sale price for a sell order. If the market does not reach the limit price, orders will not be executed [41]. Limit orders often fail to result in an immediate transaction, and are stored in a queue called the limit order book.

An order book is an electronic list of buy and sell orders for a specific security or financial instrument organized by price level. An order book lists the number of shares being bid or offered at each price point. It also identifies the market participants behind the buy and sell orders, although some choose to remain anonymous. The order book is visible for all traders and its main purpose is to ensure that all traders have the information about what is offered on the market.

Buy limit orders are called "bids", and sell limit orders are called "asks". 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 $b(t)$ [42, 43, 44]. These are also called the inside quotes or the best prices. The price gap between them is called the spread $s(t) = a(t) - b(t)$ [41, 42, 43, 45]. Spreads are significantly positively related to price and significantly negatively related to trading volume. Firms with more liquidity tend to have lower spreads. [43, 46, 47, 48].

The average of the best ask and the best bid is the midpoint price, which is defined as [41, 42, 45]

$$m(t) = \frac{a(t) + b(t)}{2}. \tag{1-1}$$

As the midpoint price depends on the quotes, it changes if the quotes change. The midpoint price grows if the best ask or the best bid grow. This happen if someone buys and consumes all the volume of the sell limit order with the price of the best ask, or someone sets a buy limit order with a bigger price than the previous best bid, or there is a cancellation of the best ask.

On the other hand, the midpoint price decreases if the best ask or the best bid decrease. This happen if someone sells and consumes all the volume of the buy limit order with the price of the best bid, or someone sets a sell limit order with a lower price than the previous best bid, or there is a cancellation of the best bid.

The midpoint price will not change if there is no activity in the market.

Price changes are typically characterized as returns. If one denotes $S(t)$ the price of an asset at time t, the return $r(t)$, at time t and time lag τ is simply the relative variation of the price from t to $t+\tau$ [42, 49, 50, 51, 52],

$$r^{g}(t,\tau) = \frac{S(t+\tau) - S(t)}{S(t)}. \tag{1-2}$$

It is also common to define the returns as [41, 42, 49, 53, 54, 55, 56, 57]

$$r^{l}(t,\tau) = \ln S(t+\tau) - \ln S(t) = \ln \frac{S(t+\tau)}{S(t)}. \tag{1-3}$$

Eq. 1-2 and Eq. 1-3 coincide if τ is small enough [42, 49].

At longer timescales, midpoint prices and transaction prices rarely differ by more than half the spread. It is more convenient to study the midpoint price because it avoids problems associated with the tendency of transaction prices to bounce back and forth between the best bid and ask [41].

We define the returns via the midpoint price as

$$r(t,\tau) = \frac{m(t+\tau) - m(t)}{m(t)} \tag{1-4}$$

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 [42].

Then we can expect three kind of values of the returns. The returns are positive values, when the midpoint price $m(t+\tau) > m(t)$, hence, there is a buy in the market or there is a cancellation of the best ask or an addition in the best bid during the time lag τ. The returns are negative values, when the midpoint price $m(t+\tau) < m(t)$, thus, there is a sell in the market, or there is a cancellation of the best bid or an addition in the best ask during the time lag τ. The returns are zero when there is no activity during the time lag τ.

The trade signs are defined for general cases as

$$\varepsilon(t) = \operatorname{sign}\left(S(t) - m(t-\delta)\right) \tag{1-5}$$

where δ is a positive time increment. Hence we have

$$\varepsilon(t) = \begin{cases} +1, & \text{If } S(t) \text{ is higher than the last } m(t) \\ -1, & \text{If } S(t) \text{ is lower than the last } m(t) \end{cases} \tag{1-6}$$

$\varepsilon(t) = +1$ indicates that the trade was triggered by a market order to buy and a trade triggered by a market order to sell yields $\varepsilon(t) = -1$ [42, 45, 56, 58, 59].

It is well-known that the series of the trade signs on a given stock exhibit large autocorrelation. A very plausible explanation of this phenomenon relies on the execution strategies of some major brokers on given markets. These brokers have large transactions to execute on the account of some clients. In order to avoid market making move because of an inconsiderable large order, they tend to split large orders into small ones [49].

1.4. Foreign exchange markets

The foreign exchange market is a 24-hour global decentralized or over-the-counter (OTC) market for the trading of currencies closing only on the weekends. The foreign exchange market is the most volatile, liquid and largest of all financial markets [60, 61, 62, 63, 64, 65, 66, 67, 68], and it has a paramount importance for the world economy. It affects employment, inflation and international capital flows, among others [63]. The major participants trading in this market include governments, central banks, global funds, retail clients and corporations [67, 68]. Trading of currency in the foreign exchange market involves the purchase and sale of two currencies at the same time [66, 67, 68]. The value of one of the currencies in that pair is relative to the value of the other. The price one currency can be exchanged with another currency is the foreign exchange rate. The foreign exchange market is a closed system. As one value increases another value has to decrease. All foreign exchange rates cannot appreciate, in contrast to the stock market [66, 68].

Depending on the country, the currencies can be "free float" or "fixed float". Free-floating currencies relative value is determined by free-market forces. Some example of free-floating currencies include the U.S. dollar, Japanese yen and Colombian peso. On the other hand, a fixed float is where a government through the central bank set the currency's relative value to other currencies, usually by pegging it to some standard. Examples of fixed floating currencies include the Chinese Yuan and the Indian Rupee [66]. In our case, we only use free float currencies.

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 [63, 65, 67, 68]. 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. London, New York and

Tokyo are the largest centers of foreign exchange trading [69]

Currency markets are divided into spot market, forward, future, currency swaps and currency options [67, 68, 69]. The spot and forward exchange markets are OTC markets [66]. In our work we particularly focus on the spot market, where as his name suggest, the trades are settled on the spot [66, 68]. In a spot market, as the currency transactions are carried in the OTC markets, information concerning open interest and volume is unavailable. The transactions in this market represent up to the 40% of the total market transactions in the foreign exchange market. This estimations are made by the Bank for International Settlements (BIS) based on a central bank survey of foreign exchange and derivatives market activities in major financial centers [70]. The most traded currencies in the spot market are the U.S. dollar, euro, Japanese yen, British pound and Swiss franc [66].

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. 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, which can be much more volatile. In this work, we will refer as the “major currency pairs” to the pairs of most traded currencies paired with the U.S. dollar, including the so called commodity currencies: Canadian dollar, Australian dollar and New Zealand dollar. The pairs and their corresponding symbol can be seen in Table **1-1**.

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

Table **1-1**.: 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

0.0001 [63, 65, 68, 71, 72].

Compared with other markets like the stock market, there are some key characteristics that differentiate the spot foreign exchange market. There are fewer rules, there are no clearing houses and central bodies that oversee the market. Some investors do not have to pay fees or commissions as on other markets. It is possible to trade at any time of day and regarding the risk and reward, it is possible to get in and out whenever the investor wants. In the foreign exchange market, the bid-ask spread is the most used transaction cost [67].

1.5. Outline of the thesis

To this point, we introduced econophysics and described how along the history, physicists were attracted to economics with different applications and topics. Then, we explained what was the motivation to carry out research focused on price response functions in two different complex systems: correlated financial markets and spot foreign exchange markets. We gave a brief overview of the market microstructure, and explained basic concepts and characteristics about financial markets in general and foreign exchange markets.

The next chapters of the thesis are organized as follows:

In Chapter 2 we introduce the time definition. We explain the basics of the different time definitions and establish which definitions will be used along the thesis. In Sect. 2.1 and in Sect. 2.2 we explain in detail the trade time scale and the physical time scale, respectively.

We analyze price response functions and spread impact in correlated financial markets in Chapter 3. In Sect. 3.1 we make a large overview about the financial markets microstructure and their dynamics. The data set used to analyze the price response functions and the spread impact is described in Sect. 3.2. We show how the state of the art of the price responses in financial markets is in Sect. 3.3. In Sect. 3.4 we go into detail on the price response mathematical definition, and using returns and trade signs we define three different response functions in Sects. 3.4.1, 3.4.2 and 3.4.3. In Sect. 3.5 we propose a time shift in the response functions to analyze the impact of the relative position between returns and trade signs. We analyze the time shift in trade time scale in Sect. 3.5.1 and the time shift in physical time scale in Sect. 3.5.2. We show how the time lag behaves in the price response function in Sect. 3.6 and present the spread impact in price response functions in Sect. 3.7. The conclusions of the chapter follow in Sect. 3.8.

In Chapter 4 we apply price response functions and analyze spread impact in foreign exchange markets to study its behavior along different years and time scales. In Sect. 4.1 we introduce the motivation to carry out this research. We establish the key concepts of foreign exchange markets in Sect. 4.2 and describe the data set used to analyze the price response functions and the spread impact in Sect. 4.3. In Sect. 4.4 we analyze the response functions in trade time scale and in physical time scale. We evaluate bid-ask spread impact in price response functions in Sect. 4.5. In Sect. 4.6 we conclude the main results of the chapter.

To conclude this thesis, we summarize and discuss our findings in Chapter 5.

2. Time definition

A direct comparison between the trade time scale and the physical time scale is not possible. To compare them directly we need to assume whether the midpoint price or the trade signs are on the same scale. We assume the midpoint prices in the trade time scale to be the same as the midpoint prices in physical time scale. Therefore, we have the time lag for both computations in seconds. This approximation allow us to directly compare both scales to have an idea of the difference and similarities they have. In the other sections, as we are not directly comparing the time scales, the corresponding quantities of each time scale are not mixed. Thus physical time scale is measured in seconds and trade time scale is measured in trades.

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 [49, 73]. In several papers are used different time definitions (calendar time, physical time, event time, trade time, tick time) [49, 74, 75]. The TAQ data used in the correlated financial market analysis has the characteristic that the trades and quotes can not be directly related due to the time stamp resolution of only one second [36]. Hence, it is impossible to match each trade with the directly preceding quote. However, using a classification for the trade signs, we can compute trade signs in two scales: trade time scale and physical time scale.

The trade time scale is increased by one unit each time a transaction happens. 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 [49].
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 [36, 74], 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.
Facing the impossibility to relate midpoint prices and trade signs with the TAQ data in trade time scale, we will use the midpoint price of the previous second with all the trade signs of the current second. This will be our definition of trade time scale analysis for the response function analysis.
For physical time scale, as we can sampling, we relate the unique value of midpoint price of a previous second with the unique trade sign value of the current second.

2.1. Trade time scale

We use the trade sign classification in trade time scale proposed in Ref. [36] and used in Refs. [35, 37, 40] that reads

$$\varepsilon^{(t)}(t,n) = \begin{cases} \operatorname{sgn}\left(S(t,n) - S(t,n-1)\right), & \text{if} \\ \quad S(t,n) \neq S(t,n-1) & \\ \varepsilon^{(t)}(t,n-1), & \text{otherwise} \end{cases} \tag{2-1}$$

$\varepsilon^{(t)}(t,n) = +1$ 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. (2-1), 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. [36], the average accuracy of the classification is 85% for the trade time scale.

The TAQ time step is one second, and as it is impossible to find the correspondences between trades and midpoint prices values inside a second step, We used the last midpoint price of every second as the representative value of each second. This introduce an apparent shift between trade signs and returns. In fact, we set the last midpoint price from the previous second as the first midpoint price of the current second [36].

As we know the second in which the trades were made, we can relate the trade signs and the midpoint prices as shown in Fig. **2-1**. For the trade time scale, there are in general, several midpoint prices in a second. For each second we select the last midpoint price value, and we relate it to the next second trades. In Fig. **2-1**, the last midpoint price (circle) between the second -1 and 0 is related to all the trades (squares and triangles) in the second 0 to 1, and so on. In the seconds when the quotes do not change, the value of the previous second (vertical line over the physical time interval) is used. Thus, all the seconds in the open market time have a midpoint price value, and in consequence returns values. We assume that as long as no changes occurred in the quotes, the midpoint price remains the same as in the previous second.

The methodology described is an approximation to compute the response in the trade time scale. A drawback in the computation could come from the fact that the return of a given second is composed by the contribution of small returns corresponding to each change in the midpoint price during a second. As we are assuming only one value for the returns in each second, we consider all the returns in one second interval to be positive or negative with the same magnitude, which could not be the case. This could increase or decrease the response signal at the end of the computation.

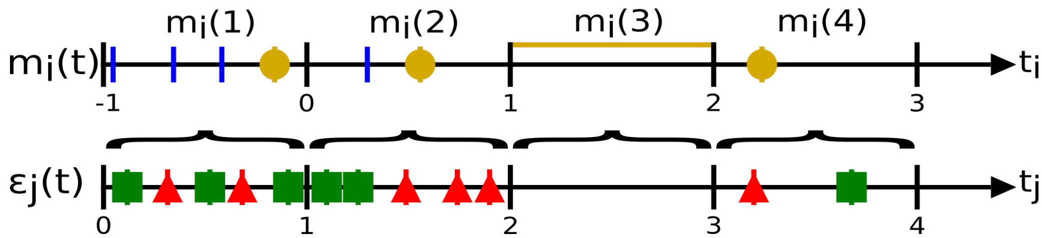

Figure **2-1**.: Sketch of data processing for trade time scale. In the midpoint price time line, the vertical lines represent the change in price of the quotes and the circles represent the last price change in a quote in a second. In the trade signs time line, the squares represent the buy market orders and the triangles represent the sell market orders. The midpoint price time line and the trade sign time line are shifted in one second.

Figure **2-2** illustrate this point. Suppose there are three different midpoint prices in one second interval and thus, three different returns for these three midpoint price values. Furthermore, suppose that the volume of limit orders with the corresponding midpoint prices are the same in the bid and in the ask (the returns have the same magnitude). In the case of the top left (top right) sketch, all the changes are due to the rise (decrease) of the midpoint price, that means, consumption of the best ask (bid), so all the contributions of the individual returns in the second are positive (negative), and in consequence, the net return is positive (negative). In the case of the bottom, the changes are due to a combination of increase and decrease of the midpoint price, so in the end, the individual returns sum up to a net return, which can be positive or negative, depending of the type of midpoint price values in the interval. Thus, in this case, we are assuming in the end that all the returns were positive or negative, which probably was not the case, and in consequence will increase or decrease the real value of the net return.

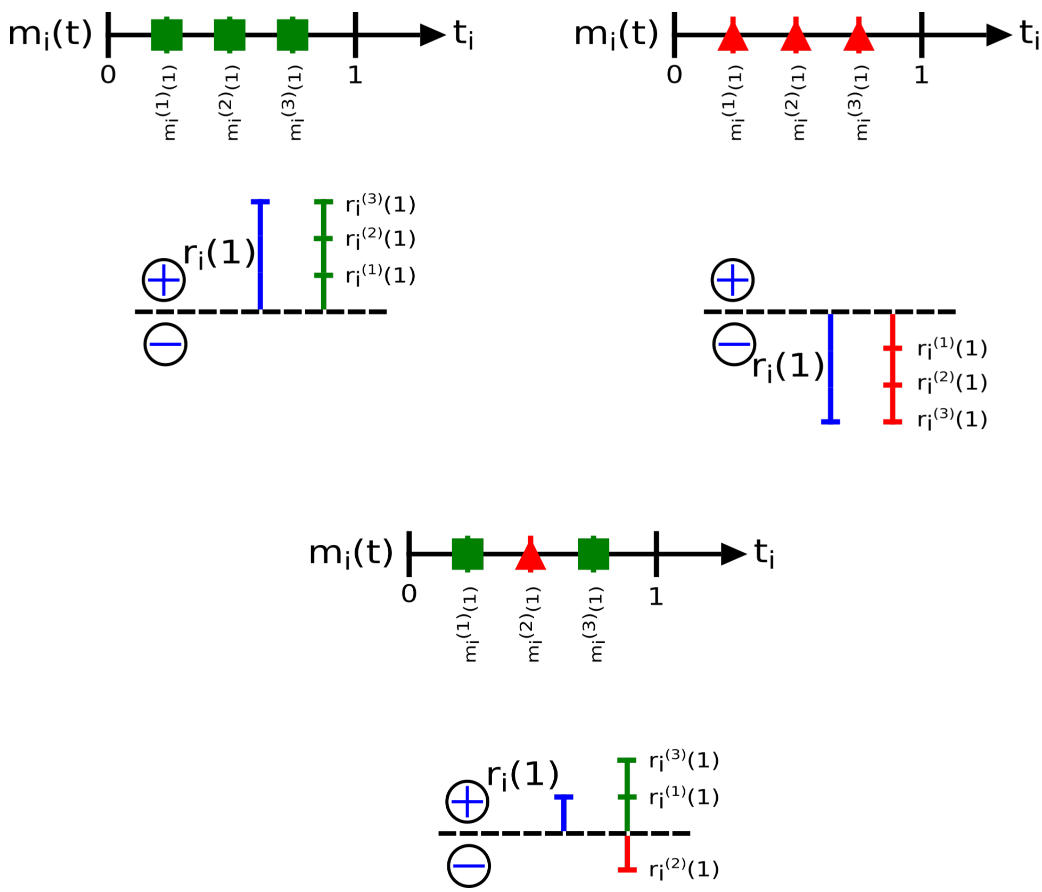

Figure **2-2**.: Sketch of the return contributions from every midpoint price change in a second. The squares represent the rise of the price of the midpoint price and the triangles represent the decrease of the price of the midpoint price. We illustrate three cases: (top left) the changes of the midpoint prices and return are due to the rise of the prices, (top right) the changes of the midpoint prices and return are due to the decrease of the prices, and (bottom) the changes of the midpoint prices and return are due to a combination of rise and decrease of the prices. The blue vertical line represents the net return in each case.

In all cases, we choose the last change in the midpoint price in a second interval as described before in Fig. **2-1**. We use this method knowing that the variation in one second of the midpoint price is not large (in average, the last midpoint price of a second differ with the average midpoint of that second in 0.007%), hence it can give us representative information on the response functions.

2.2. Physical time scale

We use the trade sign definition in physical time scale proposed in Ref. [36] and used in Refs. [35, 37], that depends on the classification in Eq. (2-1) and reads

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

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.

As the trade time scale, on the physical time scale we use the same strategy to obtain the midpoint price for every second, so all the seconds in the open market time have a midpoint price value. Even if there is no change of quotes in a second, it still has a midpoint price value and return value.

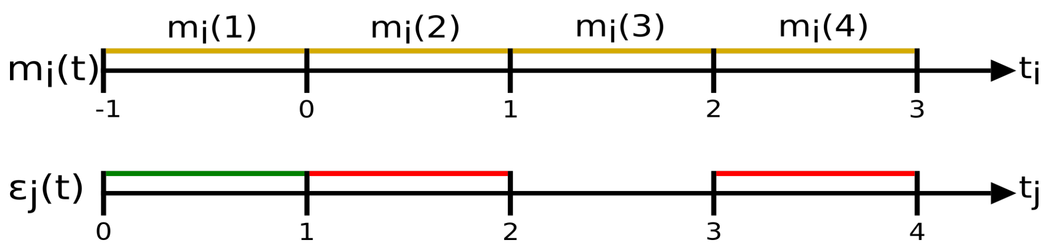

Figure **2-3**.: Sketch of data processing for physical time scale. In the midpoint price time line, the horizontal lines between seconds represent the midpoint prices. In the trade signs time line, the horizontal lines between seconds represent the trade sign values. The midpoint price time line and the trade sign time line are shifted in one second.

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. (2-2). This can be seen in Fig. **2-3**, where we related the midpoint price of the previous second with the trade sign of the current second. According to Ref. [36], this definition has an average accuracy up to 82% in the physical time scale.

3. Price response functions and spread impact in correlated financial markets

3.1. Introduction

While the definition of complexity varies, it is widely agreed upon that a system is referred to as complex if it, first, consists of a large number of interacting agents or constituents, respectively, second, is non-stationary, *i.e.* cannot be described by standard equilibrium approaches, and, third, its interactions are typically not captured by microscopic governing equations, rather, by statistical rules. There are many examples, ranging from traditional physical over biological to social and economic systems. The present interdisciplinary contribution studies financial markets, it is put forward in the proven physics spirit, first, that every quantity which is used has to be a measurable observable, second, that the results given are quantitative and statistically sound, and, third, that the methods are carefully and critically checked and verified. The emphasis of the present contribution is particularly on the third point: we evaluate the methods and show the impact of slight changes on the results. In view of an increasing interest in the analysis of response functions, we feel that this is a rewarding effort. It helps to answer the highly relevant question of the extent to which financial markets deviate from the largely Markovian behavior.

Financial markets use order books to list the number of shares bid or asked at each price. An order book is an electronic list of buy and sell orders for a specific security or financial instrument organized by price levels, where agents can place different types of instructions (orders).

In general, the dynamics of the prices follow a random walk. There are two extreme models that can describe this behavior: the Efficient Market Hypothesis (EMH) and the Zero Intelligence Trading (ZIT). The EMH states that all available information is included in the price and price changes can only be the result of unanticipated news, which by definition are totally unpredictable [42, 45, 76, 77]. On the other hand, the ZIT assumes that agents instead of being fully rational, have "zero intelligence" and randomly buy or sell. It is supposed that their actions are interpreted by other agents as potentially containing some information [36, 42, 45, 77]. In both cases the outcome is the same, the prices follow a random walk. Reality is somewhere in-between [45, 77], and non-Markovian effects due to stategies or liquidity costs are not contained either.

There are diverse studies focused on the price response [35, 36, 38, 39, 41, 42, 45, 53, 55, 56, 58, 76, 78, 79, 80, 81, 82]. In our opinion, a critical investigation of definitions and methods and how they affect the results is called for.

Regarding price self-response functions in Refs. [42, 45, 79], Bouchaud et al. found an increase to a maximum followed by a decrease as the time lag grows. In Ref. [55], Gerig found that larger sized transactions have a larger absolute impact than smaller sized transactions but a much smaller relative impact. In Ref. [78], it is found that the impact of small trades on the price is, in relative terms, much larger than that of large trades and the impact of trading on the price is quasi-permanent.

For price cross-responses functions, Refs. [36, 53] revealed that the diagonal terms are on average larger than the off-diagonal ones by a factor ~ 5. The response at positive times is roughly constant, what is consistent with the hypothesis of a statistically efficient price. Thus, the current sign does not predict future returns. In Ref. [36] the trends in the cross-responses were found not to depend on whether or not the stock pairs are in the same economic sector or extend over two sectors.

Here, we want to discuss, based on a series of detailed empirical results obtained on trade by trade data, that the variation in the details of the parameters used in the price response definition modify the characteristics of the results. Aspects like time scale, time shift, time lag and spread used in the price response calculation have an influence on the outcomes. To facilitate the reproduction of our results, the source code for the data analysis is available in Ref. [83].

We delve into the key details needed to compute the price response functions, and explore their corresponding roles. We perform an empirical study in different time scales. We show that the order between the trade signs and the returns have a key importance in the price response signal. We split the time lag to understand the contribution of the immediate returns and the late returns. Finally, we shed light on the spread impact in the response functions for single stocks.

The chapter is organized as follows: in Sect. 3.2 we present our data set of stocks. We then analyze the definition of the price response functions in Sect. 3.3. We implement different price responses for several stocks and pairs of stocks in Sect. 3.4. In Sect. 3.5 we show how the relative position between trade signs and returns has a huge influence in the results of the computation of the response functions. In Sect. 3.6 we explain in detail how the time lag τ behaves in the response functions. Finally, in Sect. 3.7 we analyze the spread impact in the price response functions. Our conclusions follow in Sect. 3.8.

3.2. Data set

Modern financial markets, are organized as a double continuous auctions. Agents can place different types of orders to buy or to sell a given number of shares, roughly categorized as market orders and limit orders.

In this study, we analyzed trades and quotes (TAQ) data from the NASDAQ stock market. We selected NASDAQ because it is an electronic exchange where stocks are traded through an automated network of computers instead of a trading floor, which makes trading more efficient, fast and accurate. Furthermore, NASDAQ is the second largest stock exchange based on market capitalization in the world.

In the TAQ data set, there are two data files for each stock. One gives the list of all successive quotes. Thus, we have the best bid price, best ask price, available volume and the time stamp accurate to the second. The other data file is the list of all successive trades, with the traded price, traded volume and time stamp accurate to the second. Despite the one second accuracy of the time stamps, in both files more than one quote or trade may be recorded in the same second.

To analyze the response functions across different stocks in Sects. 3.4, 3.5 and 3.6, we select the six companies with the largest average market capitalization (AMC) in three economic sectors of the S&P index in 2008. Table **3-1** shows the companies analyzed with their corresponding symbol and sector, and three average values for a year.

To analyze the spread impact in response functions (Sect. 4.5), we select 524 stocks in the NASDAQ stock market for the year 2008. The selected stocks are listed in Appendix A.

This contribution specifically addresses methodical aspects related to the price response functions and spread impact in correlated financial markets. We carefully check and verify the methods used to evaluate response functions, spread impact and related quantities. This is important as such observables quantify the deviation from the largely Markovian behavior of

Table **3-1**.: Analyzed companies.

Company	Symbol	Sector	Quotes[1]	Trades[2]	Spread[3]
Alphabet	GOOG	Information (IT)	164489	19029	0.40$
Mastercard	MA	Information (IT)	98909	6977	0.38$
CME Group	CME	Financials (F)	98188	3032	1.08$
Goldman Sachs	GS	Financials (F)	160470	26227	0.11$
Transocean	RIG	Energy (E)	107092	11641	0.12$
Apache Corp.	APA	Energy (E)	103074	8889	0.13$

[1] Average number of quotes from 9:40:00 to 15:50:00 New York time during 2008.

[2] Average number of trades from 9:40:00 to 15:50:00 New York time during 2008.

[3] Average spread from 9:40:00 to 15:50:00 New York time during 2008.

financial markets. We chose the year 2008 to clarify these methodical aspects. We plan to extend our results in a future study to different years for a comparison of price response functions and spread impact.

In order to avoid overnight effects and any artifact due to the opening and closing of the market, we systematically discard the first ten and the last ten minutes of trading in a given day [36, 41, 45, 56]. Therefore, we only consider trades of the same day from 9:40:00 to 15:50:00 New York local time. We will refer to this interval of time as the "market time". The year 2008 corresponds to 253 business days.

3.3. Price response function definitions

The response function measures price changes resulting from execution of market orders. In Refs. [42, 45, 79], Bouchaud et al. use a self-response function that only depends on the time lag τ. This function measures how much, on average, the price moves up (down) at time τ conditioned to a buy (sell) order at time zero. They found for France Telecom that the response function increases by a factor 2 between $\tau = 1$ and $\tau \approx 1000$ trades, before decreasing back. For larger τ, the response function decreases, and even becomes negative beyond $\tau \approx 5000$. However, in some cases the maximum is not observed and rather the price response function keeps increasing mildly [42].

In Ref. [55], the price impact function, is defined as the average price response due to a transaction as a function of the transaction's volume. Empirically the function is highly concave [55]. The curvature of the price impact function is entirely due to the probability that a transaction causes a nonzero impact. The larger the size of the transaction, the larger the probability. In Ref. [78], they found that the response function for three French stocks first increases from $\tau = 10s$ to a few hundred seconds, and then appears to decrease back to a finite value.

In Ref. [53] they defined a response function who measures the average price change of a contract i at time $t + \tau$, after experiencing a sign imbalance in contract j at time t. In this work τ is used in units of five minutes.

In Ref. [84], local Gaussian correlations in financial and commodity markets were analyzed. These correlations distinguish between positive and negative local dependence. In this work, a breakpoint in August 2008 is found. The increased comovements between commodities and financial markets are more critical after the breakpoint, not only between commodities and the S&P500 and 10-year Treasuries, but also within commodities themselves.

In later works [36, 56], Grimm et al. and Wang et al. use the logarithmic return for stock i and time lag τ, defined via the midpoint price $m_i(t)$ to define a cross-response function. The response function measures how a buy or sell order at time t influences on average the price at a later time $t + \tau$. The physical time scale was chosen since the trades in different stocks are not synchronous (TAQ data). They found that in all cases, an increase to a maximum is followed by a decrease. The trend is eventually reversed.

Finally, in Ref. [39], Wang et al. define the response function on a trade time scale (Totalview data), as the interest is to analyze the immediate responses. Here, the time lag τ is restricted to one trade, such that the price response quantifies the price impact of a single trade.

3.4. Price response function implementations

The main objective of this work is to analyze the price response functions. In general we define the self- and cross-response functions in a correlated financial market as

$$R_{ij}^{(scale)}(\tau) = \left\langle r_i^{(scale)}(t-1,\tau)\,\varepsilon_j^{(scale)}(t)\right\rangle_{average} \tag{3-1}$$

where the index i and j correspond to stocks in the market, $r_i^{(scale)}$ is the return of the stock i in a time lag τ in the corresponding scale and $\varepsilon_j^{(scale)}$ is the trade sign of the stock j 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 ($average = T$).
We use the returns and the trade signs to define three response functions: trade time scale response, physical time scale response and activity response. To compare the three response functions, we define the following quantities

$$E_{j,d}(t) = \sum_{n=1}^{N(t)} \varepsilon_{j,d}^{(t)}(t,n) = \mathrm{sgn}\left(E_{j,d}(t)\right)\left|E_{j,d}(t)\right| \tag{3-2}$$

$$\varepsilon_{j,d}^{(p)}(t) = \mathrm{sgn}\left(E_{j,d}(t)\right) \tag{3-3}$$

where the subscript d refers to the days used in the response computation. We use Eq. (3-2) to make easier the comparison between the results, as all the defined responses use the trade sign term.

In Sect. 4.4.1 we analyze the responses functions in trade time scale, in Sect. 4.4.2 we analyze the responses functions in physical time scale and in Sect. 3.4.3 we define a response function to analyze the influence of the frequency of trades in a second.

3.4.1. Response functions on trade time scale

We define the self- and cross-response functions in trade time scale, using the trade signs in trade time scale. For the returns, we select the last midpoint price of every second and compute them. We use this strategy with the TAQ data set considering that the price response in trade time scale can not be directly compared with the price response in physical time scale. In this case we relate each trade sign in one second with the midpoint price of the previous second. Then, to compute the returns, instead of using trades as the time lag (it would make no sense as all the midpoint price are the same in one second) we use seconds. Thus, we force the response in trade time scale to have a physical time lag, and then, be able to compare with the physical time scale response. This approximation is feasible considering the discussion in Sect. 3.3. The price response function in trade time scale is defined as

$$R_{ij}^{(t)}\left(\tau\right) = \left\langle r_{i}^{(p)}\left(t-1,\tau\right)\varepsilon_{j}^{(t)}\left(t,n\right)\right\rangle_{T} \tag{3-4}$$

where the superscript t refers to the trade time scale. We explicitly calculate the average in Eq. (4-2),

$$R_{ij}^{(t)}(\tau) = \frac{1}{\sum_{d=d_0}^{d_f} \sum_{t=t_0}^{t_f} N_{j,d}(t)} \sum_{d=d_0}^{d_f} \sum_{t=t_0}^{t_f} \sum_{n=1}^{N(t)} r_{i,d}^{(p)}(t-1,\tau)\, \varepsilon_{j,d}^{(t)}(t,n) \tag{3-5}$$

$$= \sum_{d=d_0}^{d_f} \sum_{t=t_0}^{t_f} r_{i,d}^{(p)}(t-1,\tau) \frac{\sum_{n=1}^{N(t)} \varepsilon_{j,d}^{(t)}(t,n)}{\sum_{d=d_0}^{d_f} \sum_{t=t_0}^{t_f} N_{j,d}(t)}$$

$$= \sum_{d=d_0}^{d_f} \sum_{t=t_0}^{t_f} r_{i,d}^{(p)}(t-1,\tau)\, \mathrm{sgn}\left(E_{j,d}(t)\right) w_{j,d}^{(t)}(t) \tag{3-6}$$

where

$$w_{j,d}^{(t)}(t) = \frac{\left|E_{j,d}(t)\right|}{\sum_{d=d_0}^{d_f} \sum_{t=t_0}^{t_f} N_{j,d}(t)} \tag{3-7}$$

is a weight function that depends on the normalization of the response.

To compute the response functions on trade time scale, we used all the trade signs during a day in market time. As we can not associate an individual midpoint price with their corresponding trade signs, all the trade signs in one second are associated with the midpoint price of the previous second. As τ depends on the midpoint price, even if we are using trade signs in trade time scale, the value of τ is in seconds.

The results of Fig. **4-1** show the self- responses of the six stocks used in the analysis and the cross-responses for pairs of stocks representing three different economic sectors.

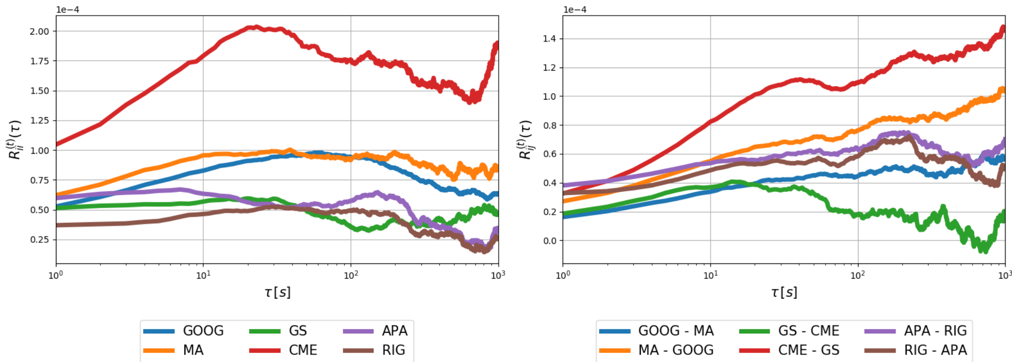

Figure **3-1**.: Self- and cross-response functions $R_{ij}^{(t)}(\tau)$ in 2008 versus time lag τ on a logarithmic scale in trade time scale. Self-response functions (left) of individual stocks and cross-response functions (right) of stock pairs from the same economic sector.

The self-response functions increase to a maximum and then slowly decrease. In some stocks this behavior is more pronounced than in others. For our selected tickers, 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 self-response functions is eventually reversed. On the other hand, the cross-response functions have smaller signal strength than the self-response functions. For our cross-response functions of stocks in the same sectors, some couples exhibit the increase-decrease behavior inside a time lag of $\tau = 10^3 s$. Other couples seems to need a larger time lag to reach the decrease behavior.

3.4.2. 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 $\varepsilon_j^{(p)}(t) = 0$ [36]. 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 [35]. For a deeper analysis of the influence of the term $\varepsilon_{j}^{(p)}(t) = 0$, we suggest to check Refs. [35, 36]. We will only take in account the response functions excluding $\varepsilon_{j}^{p}(t) = 0$.

We define the self- and cross-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

$$R_{ij}^{(p)}(\tau) = \left\langle r_{i}^{(p)}(t-1,\tau)\,\varepsilon_{j}^{(p)}(t) \right\rangle_{P} \tag{3-8}$$

where the superscript p refers to the physical time scale. The explicit expression corresponding to Eq. (4-3) reads

$$\begin{aligned} R_{ij}^{(p)}(\tau) = {} & \frac{1}{\sum_{d=d_0}^{d_f}\sum_{t=t_0}^{t_f}\eta\left[\varepsilon_{j,d}^{(p)}(t)\right]} \\ & \sum_{d=d_0}^{d_f}\sum_{t=t_0}^{t_f} r_{i,d}^{(p)}(t-1,\tau)\,\varepsilon_{j,d}^{(p)}(t)\,\eta\left[\varepsilon_{j}^{(p)}(t)\right] && \text{(3-9)} \\ = {} & \sum_{d=d_0}^{d_f}\sum_{t=t_0}^{t_f} r_{i,d}^{(p)}(t-1,\tau)\,\frac{\varepsilon_{j,d}^{(p)}(t)\,\eta\left[\varepsilon_{j,d}^{(p)}(t)\right]}{\sum_{d=d_0}^{d_f}\sum_{t=t_0}^{t_f}\eta\left[\varepsilon_{j,d}^{(p)}(t)\right]} \\ = {} & \sum_{d=d_0}^{d_f}\sum_{t=t_0}^{t_f} r_{i,d}^{(p)}(t-1,\tau)\,\mathrm{sgn}\left(E_{j,d}(t)\right) w_{j,d}^{(p)}(t) && \text{(3-10)} \end{aligned}$$

where

$$\eta(x) = \begin{cases} 1, & \text{If } x \neq 0 \\ 0, & \text{otherwise} \end{cases} \tag{3-11}$$

take only in account the seconds with trades and

$$w_{j,d}^{(p)}(t) = \frac{\eta\left[\operatorname{sgn}\left(E_{j,d}(t)\right)\right]}{\sum_{d=d_0}^{d_f}\sum_{t=t_0}^{t_f}\eta\left[\operatorname{sgn}\left(E_{j,d}(t)\right)\right]} \tag{3-12}$$

is a weight function that depends on the normalization of the response.

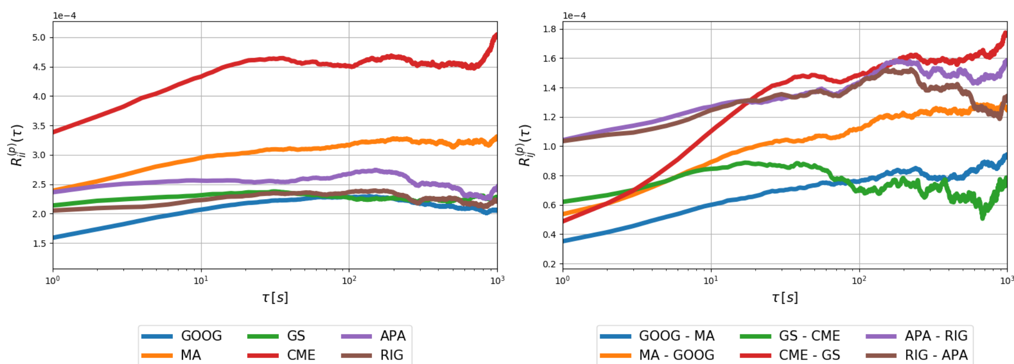

Figure **3-2**.: Self- and cross-response functions $R_{ij}^{(p)}(\tau)$ excluding $\varepsilon_j^{(p)}(t) = 0$ in 2008 versus time lag τ on a logarithmic scale in physical time scale. Self-response functions (left) of individual stocks and cross-response functions (right) of stock pairs from the same economic sector.

The results showed in Fig. **3-2** are the self- and cross-response functions in physical time scale. For the self-response functions we can say again that in almost all the cases, an increase to a maximum is followed by a decrease. Thus, the trend in the self- and cross-response is eventually reversed. In the cross-response functions, we have a similar behavior with the previous subsection, where the time lag in some pairs was not enough to see the decrease of the response.

Compared with the response functions in trade time scale, the response functions in physical time scale are stronger.

3.4.3. Activity response functions on physical time scale

Finally, we define the activity self- and cross-response functions in physical time scale, using the trade signs and the returns in physical time scale. We add a factor $N_{j,d}\left(t\right)$ to check the influence of the frequency of trades in a second in the response functions. The activity price response function is defined as

$$R_{ij}^{(p,a)}\left(\tau\right) = \left\langle r_{i}^{(p)}\left(t-1,\tau\right)\varepsilon_{j}^{(p)}\left(t\right)N\left(t\right)\right\rangle_{P} \tag{3-13}$$

where the superscript a refers to the activity response function. The corresponding explicit expression reads

$$R_{ij}^{(p,a)}(\tau) = \frac{1}{\sum_{d=d_0}^{d_f} \sum_{t=t_0}^{t_f} N_{j,d}(t)} \sum_{d=d_0}^{d_f} \sum_{t=t_0}^{t_f} r_{i,d}^{(p)}(t-1,\tau)\, \varepsilon_{j,d}^{(p)}(t)\, N_{j,d}(t) \tag{3-14}$$

$$= \sum_{d=d_0}^{d_f} \sum_{t=t_0}^{t_f} r_{i,d}^{(p)}(t-1,\tau) \frac{\varepsilon_{j,d}^{(p)}(t)\, N_{j,d}(t)}{\sum_{d=d_0}^{d_f} \sum_{t=t_0}^{t_f} N_{j,d}(t)}$$

$$= \sum_{d=d_0}^{d_f} \sum_{t=t_0}^{t_f} r_{i,d}^{(p)}(t-1,\tau)\, \mathrm{sgn}\left(E_{j,d}(t)\right) w_{j,d}^{(a)}(t) \tag{3-15}$$

where

$$w_{j,d}^{(a)}(t) = \frac{N_{j,d}(t)}{\sum_{d=d_0}^{d_f} \sum_{t=t_0}^{t_f} N_{j,d}(t)} \tag{3-16}$$

is a weight function that depends on the normalization of the response.

As $E_{j,d}(t)$ is the sum of $+1$ and -1 in one second and $N_{j,d}(t)$ is the number of trades in a second, $N_{j,d}(t) \geq E_{j,d}(t)$. $N_{j,d}(t) = E_{j,d}(t)$ only when all the trades in a second are buys $(+1)$.

The trade weight $w_{j,d}^{(t)}(t)$ reduces noises, the physical weight $w_{j,d}^{(p)}(t)$ gives every step the same weight, and the activity weight $w_{j,d}^{(a)}(t)$ emphasizes seconds with large activity.

In Fig. **3-3**, we can see how the three responses have approximately the same shape, but the strength of the signal varies depending on the definition. The frequency of trades have a large influence in the responses.

As predicted by the weights, the event response is weaker than the physical response, and the activity response is the strongest response.

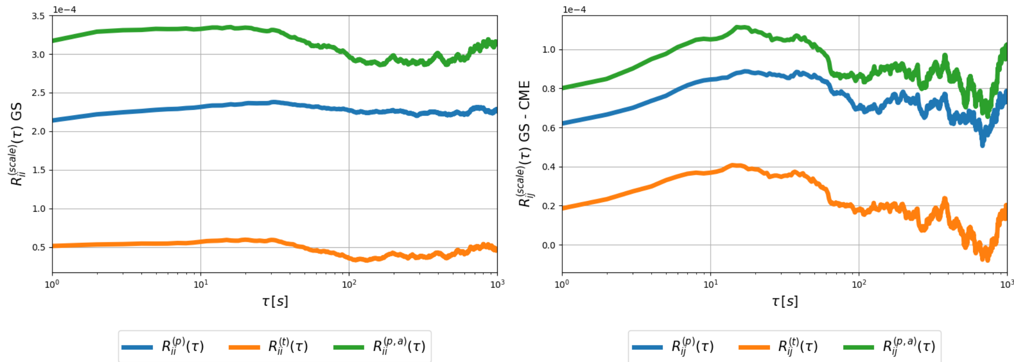

Figure **3-3**.: Self- and cross-response functions $R_{ij}^{(scale)}(\tau)$ excluding $\varepsilon_j^{(p)}(t) = 0$ in 2008 versus time lag τ on a logarithmic scale. Self-response functions (left) of Goldman Sachs Group Inc. stock and cross-response functions (right) of Goldman Sachs Group Inc.-CME Group Inc. stocks.

We propose a methodology to directly compare price response functions in trade time scale and physical time scale. Additionally, we suggest a new definition to measure the impact of the number of trades in physical time scale. In the three curves in the figure can be seen the increase-decrease behavior of the response functions.

Our results are consistent with the current literature, where the results differ about a factor of two depending on the time scale. We note that the activity response function implementation is only a test and was never defined in previous works. That is why the difference of a factor of two can not be seen in Fig. **3-3** for $R_{ij}^{(p,a)}(\tau)$.

A special situation occurs when financial and commodity markets are analyzed to find correlations as shown in Ref. [84]. In this analysis a breakpoint in August 2008 is found, where, before and after the point, the results are qualitatively different. However, our work is only focused in correlated financial markets. Our price response functions on average, have the same behavior despite the time of the year.

3.5. Time shift response functions

The relative position between returns and trade signs directly impact the result of the response functions. Shifting the values to the right or to the left either in trade time scale or physical time scale have approximately the same effect.

To test this claim, we used the definition of the response function from Ref. [36] and add a parameter t_s that shifts the position between returns and trade signs. To see the impact of the time shift we analyzed the stocks showed in Table **3-1** in the year 2008. We used different time shifts in the response function

$$R_{ij}^{(scale,s)}\left(\tau\right) = \left\langle r_{i}^{(scale)}\left(t - t_{s}, \tau\right) \varepsilon_{j}^{(scale)}\left(t\right) \right\rangle_{average} \tag{3-17}$$

where the index i and j correspond to stocks in the market, $r_{i}^{(scale)}$ is the return of the stock i in a time lag τ with a time shift t_s in the corresponding scale and $\varepsilon_{j}^{(scale)}$ is the trade sign of the stock j in the corresponding scale. The superscript $scale$ refers to the time scale used, whether physical time scale ($scale = p$) or trade time scale ($scale = t$). $R_{ij}^{(scale,s)}$ is the time shift price response function, where the superscript s refers to the time shift. 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 ($average = T$).

We compute the response functions according to two cases. In one case we set τ to a constant value and vary t_s, and in the other case we set t_s to a constant value and vary τ.

In Sect. 3.5.1 we analyze the influence of the time shift between the trade signs and returns in trade time scale and in Sect. 3.5.2 we analyze the influence of the time shift between the trade signs and returns in physical time scale.

3.5.1. Trade time scale shift response functions

On the trade time scale we compute the response function

$$R_{ij}^{(t,s)}(\tau) = \left\langle r_i^{(t)}(t - t_s, \tau)\, \varepsilon_j^{(t)}(t) \right\rangle_T \tag{3-18}$$

In this case for $r_i^{(t)}$, we associate all the trade signs to a return value and create pseudo midpoint price values in trade time scale. Then, we shift the trade signs and the returns by trades. Hence, the time lag and time shift are in trade time scale.

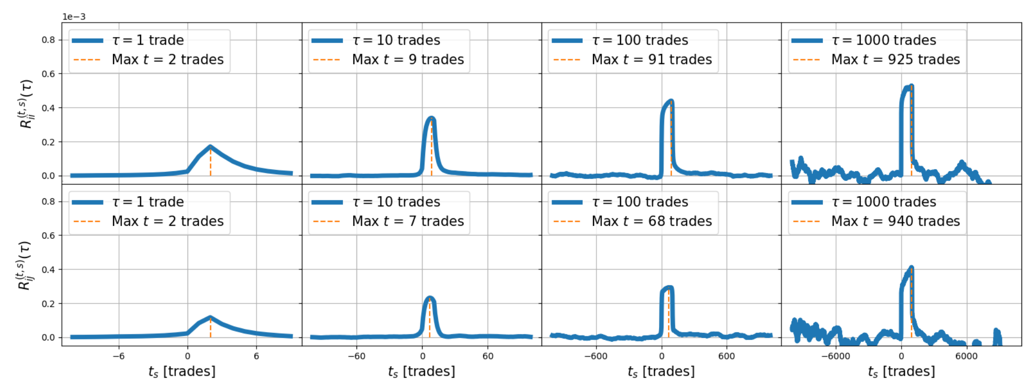

Figure **3-4**.: Self-response functions $R_{ii}^{(t,s)}(\tau)$ in 2008 versus shift for the Transocean Ltd. stock (top) and cross-response functions $R_{ij}^{(t,s)}(\tau)$ in 2008 versus shift for the Transocean Ltd.-Apache Corp. stocks (bottom) in trade time scale.

In Fig. **3-4**, we show the response functions results for fixed τ values while t_s is variable. In the different τ values figures, the results are almost the same. The response functions are zero either if the time shift is larger than τ, or if the time shift is smaller than zero. However, related to the time lag, there is a zone where the signal is different from zero. For values between

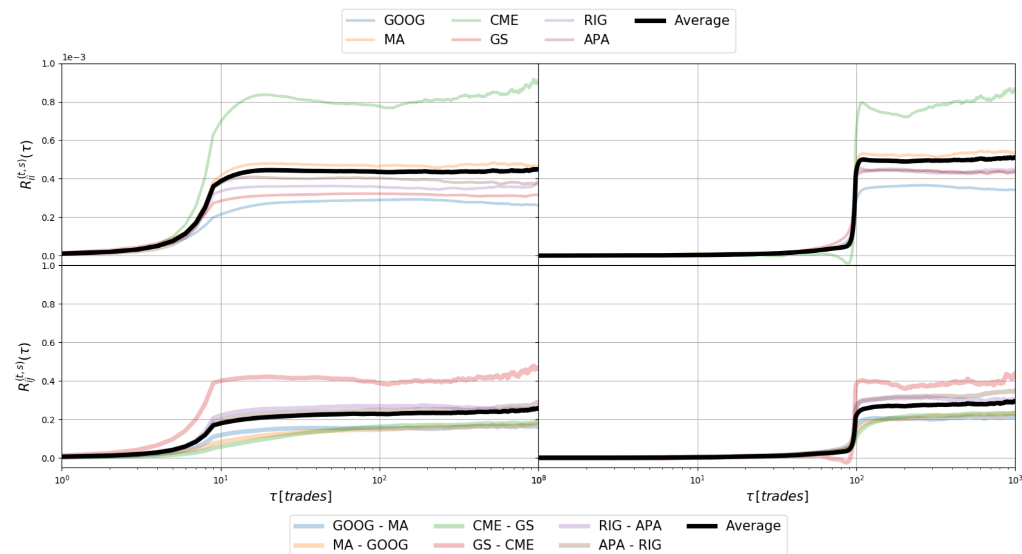

Figure **3-5**.: Self- and cross-response functions $R_{ij}^{(t,s)}(\tau)$ in 2008 versus time lag τ on a logarithmic scale for different shifts in trade time scale. Self-response functions (top) of individual stocks and cross-response functions (bottom) of stocks pairs from the same economic sector. We use time lag values $\tau = 10$ trades (left) and $\tau = 100$ (right).

zero and τ there is a peak in a position related to τ. The response function grows and decreases relatively fast.
We tested the response function for fixed time shift values while τ is variable. In Fig. **3-5** we use a time shift of 10 trades (left) and 100 trades (right). In both, self- and cross-response results are qualitatively the same. It can be seen that the response functions have a zero signal before the time shift. After the returns and trade signs find their corresponding order the signals grow. In comparison with the values obtained in Fig. **4-1**, it looks like the response function values with large time shift are stronger. However, this is an effect of the averaging of the functions. As the returns and trade signs are shifted, there are less values to average, and then the signals are stronger. Anyway, the figure shows the importance of the position order between the trade signs and returns to compute the response function.

3.5.2. Physical time scale shift response functions

In the physical time scale we compute the response function

$$R_{ij}^{(p,s)}(\tau) = \left\langle r_i^{(p)}(t - t_s, \tau)\, \varepsilon_j^{(p)}(t) \right\rangle_P \tag{3-19}$$

Similar to the results in Subsect. 3.5.1, Fig. **3-6** shows the responses functions for fixed τ values while t_s is variable. Again, the response functions are zero if the time shift is larger than the time lag, or if the time shift is smaller than zero. For every τ value, there is a peak. The peak grows and decay relatively fast. The response signal usually starts to grow in zero or a little bit earlier and grows to a value around to τ. In this zone the response functions are different to zero.
The results for fixed time shift values and variable time lag ($t_s = 10s$ and $t_s = 100s$) are shown in Fig. **3-7**. The self- and cross-response results are qualitatively the same compared with the previous subsection. The response functions are zero before the time shift value. After the returns and the trade signs reach their order, the signals grow. The same effect of the apparent

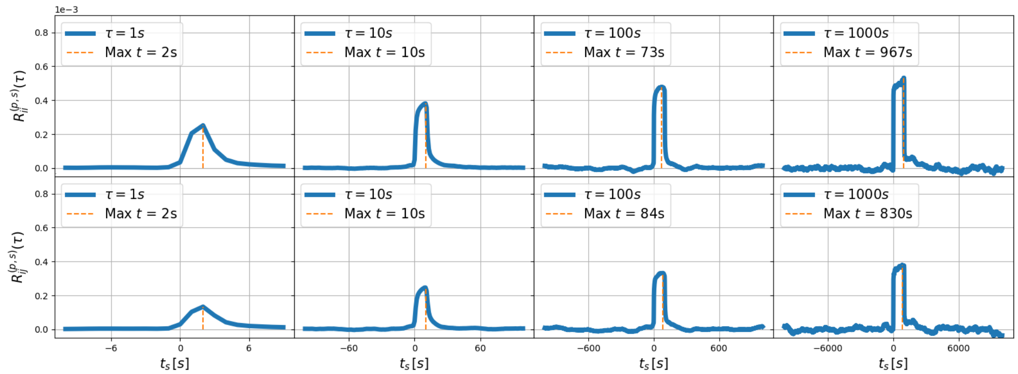

Figure **3-6**.: Self-response functions $R_{ii}^{(p,s)}(\tau)$ excluding $\varepsilon_i^{(p)}(t) = 0$ in 2008 versus shift for the Transocean Ltd. stock (top) and cross-response functions $R_{ij}^{(p,s)}(\tau)$ excluding $\varepsilon_j^{(p)}(t) = 0$ in 2008 versus shift for the Transocean Ltd.-Apache Corp. stocks (bottom) in physical time scale.

stronger signal can be seen here, and again, it is due to the averaging values. The results in trade time scale and physical time scale can be explained understanding the dynamics of the market. A trade can or can not change the price of a ticker. Therefore, when a change in price happens, a change in midpoint price, and consequently in returns happens. Thus, it is extremely important to keep the order of the events and the relation between them. When we shift the trade signs and returns, this order is temporarily lost and as outcome the signal does not have any meaningful information. When the order is recovered during the shift, the signal grows again, showing response function values different to zero. In this section we were interested only in the order (shift) and not in the responses values, which were analyzed in Sect. 3.4. A time shift smaller than zero does not have any useful information about the response. If the time shift is equal to zero, the signal is weak, due to the time needed by the market to react to the new information. On the other hand, a time shift larger than two steps shows the information is lost and the signal only grows when the original order is resumed.

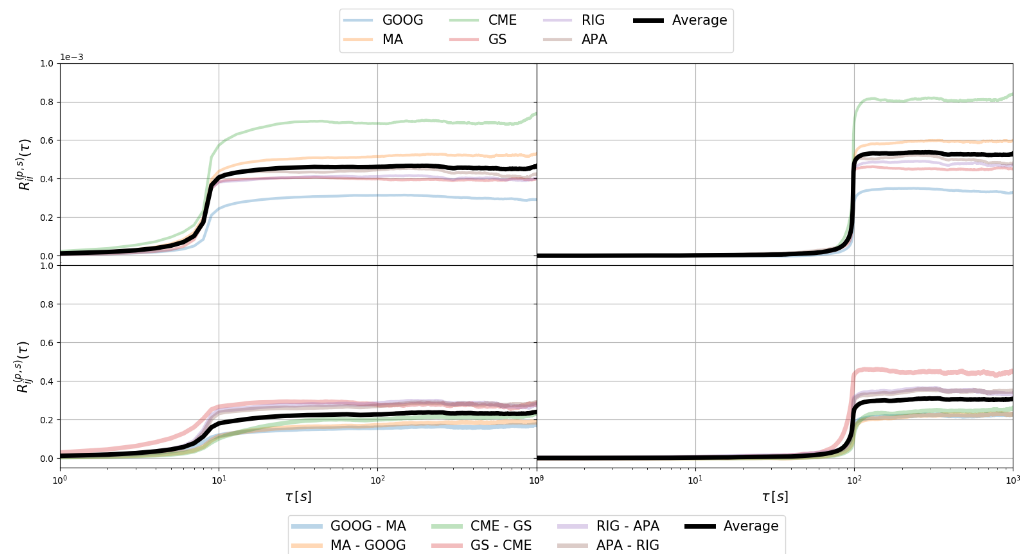

Figure **3-7**.: Self- and cross-response functions $R_{ij}^{(p,s)}(\tau)$ excluding $\varepsilon_j^{(p)}(t) = 0$ in 2008 versus time lag τ on a logarithmic scale for different shifts in physical time scale. Self-responses functions (top) of individual stocks and cross-response functions (bottom) of stocks pairs from the same economic sector. We use time lag values $\tau = 10$ trades (left) and $\tau = 100$ (right).

Then the question is what is the ideal time shift to compute the response functions. Our approach in Sect. 3.4 takes in account that the changes in the quotes are the ones that attract the agents to buy or sell their shares. Hence, they directly impact the trade signs. According to the results, the response can take up to two time steps in the corresponding scale to react to the change in quotes. Thus, a time shift larger than two time steps makes no sense. On the other hand, in the case of the physical time scale, where a sampling is used, to assure the selection of a midpoint price at the beginning of a second, it is a good strategy to use the last midpoint of the previous second as the first midpoint price of the current second. In this case an apparent one second shift is used between returns and trade signs.

3.6. Time lag analysis

Regarding Equation (1-2), we use a time lag τ in the returns to see the gains or loses in a future time. However, the strength of the return in the time lag should not be equal along its length. Then, we divide the full range time lag τ in an immediate time lag and in a late time lag as show in Fig. **3-8**, where

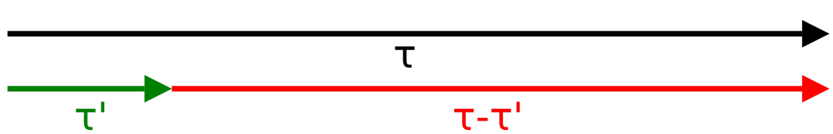

Figure **3-8**.: τ value divided in short and long time lag.

$$\tau = \tau' + \left(\tau - \tau'\right) \tag{3-20}$$

for $\tau' < \tau$. This distinguish the returns depending on the time lag as the short (immediate) return τ' with the long return $\tau - \tau'$. This approach is similar to the concept used in Ref. [39], where the price impact for a single trade is estimated by the immediate response on an event time scale. In our case, we check all over the range of the time lag in the price response function on a physical time scale.

To use the short and long time lag, we rewrite the returns in physical time scale as

$$\begin{aligned} r_i^{(p,sl)}(t,\tau) &= \ln\left(\frac{m_i(t+\tau)}{m_i(t)}\right) \\ &= \ln\left[\left(\frac{m_i(t+\tau)}{m_i(t+\tau')}\right)\left(\frac{m_i(t+\tau')}{m_i(t)}\right)\right] \\ &= \ln\left(\frac{m_i(t+\tau)}{m_i(t+\tau')}\right) + \ln\left(\frac{m_i(t+\tau')}{m_i(t)}\right) \\ &\approx \frac{m_i(t+\tau) - m_i(t+\tau')}{m_i(t+\tau')} + \frac{m_i(t+\tau') - m_i(t)}{m_i(t)} \end{aligned} \tag{3-21}$$

where the superscript sl refers to short-long and the second term of the right part is constant with respect to τ. Replacing Eq. (3-21) in the price response function in physical time scale (Eq. (4-3)) we have

$$\begin{aligned} R_{ij}^{(p,sl)}(\tau) &= \left\langle r_i^{(p,sl)}(t-1,\tau)\,\varepsilon_j^{(p)}(t)\right\rangle_P \\ &\approx \left\langle \frac{m_i(t-1+\tau) - m_i(t-1+\tau')}{m_i(t-1+\tau')}\varepsilon_j^{(p)}(t)\right\rangle_P \\ &+ \left\langle \frac{m_i(t-1+\tau') - m_i(t-1)}{m_i(t-1)}\varepsilon_j^{(p)}(t)\right\rangle_P \end{aligned} \tag{3-22}$$

Where the first term in the right side of Eq. (3-22) is the long response and the right term is the short response. Again, the right term of Eq. (3-22) is independent of τ.

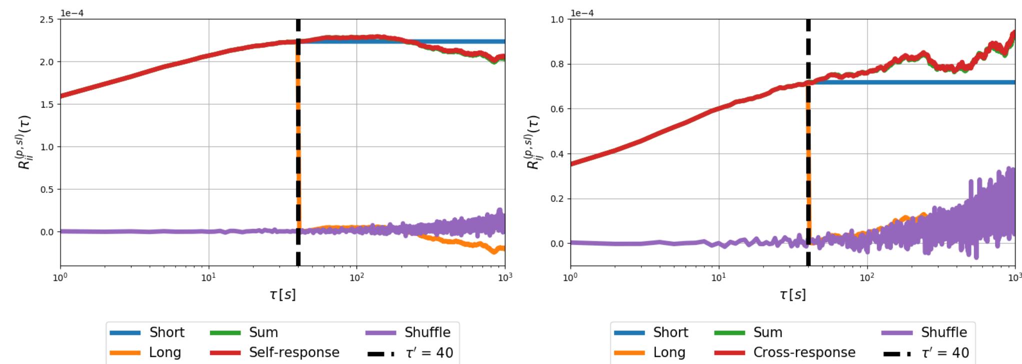

Figure **3-9**.: Self- and cross-response functions $R_{ij}^{(p,sl)}(\tau)$ excluding $\varepsilon_j^{(p)}(t) = 0$ in 2008 versus time lag τ on a logarithmic scale using a $\tau' = 40$ in physical time scale. Self-response functions (left) of Alphabet Inc. stock and cross-response functions (right) of Alphabet Inc.-Mastercard Inc. stocks.

The results in Fig. **3-9** show the short response, the long response, the addition of the short response and long response (Sum), the original response, a random response and the value of τ'.

The main signal of the response function come from the short response. Depending on the stock and the value of τ' the long response can increase or decrease the short response signal, but in general the long response does not give a significant contribution to the complete response.

Before τ', the short response and long response are the same, as the self and cross-response definition do not define values smaller than τ', so it is computed as the original response. In the figure, the curves of the short and long response are under the curve of the original response. After τ', the short response is a strong constant signal. On the other hand, the long response immediately fades, showing the small contribution to the final response. To compare the significance of the long response, We added a random response made with the trade signs used to compute the response but with a shuffle order. The long response and the random response are comparable, and show how the long response is not that representative in the final response. If we add the short and long response, we obtain the original response. In Fig. **3-9**, the original response (red line) has the same shape to the addition of the short and long response (green line).

For the response functions that show the increase-decrease behavior in between the time lag $\tau = 10^3$, the peak is usually between $\tau = 10^1$ and $\tau = 10^2$. In these cases the long response are always negative after the τ' value and is comparable in magnitude with the random signal. On the other hand, the response functions that requires a bigger time lag to show the increase-decrease behavior, have non negative long responses, but still they are comparable in magnitude with the random signal.

According to our results, price response functions show a large impact on the first instants of the time lag. We proposed a new methodology to measure this effect and evaluate their consequences. The short response dominates the signal, and the long response vanishes.

3.7. Spread impact in price response functions

When we calculate the price response functions, the signal of the response depends directly on the analyzed stock. Thus, even if the responses functions are in the same scale, their values differ from one to another. We choose the spread [85] to group 524 stocks in the NASDAQ stock market for the year 2008 in physical time scale, and check how the average strength of the price self-response functions in physical time scale behaved for this groups. For each stock we compute the spread in every second along the market time.

Then we average the spread during the 253 business days in 2008. With this value we group the stocks.

We used three intervals to select the stocks groups ($s < 0.05\$$, $0.05\$ \leq s < 0.10\$$ and $0.10\$ \leq s < 0.40\$$). The detailed information of stocks, the 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. **3-10** we show the average response functions for the three groups. The average price response function for the stocks with smaller spreads (more liquid) have in average the weakest signal in the figure. On the other hand, the average price response function for the stocks with larger spreads (less liquid) have in average the strongest signal. According to the results described in Sect. 3.3 and 3.4, the average price response functions for all the groups follow the increment to a maximum followed by a decrease in the signal intensity.

The strength of the price self-response function signals grouped by the spread can be explained knowing that the response functions directly depend on the trade signs. As long as the stock is liquid, the number of trade signs grow. Thus, at the moment of the averaging, the large amount of trades, reduces the response function signal. Therefore, the response function decrease as long as the liquidity grows, and as stated in the introduction the spread is negatively related to trading volume, hence, firms with more liquidity tend to have lower spreads.

Finally, an interesting behavior can be seen in Fig. **3-10**. Despite each stock has a particular price response according to the returns and trade signs, the average price response function for the different groups seems to be quite similar. As all the analyzed stocks come from the same market we can infer that the general behavior of the market affect all the stocks, influencing in average a group response.

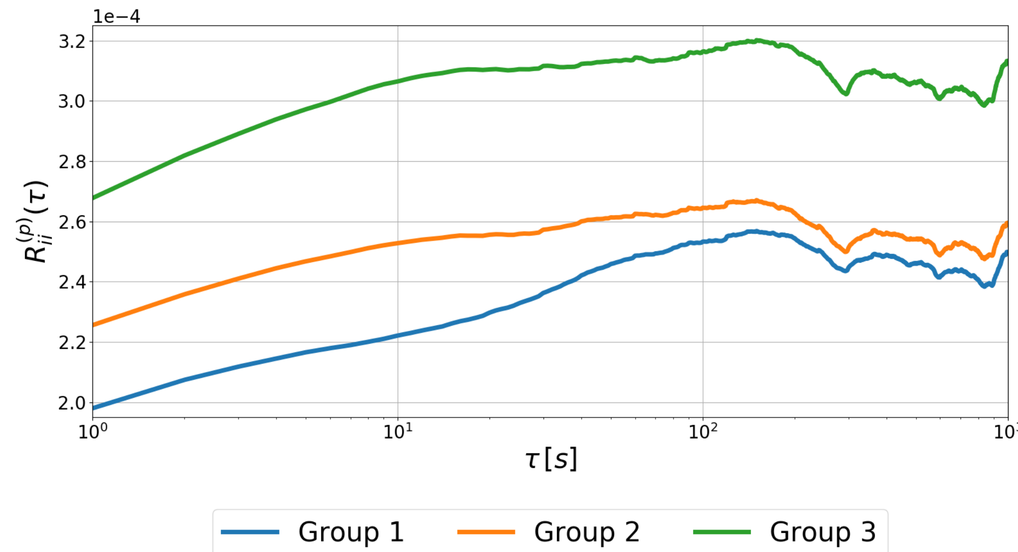

Figure **3-10**.: Average price self-response functions $R_{ii}^{(p)}(\tau)$ excluding $\varepsilon_i^{(p)}(t) = 0$ in 2008 versus time lag τ on a logarithmic scale in physical time scale for 524 stocks divided in three representative groups.

3.8. Conclusion

We went into detail about the response functions in correlated financial markets. We define the trade time scale and physical time scale to compute the self- and cross-response functions for six companies with the largest average market capitalization for three different economic sectors of the S&P index in 2008. Due to the characteristics of the data used, we had to classify and sampling values to obtain the corresponding quantities in different time scales. The classification and sampling of the data had impact on the results, making them smoother or stronger, but always keeping their shape and behavior.

The response functions were analyzed according to the time scales. We proposed a new approach to compare price response functions from different scales. We used the same midpoint prices in physical time scale with the corresponding trade signs in trade time scale or physical time scale. This assumption allowed us to compare both price response functions and get an idea of how representative was the behavior obtained in both cases. For trade time scale, the signal is weaker due to the large averaging values from all the trades in a year. In the physical time scale, the response functions had less noise and their signal were stronger. We proposed an activity response to measure how the number of trades in every second highly impact the responses. As the response functions can not grow indefinitely with the time lag, they increase to a peak, to then decrease. It can be seen that the market needs time to react and revert the growing. In both time scale cases depending on the stocks, two characteristics behavior were shown. In one, the time lag was large enough to show the complete increase-decrease behavior. In the other case, the time lag was not enough, so some stocks only showed the growing behavior.

We modify the response function to add a time shift parameter. With this parameter we wanted to analyze the importance in the order of the relation between returns and trade signs. In trade time scale and physical time scale we found similar results. When we shift the order between returns and trade signs, the information from the relation between them is temporarily lost and as outcome the signal does not have any meaningful information. When the order is recovered, the response function grows again, showing the expected shape. We showed that this is not an isolated conduct, and that all the shares used in our analysis exhibit the same behavior. Thus, even if they are values of time shift that can give a response function signal, empirically we propose this time shift should be a value between $t_s = (0, 2]$ time steps.

We analyzed the impact of the time lag in the response functions. We divided the time lag in a short and long time lag. With this division we adapted the price response function in physical time scale. The response function that depended on the short time lag, showed a stronger response. The long response function vanish, and depending on the stock could take negative and non-negative values comparable to a random signal.

Finally, we checked the spread impact in price self-response functions. We divided 524 stocks from the NASDAQ stock market in three groups depending on the year average spread of every stock. The response functions signal were stronger for the group of stocks with the larger spreads and weaker for the group of stocks with the smaller spreads. A general average price response behavior was spotted for the three groups, suggesting a market effect on the stocks.

4. Foreign exchange markets: price response and spread impact

4.1. 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 consist of similar, yet clearly distinguishable complex subsystems. Financial markets, for example, have well defined subsystems as foreign exchange markets, stock markets, bond markets, among others. The degree of universality found in one particular subsystem can then be assessed if this type of universality is also seen in another subsystem. If applicable, useful information on the impact of specific system features on this universality may then be inferred.
In spite of the considerable interest, a thorough statistical analysis of the microstructure in 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.
Here, we carry out such a study for finance, because a tremendous amount of data is available [86]. Markets may be viewed as macroscopic complex systems with an internal microscopic structure that is to a large extent

accessible by big data analysis [87]. 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 spot 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 has attracted a lot of attention in the last 20 years. Electronic trading has changed an opaque market to a fairly transparent one with transaction costs that are a fraction of their former level. The large amount of data that is now available to the public makes possible different kinds of data analysis. Intense research is currently carried out in different directions [60, 61, 62, 63, 64, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98].

McGroarty et al. [71] found that smaller volumes cause larger bid-ask spreads for technical reasons related to the measurement, whereas Hau et al. [93, 99] claim that larger bid-ask spreads caused smaller volumes due to the traders' behavior.

Burnside et al. [91] found the bid-ask spreads to be between two and four times larger for emerging market currencies than for developed country currencies. According to Huang and Masulis [94], bid-ask spreads increase when the foreign exchange market volatility increases, and decrease when the competition between the dealers increases. Ding and Hiltrop [89] showed that the Electronic Broking Services (EBS) reduces bid-ask spreads significantly, but dealers with information advantage tend to quote relatively wider bid-ask spreads. King [100] 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 [62] 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 [97] 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.

Price response functions are a powerful tool to obtain dynamical information because they measure price changes implied by 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 [1, 35, 36, 42, 45, 48, 53, 55, 79] 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 or related quantities in the foreign exchange markets [60, 96, 101]. Melvin and Melvin [96] 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. [60] model the price impact and return reversal to analyze liquidity. Their model predicts that more liquid assets should exhibit narrower bid-ask spreads and lower price impact.

To the best of our knowledge, no large-scale data analysis of response functions for the spot 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 bid-ask spread impact in the response functions for foreign exchange pairs. We use a pip bid-ask spread definition to group different foreign exchange pairs and show that large pip bid-ask spreads have a stronger impact on the response. To facilitate the reproduction of our results, the source code for the data analysis is available in Ref. [102].

The chapter is organized as follows: in Sect. 4.2 we introduce the foreign exchange market. In Sect. 4.3 we present our data set of spot foreign exchange pairs and briefly describe the physical and trade time scale. We compute the price response functions for foreign exchange pairs in Sect. 4.4. In Sect. 4.5 we show how the bid-ask spread impact the values of the response functions. Our conclusions follow in Sect. 4.6.

4.2. Key concepts

In spot 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 [63, 65, 78, 103, 104, 105]. 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. [1].

In spot foreign exchange markets, the existing bid-ask spread in any currency will vary depending on the currency trader, the currency being traded and the conditions in the market. Although 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 [67, 88]. These differences can be directly seen in the bid-ask spread. The bid-ask spread will tend to increase for currencies that do not generate a large volume of trading [67]. Furthermore, the bid-ask spread is directly related with the transaction costs to the dealer [64, 67, 100].

Generally, price response functions measure price changes implied by execution of market orders and are defined as follows:

$$R_i^{(\text{scale})}(\tau) = \left\langle r_i^{(\text{scale})}(t-1, \tau)\, \varepsilon_i^{(\text{scale})}(t) \right\rangle_{\text{average}}, \tag{4-1}$$

where the index i corresponds to currency pairs in the market, $r_i^{(\mathrm{scale})}$ is the return of the pair i in a time lag τ in the corresponding scale and $\varepsilon_i^{(\mathrm{scale})}$ 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). The main objective of this work is to analyze the price response functions for the spot foreign exchange markets.

For correlated financial markets, the price response function increases to a maximum and then slowly decreases with increasing τ. This result is observed empirically in trade time scale and in physical time scale [1, 35].

4.3. Data set

The spot 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. This tick-by-tick data is sampled for each transaction. 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. With both best bid and best ask quotes it is easy to compute the pip bid-ask spread of the data. No information about the size of each transaction is provided. Also, the identity of the participants is not given. Furthermore, trading volumes in spot foreign exchange market are not aggregated and the only volumes that are possible to find are the Broker Specific Volumes. Therefore, the data provider decided to remove the volume information from the delivered data.

Regarding the data for the time definitions in Chapter 2, for the trade time scale we use the data as it is, considering that it is sampled for each transaction. On the physical time scale, for each exchange rate, we process the irregularly spaced raw data to construct second-by-second price series, each containing 86,400 observations per day. For every second, the midpoint of best bid and ask quotes are used to construct one-second log-returns.

Another goal in this paper is to compare the price response functions in different calendar years to see the differences and similarities along time. To analyze the price response functions in Sect. 4.4, we select the seven major currency pairs (see Table **1-1**) in three different years: 2008, 2014 and 2019.

Additionally, we analyze the pip bid-ask spread impact in price response functions (Sect. 4.5). We select 46 currency pairs in three different years (2011, 2015 and 2019). The selected pairs are listed in B.

The selection of the calendar years to be analyzed was made considering the availability of the data, the completeness of the time series and the option to have a constant gap between the years.

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 [1, 36, 41, 45, 56]. 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”.

4.4. Price response functions

In Sect. 4.4.1 we analyze the responses functions in trade time scale and in Sect. 4.4.2 we analyze the responses functions in physical time scale.

4.4.1. Response functions on trade time scale

The price response function in trade time scale is defined as [1]

$$R_i^{(\mathrm{t})}(\tau) = \left\langle r_i^{(\mathrm{t})}(t-1,\tau)\,\varepsilon_i^{(\mathrm{t})}(t,n)\right\rangle_T . \tag{4-2}$$

To compute the response functions on trade time scale, we use both, the trade signs and the returns from the tick-by-tick original data during a week in market time. Then, the response is averaged by the number of trades.
The results of Fig. **4-1** show the price response functions of the seven foreign exchange major pairs used in the analysis (see Table **1-1**) for three different years. The results found for all the years are entirely in line with price responses seen in other financial markets, particularly with correlated financial markets. The response functions have an initial increasing trend to a maximum, that flattens out and saturates at some level, and eventually slowly decrease. This shape is explained by an initial increase caused by autocorrelated transaction flow. The flattening out is due to the market liquidity adapting to this flow and assuring diffusive prices [76]. For our selected pairs, a time lag of $\tau = 10^3$ trades 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 varies from one year to the other. In 2008 the strength of the signal was one order of magnitude stronger than the response in 2014, but the signals in 2014 have approximately twice the strength of 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.

4.4.2. 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

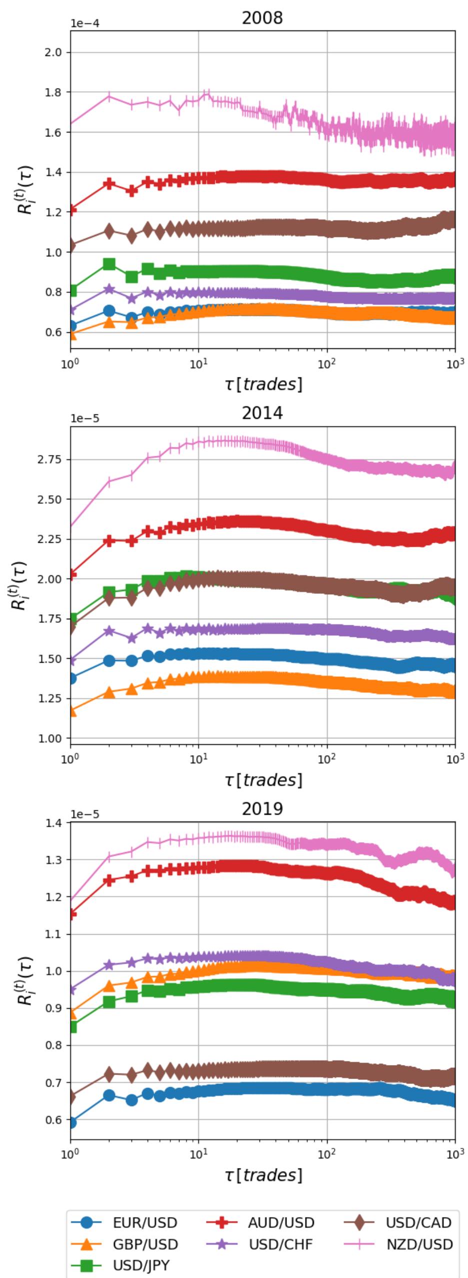

Figure **4-1**.: Price response functions $R_i^{(\mathrm{t})}(\tau)$ versus time lag τ on a logarithmic scale in trade time scale for the years 2008 (top), 2014 (middle) and 2019 (bottom).

the response functions highly differ when we include or exclude $\varepsilon_j^{(\mathrm{p})}(t) = 0$ [36]. The price responses including $\varepsilon_j^{(\mathrm{p})}(t) = 0$ are weaker than the excluding ones due to the omission of direct influence of the lack of trades. However, either including or excluding $\varepsilon_j^{(\mathrm{p})}(t) = 0$ does not change the trend of price reversion versus the time lag, but it does affect the response function strength [35]. For a deeper analysis of the influence of the term $\varepsilon_j^{(\mathrm{p})}(t) = 0$ in price response functions, we suggest reviewing Refs. [35, 36]. 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 sampled in seconds from the original data on physical time scale. The price response function on physical time scale is defined as [1]

$$R_i^{(\mathrm{p})}(\tau) = \left\langle r_i^{(\mathrm{p})}(t-1,\tau)\,\varepsilon_i^{(\mathrm{p})}(t)\right\rangle_P \tag{4-3}$$

The results shown in Fig. **4-2** 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 decreases 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 from the one

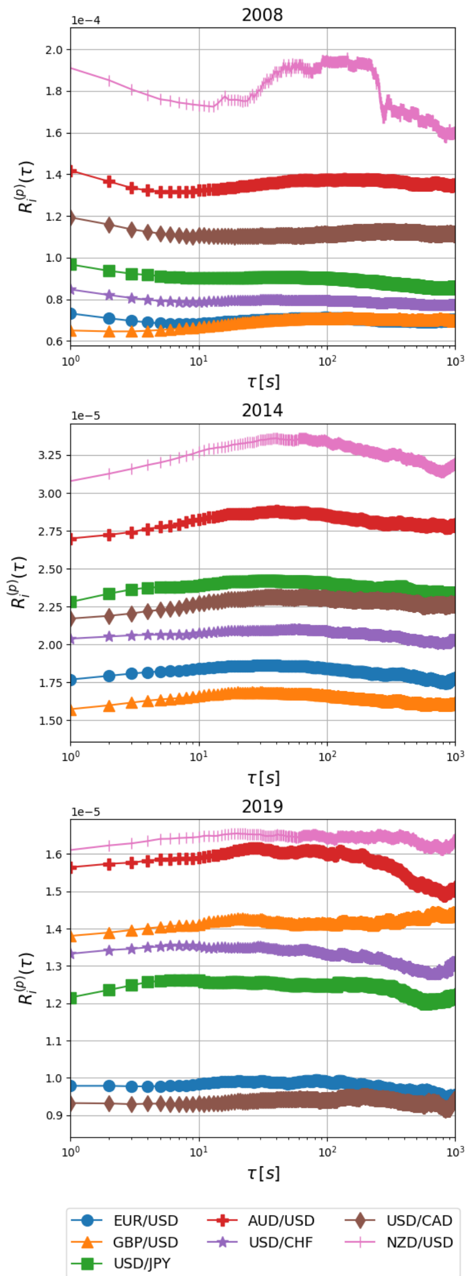

Figure **4-2**.: Price response functions $R_i^{(\mathrm{p})}(\tau)$ excluding $\varepsilon_i^{(\mathrm{p})}(t) = 0$ versus time lag τ on a logarithmic scale in physical time scale for the years 2008 (top), 2014 (middle) and 2019 (bottom).

presented in correlated financial markets, where the results differ about a factor of two depending on the time scale [1].

On physical time scale, we can see that the liquid pairs have a smaller price response compared with non-liquid pairs. The liquidity of the pairs vary regarding the analyzed year. For the years 2008 and 2014, the most liquid pairs are the EUR/USD and the GBP/USD. For 2019 the most liquid pairs are EUR/USD and USD/CAD. Therefore, the price response of a foreign exchange pair with large activity is smaller to the small impact of each trade. Also, the former year responses have stronger signals. We consider the same argument of algorithm trading to explain why the signals in recent years are weaker than in older years.

4.5. Bid-ask spread impact in price response functions

To analyze the bid-ask spread impact in price response functions, we use 46 foreign exchange pairs from three different years (Appendix B). As we showed in Sect. 1.4, 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 [71]

$$s_{\text{pip}} = \left(a\left(t\right) - b\left(t\right)\right) \cdot \text{scaling factor}. \tag{4-4}$$

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 of the order book at each time a trade accrued. Then we average the bid-ask spread during the trade weeks in the different years. With this value we group the foreign exchange pairs in several groups considering different interval values. We start to reduce the number of groups and find out that for the years 2011 and 2015 two clusters and for 2019 three clusters are clearly distinguishable.

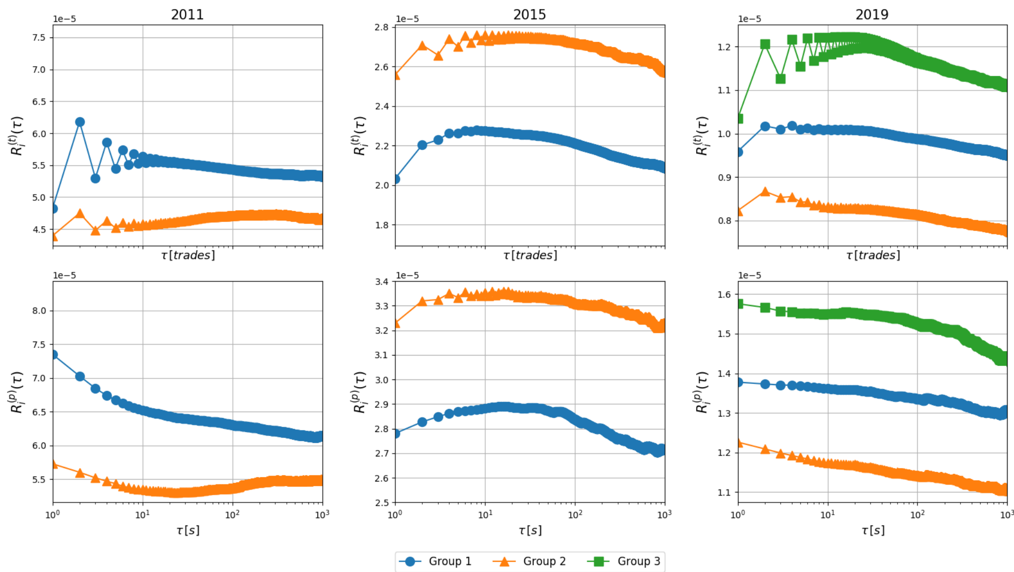

Figure **4-3**.: Average price response functions $R_i^{(t)}(\tau)$ versus time lag τ on a logarithmic scale in trade time scale (Top) and $R_i^{(p)}(\tau)$ excluding $\varepsilon_i^{(p)}(t) = 0$ versus time lag τ on a logarithmic scale in physical time scale (Bottom) for 46 foreign exchange pairs divided in representative groups in three different years (2011, 2015 and 2019).

Depending on the year, we identify different numbers of groups according to the pip bid-ask spread s_{pip}. For the years 2011 and 2015, we use two intervals to select the foreign exchange pairs groups ($s_{\text{pip}} < 10$ and $10 \leq s_{\text{pip}}$). In the year 2019 we use three intervals to select the foreign exchange pairs groups ($s_{\text{pip}} < 4$, $4 \leq s_{\text{pip}} < 10$ and $10 \leq s_{\text{pip}}$). The detailed information of the foreign exchange pairs, bid-ask spread and the groups can be seen in B. With the groups of currency pairs defined, we average the price response functions of each group.

In Fig. **4-3** 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 bid-ask spread. The average price response function for the pairs with smaller pip bid-ask spreads (more liquid) have on 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 bid-ask spread (less liquid) have on average the strongest signal for all the years in both time scales.

From Sect. 4.4 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. 4.4 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 an instantaneous high response that slowly decreases 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 decreased 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 [1].

4.6. Conclusion

Price response functions provide quantitative information on the deviation from Markovian behavior. They measure price changes resulting from execution of market orders. We used these functions in big data analysis for spot foreign exchange markets. Such a study was, to the best of our knowledge, never done before.

We analyzed price response functions in spot 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 use of different time scales and calendar years in the work had the intention to display the different behaviors the price response function could take when the time parameters differ.

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 increases to a maximum and then starts to slowly decrease. However, for the year 2008 the shape of the signals is not as well defined as in the other years. The increase-decrease behavior observed in the spot foreign exchange market was also reported in correlated financial markets [1, 35]. These results show that the price response functions conserve their behavior in different years and in different markets. The shape of the price response functions is qualitatively explained considering an initial increase caused by the autocorrelated transaction flow. To assure diffusive prices, price response flattens due to market liquidity adapting to the flow in the initial increase.

On 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 years and scales, the price response signal is stronger in past than in recent years. As algorithmic trading has gained 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 bid-ask 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 bid-ask 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 bid-ask spreads and weaker for the group of pairs with smaller bid-ask 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 on trade time scale. Hence, the noise in the cross and exotic pairs due to the lack of trading compared with the majors seems stronger. 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 spot 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.

5. Summary and Outlook

Market microstructure is a key concept to understand the basic elements and the dynamics of the markets. Furthermore, the large amount of data available in quantitative finance makes the study of markets really appealing for physicists. In this thesis we wanted to better understand the impact of trading on price changes, and to achieve this goal we studied in detail response functions. This quantity measures how much, on average, the price moves up or down restricted to a buy or sell order at time zero to a time lag later. We started our research using relevant literature produced in the research group Guhr and extended the analysis of previous works.

To improve the understandability of this thesis, we explained in detail the structure of the correlated financial markets and foreign exchange markets. We defined the basic concepts to fully understand the analysis that was made along the chapters. We tried to be the most clear possible to make the complete research easy to reproduce and easy to understand. Moreover, all the implementations are available for readers and researchers, so they can check how we made the analysis and if needed, use our code to expand new research ideas in related topics.

Our first major task was to specify and establish the time definition used in the different parts of our research. As we used tick-by-tick data, we decided to use a trade time scale and a physical time scale to implement the price response functions in the analyzed markets. Due to the characteristics of our data sets, it was possible to classify the trade signs for correlated financial markets and to infer the trades for foreign exchange markets.

Then, we carried out the analysis of price response functions and spread impact in correlated financial markets. We focused on the key details needed to compute the response functions and explored their corresponding roles. We used trades and quotes (TAQ) data from the NASDAQ stock market. For our analysis of response functions we selected the six companies with the largest average market capitalization (AMC) in three economic sectors of the S&P index in 2008. To analyze the spread impact in response functions we selected 524 stocks from the NASDAQ stock market for the year 2008. Due to the characteristics of the data we performed an empirical study on different time scales. We had to classify and sampling values to obtain the corresponding quantities. The classification and sampling of the data had an impact on the results, making them smoother or stronger, but always keeping their shape and behavior. We used the same midpoint prices in physical time scale with the corresponding trade signs in trade time scale or physical time scale. This assumption allowed us to compare both price response functions and get an idea of how representative the behavior obtained in both cases was. For the trade time scale, the signal is weaker due to the large averaging values from all the trades in a year. In the physical time scale, the response functions had less noise and their signals were stronger. We proposed an activity response to measure how the number of trades in every second highly impacts the responses. As the response functions can not grow indefinitely with the time lag, they increase to a peak, to then decrease. It can be seen that the market needs time to react and revert the growth. We modified the response function to add a time shift parameter to show the importance in the order of the relation between returns and trade signs. When we shifted the order between returns and trade signs, the information from the relation between them was temporarily lost and as outcome the signal did not have any meaningful information. When the order was recovered, the response function grew again, showing the expected shape. We showed that this is not an isolated conduct, and that all the shares used in our analysis exhibit the same behavior. We split the time lag to understand the contribution of the immediate returns and the late returns. With this division we adapted the price response function in a physical time scale. The response function that depended on the short time lag, showed a stronger response. The long response function vanishes, and depending on the stock could take negative and non-negative values comparable to a random signal. Finally, we shed light on the spread impact in the response functions for single stocks. The response functions' signals were stronger for the group of stocks with the larger spreads and weaker for the group of stocks with the smaller spreads. A general average price response behavior was spotted for the three groups, suggesting a market effect on the stocks.

We analyzed the market microstructure of foreign exchange markets through price response functions. We took advantage of the tremendous amount of available data to carry out an analysis that was not possible in the past by the limited access to data, and to the best of our knowledge, no large-scale data analysis of response functions for the spot foreign exchange market were done before. Based on a series of detailed empirical results obtained on trade by trade data, we showed that the price response functions in the foreign exchange markets behave qualitatively similar as the ones in correlated stocks markets. We considered different time scales, years and currency pairs to compute the price response functions in spot foreign exchange markets. 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. On trade time scale, the signals were noisier. For both time scales we observed that the signal for all the pairs increases to a maximum and then starts to slowly decrease. The increase-decrease behavior observed in the spot foreign exchange market was also reported in correlated financial markets. These results show that the price response functions conserve their behavior in different years and in different markets. The shape of the price response functions is qualitatively explained considering an initial increase caused by the autocorrelated transaction flow. To assure diffusive prices, price response flattens due to market liquidity adapting to the flow in the initial increase. Finally, we shed light on the bid-ask spread impact in the response functions for foreign exchange pairs. We used a pip bid-ask spread definition to group different foreign exchange pairs and showed that large pip bid-ask spreads have a stronger impact on the response.

For future research, it will be interesting to compare the results in correlated financial markets for the year 2008 with recent years, so it could be possible to analyze how universal the results of price response functions in 2008 are when compared to a later year to determine time-dependent trends and market efficiency. With the data set that the research group already owns and recent year data, it can be possible to analyze the impact of high frequency trading and algorithmic trading in correlated financial markets and foreign exchange markets.

A. NASDAQ stocks used to analyze the spread impact

We analyzed the spread impact in the response functions for 524 stocks from the NASDAQ stock market for the year 2008. In Tables **A-1**, **A-2**, **A-3** **A-4** and **A-5**, we listed the stocks in their corresponding spread groups.

Table **A-1**.: Information of the stocks in Group 1.

Group 1		
Symbol	Company	Spread[1]
F	Ford Motor Company	0.01$
Q	Qwest Communications Int.	0.01$
ETFC	E-Trade Financial Corp.	0.01$
PFE	Pfizer Inc.	0.01$
MOT	Motus GI Holdings Inc.	0.01$
AMD	Advanced Micro Devices	0.01$
TLAB	Tellabs Inc.	0.01$
INTC	Intel Corp.	0.01$
TWX	Time Warner Inc.	0.01$
CSCO	Cisco Systems Inc.	0.01$
THC	Tenet Healthcare Corp.	0.01$
LSI	Life Storage Inc.	0.01$
MU	Micron Technology Inc.	0.01$
EMC	EMC Corp.	0.01$
MSFT	Microsoft Corp.	0.01$
NOVL	Novell Inc.	0.01$
JAVA	Sun Microsystems Inc.	0.01$
ORCL	Oracle Corp.	0.01$
S	Sprint Nextel Corp.	0.01$
DELL	Dell Technologies Inc.	0.01$
AMAT	Applied Material Inc.	0.01$
SLE	Spark Energy Inc.	0.01$
SBUX	Starbucks Corp.	0.01$
DYN	Dynergy Inc.	0.01$
DUK	Duke Energy Corp.	0.01$
CMCSA	Comcast Corp.	0.01$
IPG	Interpublic Group of Co.	0.01$
BSX	Boston Scientific Corp.	0.01$
GE	General Electric Company	0.01$
SYMC	Symantec Corp.	0.01$
C	Citigroup Inc.	0.01$

Symbol	Company	Spread[1]
LUV	Southwest Airlines Company	0.01$
BRCM	Broadcom Inc.	0.01$
TXN	Texas Instruments Inc.	0.01$
TER	Teradyne Inc.	0.01$
MYL	Mylan N.V.	0.01$
HCBK	Hudson City Bancorp	0.01$
SPLS	Staples Inc.	0.01$
SGP	Siamgas and Petrochemicals	0.01$
HST	Host Hotels & Resorts Inc.	0.01$
AES	Aes Corp.	0.01$
KFT	Kraft Foods Inc.	0.01$
NTAP	NetApp Inc.	0.01$
BAC	Bank of America Corp.	0.01$
HD	Home Depot Inc.	0.01$
SOV	Life Storage Inc.	0.01$
QLGC	QLogic Corp.	0.01$
T	AT&T Inc.	0.01$
GPS	Gap Inc.	0.01$
DIS	Walt Disney Company	0.01$
GM	General Motors Company	0.01$
JNPR	Juniper Networks Inc.	0.01$
LOW	Lowe's Companies Inc.	0.01$
CBS	CBS Corp.	0.01$
CAG	ConAgra Brands Inc.	0.01$
LLTC	Linear Technology Corp.	0.01$
DTV	DirecTV Group	0.01$
HBAN	Huntington Bancshares Inc.	0.01$
KG	Kinross Gold Corp.	0.01$
CMS	CMS Energy Corp.	0.01$
ODP	Office Depot Inc.	0.01$
NVLS	Nivalis Therapeutics Inc.	0.01$
WFC	Wells Fargo & Company	0.01$

Symbol	Company	Spread[1]
TSN	Tyson Foods Inc.	0.02$
CA	CA Inc.	0.02$
XEL	Xcel Energy Inc.	0.02$
AA	Alcoa Corp.	0.02$
KR	Kroger Company	0.02$
MRK	Merck & Company Inc.	0.02$
NSM	Nationstar Mortgage Holdings	0.02$
WMT	Walmart Inc.	0.02$
FITB	Fifth Third Bancorp	0.02$
EK	Eastman Kodak Company	0.02$
PHM	PulteGroup Inc.	0.02$
JPM	JP Morgan Chase & Co.	0.02$
WAG	Walgreen Co.	0.02$
SCHW	Charles Schwab Corp.	0.02$
RF	Regions Financial Corp.	0.02$
ADBE	Adobe Inc.	0.02$
MAT	Mattel Inc.	0.02$
PAYX	Paychex Inc.	0.02$
PGR	Progressive Corp.	0.02$
HPQ	HP Inc.	0.02$
DOW	Dow Inc.	0.02$
TE	TECO Energy Inc.	0.02$
BBBY	Bed Bath & Beyond Inc.	0.02$
JNJ	Johnson & Johnson	0.02$
IP	International Paper Company	0.02$
RSH	Respiri Ltd.	0.02$
MER	Mears Group PLC	0.02$
HAL	Halliburton Company	0.02$
KO	Coca-Cola Company	0.02$
PBCT	People's United Financial Inc.	0.02$
WU	Western Union Company	0.02$
USB	U.S. Bancorp	0.02$

[1] Average spread from 9:40:00 to 15:50:00 New York time during 2008.

Table **A-2.**: Information of the stocks in Group 1.

Group 1		
Symbol	Company	Spread[1]
CPWR	Ocean Thermal Energy	0.01$
NVDA	Nvidia Corp.	0.01$
YHOO	Yahoo Inc.	0.01$
BMY	Bristol-Myers Squibb Co.	0.01$
ALTR	Altair Engineering Inc.	0.01$
GLW	Corning Inc.	0.01$
JDSU	JDS Uniphase Corp.	0.01$
NCC	NCC Group	0.01$
EBAY	eBay Inc.	0.01$
EP	El Paso Corp.	0.01$
XRX	Xerox Holdings Corp.	0.01$
WIN	Windstream Holdings Inc.	0.01$
XLNX	Xilinx Inc.	0.01$
WMB	Williams Companies Inc.	0.02$
SE	Sea Ltd American Dep.	0.02$
PG	Procter & Gamble Co.	0.02$
CIEN	Ciena Corp.	0.02$
LEN	Lennar Corp.	0.02$
AKAM	Akamai Technologies	0.02$
UNH	UnitedHealth Group Inc.	0.02$
DD	DuPont de Nemours Inc.	0.02$
KLAC	KLA Corp.	0.02$
CIT	CIT Group Inc.	0.02$
LEG	Leggett & Platt Inc.	0.02$
WFMI	Whole Foods Market Inc.	0.02$
MS	Morgan Stanley	0.02$
VRSN	VeriSign Inc.	0.02$
AN	AutoNation Inc.	0.02$
RHT	Red Hat Inc.	0.02$
CTXS	Citrix Systems Inc.	0.02$
MDT	Medtronic plc.	0.02$
NBR	Nabors Industries	0.02$

Symbol	Company	Spread[1]
TGT	Target Corp.	0.02$
MO	Altria Group Inc.	0.01$
VZ	Verizon Communications	0.01$
DHI	D. R. Horton Inc.	0.01$
SNDK	Sandisk Corp.	0.01$
CCE	Coca-Cola Enterprises	0.01$
NI	NiSource Inc.	0.01$
EXPE	Expedia Group Inc.	0.01$
AIG	American International	0.01$
INTU	Intuit Inc.	0.01$
LTD	Limited Brands Inc.	0.01$
CNP	CenterPoint Energy Inc.	0.02$
QCOM	Qualcomm Inc.	0.02$
JBL	Jabil Inc.	0.02$
VLO	Valero Energy Corp.	0.02$
MMC	Marsh & McLennan Co.	0.02$
CPB	Campbell Soup Company	0.02$
TYC	Tyco International PLC	0.02$
MCD	McDonald's Corp.	0.02$
HON	Honeywell International Inc.	0.02$
DF	Dean Foods Company	0.02$
NWSA	News Corp.	0.02$
URBN	Urban Outfitters Inc.	0.02$
RX	Recylex	0.02$
BBY	Best Buy Inc.	0.02$
CCL	Carnival Corp.	0.02$
WMI	WMI Investment Corp.	0.02$
POM	Polymet Mining Corp.	0.02$
ERTS	Electronic Arts Inc.	0.03$
MBI	MBIA Inc.	0.03$
ADM	Archer-Daniels-Midland Co.	0.03$
PEP	PepsiCo Inc.	0.03$
CBG	CBRE Group Inc.	0.03$

Symbol	Company	Spread[1]
MI	Marshall and Lisley Corp.	0.03$
MCHP	Microchip Technology Inc.	0.02$
SO	Southern Company	0.02$
BJS	BJ's Wholesale Club Holdings	0.02$
MAS	Masco Corp.	0.02$
NWL	Newell Brands Inc.	0.02$
M	Macy's Inc.	0.02$
CVS	CVS Health Corp.	0.02$
CTSH	Cognizant Tech. Solutions	0.02$
GNW	Genworth Financial Inc.	0.02$
DFS	Discover Financial Services	0.02$
KEY	KeyCorp	0.02$
ADI	Analog Devices Inc.	0.02$
SYY	Sysco Corp.	0.02$
AEP	American Electric Power Co.	0.03$
NEM	Newmont Corp.	0.03$
MRO	Marathon Oil Corp.	0.03$
ITW	Illionois Tool Works Inc.	0.03$
FFIV	F5 Networks Inc.	0.03$
CVX	Chevron Corp.	0.03$
PCAR	PACCAR Inc.	0.03$
OMC	Omnicom Group Inc.	0.03$
XRAY	DENTSPLY SIRONA Inc.	0.03$
COP	ConocoPhillips	0.03$
PCS	MetroPCS Communications	0.03$
RHI	Robert Half International Inc.	0.03$
SEE	Sealed Air Corp.	0.03$
COST	Costco Wholesale Corp.	0.03$
FIS	Fidelity National Info. Services	0.03$
PKI	PerkinElmer Inc.	0.03$
BMC	BMC Software Inc.	0.03$
RRD	R.R. Donnelley & Sons Co.	0.03$
UTX	United Technologies Corp.	0.03$

[1] Average spread from 9:40:00 to 15:50:00 New York time during 2008.

Table **A-3.**: Information of the stocks in Group 1.

Group 1			Symbol	Company	Spread[1]	Symbol	Company	Spread[1]
Symbol	Company	Spread[1]	DOV	Dover Corp.	0.05$	CAM	Corporate Actions Middleware	0.06$
MOLX	Molex Inc.	0.02$	IR	Ingersoll Rand Inc.	0.03$	D	Dominion Energy Inc.	0.03$
GILD	Gilead Sciences Inc.	0.02$	HNZ	Heinz Company	0.03$	PBI	Pitney Bowes Inc.	0.03$
CHK	Chesapeake Energy	0.02$	CTX	Qwest Corp.	0.03$	ACAS	American Capital Ltd.	0.03$
TJX	TJX Companies Inc.	0.02$	TSO	Tesoro Corp.	0.03$	K	Kellogg Company	0.03$
AMGN	Amgen Inc.	0.02$	IGT	International Game Tech.	0.03$	JCP	J. C. Penney Company	0.03$
SWY	Safeway Inc.	0.02$	WYN	Wynnstay Group PLC	0.03$	AMT	American Tower Corp.	0.03$
XOM	Exxon Mobil Corp.	0.02$	GT	The Goodyear Tire & Rubber	0.03$	ALL	Allstate Corp.	0.03$
STZ	Constellation Brands	0.02$	JCI	Johnson Controls Int.	0.03$	MWV	MeadWestvaco Corp.	0.03$
ADSK	Autodesk Inc.	0.02$	JWN	Nordstrom Inc.	0.03$	HRB	H&R Block Inc.	0.03$
LLY	Eli Lilly and Company	0.02$	FRX	Fennec Pharmaceutical Inc.	0.03$	NYT	New York times Company	0.04$
CTAS	Cintas Corp.	0.02$	FHN	First Horizon National Corp.	0.03$	RDC	Redcape Hotel Group	0.04$
LIZ	Liz Claiborne Inc.	0.02$	ABT	Abbott Laboratories	0.03$	PTV	Pactiv Company	0.04$
GCI	Gannett Co. Inc.	0.02$	ADP	Automatic Data Processing	0.03$	FISV	Fiserv Inc.	0.04$
AXP	American Express Co.	0.02$	PBG	Pacific Brands Ltd.	0.03$	EXPD	Expeditors Int.of Washington	0.04$
TIE	Titanium Metals Corp.	0.02$	ROST	Ross Stores Inc.	0.03$	BBT	BB&T Corp.	0.04$
SAI	SAIC Inc.	0.02$	KBH	KB Home	0.03$	PCG	Pacific Gas & Electric Co.	0.04$
PDCO	Patterson Companies	0.02$	YUM	Yum! Brands Inc.	0.03$	BIG	Big Lots Inc.	0.04$
WYE	Wyeth Inc.	0.02$	MAR	Marriott International	0.03$	KMX	CarMax Inc.	0.04$
COH	Cochlear Ltd.	0.02$	STJ	St Jude Medical Inc.	0.03$	TSS	Total System Services Inc.	0.04$
CVG	Convergys Corp.	0.02$	FDO	Family Dollar Stores Inc.	0.03$	BK	The Bank of N. Y. Mellon Corp.	0.04$
WDC	Western Digital Corp.	0.02$	ED	Consolidated Edison Inc.	0.03$	TEL	Tellurian Inc.	0.04$
AVP	Avon Products Inc.	0.02$	UNM	Unum Group	0.03$	KSS	Kohl's Corp.	0.04$
A	Agilent Technologies	0.02$	ORLY	O'Reilly Automotive Inc.	0.03$	CAT	Caterpillar Inc.	0.04$
JNY	Jones Apparel Group	0.02$	SVU	SUPERVALU Inc.	0.03$	HSY	The Hershey Company	0.04$
SLM	SLM Corp.	0.02$	EMR	Emerson Electric Company	0.03$	GIS	General Mills Inc.	0.04$
HAS	Hasbro Inc.	0.04$	VIAB	Viacom Inc.	0.05$	RAI	Reynolds American Inc.	0.06$
XTO	XTO Energy Inc.	0.04$	ABC	AmerisourceBergen Corp.	0.05$	NOC	Northrop Grumman Corp.	0.06$
PPL	PPL Corp.	0.04$	APC	Anadarko Petroleum Corp.	0.05$	PLL	Piedmont Lithium Ltd.	0.06$
HOG	Harley-Davidson Inc.	0.04$	CBE	Cooper Industries	0.05$	SYK	Stryker Corp.	0.06$
UPS	United Parcel Service	0.04$	FAST	Fastenal Company	0.05$	SRE	Sempra Energy	0.06$
HSP	Hospira Inc.	0.04$	MHP	McGraw-Hill Companies Inc.	0.05$	TIF	Tiffany & Co.	0.06$
CTL	CenturyLink Inc.	0.04$	AMZN	Amazon.com Inc.	0.05$	NUE	Nucor Corp.	0.06$

[1] Average spread from 9:40:00 to 15:50:00 New York time during 2008.

Table **A-4.**: Information of the stocks in Group 1 and 2.

Group 1

Symbol	Company	Spread[1]
TDC	Teradata Corp.	0.04$
BA	Boeing Company	0.04$
BAX	Baxter International Inc.	0.04$
PGN	Progress Energy Inc.	0.04$
DRI	Darden Restaurants Inc.	0.04$
JNS	Janus Capital Group Inc.	0.04$
BMS	Bristol-Myers Squibb	0.04$
RTN	Raytheon Company	0.04$
CVC	Cablevision Systems	0.04$
PWR	Quanta Services Inc.	0.04$
LXK	Lexmark International	0.04$
CELG	Celgene Corp.	0.04$
MMM	3M Company	0.04$
RSG	Republic Services Inc.	0.04$
DNR	Denbury Resources Inc.	0.04$
MTW	Manitowoc Company	0.04$
NE	Noble Corp.	0.04$
NDAQ	Nasdaq Inc.	0.04$
CINF	Cincinnati Financial	0.04$
BIIB	Biogen Inc.	0.04$
KMB	Kimberly-Clark Corp.	0.04$
EIX	Edison International	0.04$
NRG	NRG Energy Inc.	0.04$
IVZ	Invesco Ltd.	0.04$
AEE	Ameren Corp.	0.04$
AAPL	Apple Inc.	0.04$
CAH	Cardinal Health Inc.	0.04$
MCO	Moody's Corp.	0.04$

Group 2

Symbol	Company	Spread[1]
HOT	Hot Topic Inc.	0.05$
GPC	Genuine Parts Co	0.05$
PEG	Public Service Ent.	0.05$
DOV	Dover Corp.	0.05$
EQR	Equity Residential	0.05$
CL	Colgate-Palmolive Company	0.05$
ECL	Ecolab Inc.	0.05$
MKC	McCormick & Company Inc.	0.05$
AOC	Aon Corp.	0.05$
TXT	Textron Inc.	0.05$
CSX	CSX Corp.	0.05$
PNW	Pinnacle West Capital Corp.	0.05$
KIM	Kimco Realty Corp.	0.05$
WPI	Watson Pharmaceuticals	0.05$
MET	Metlife Inc.	0.05$
UST	ProShares Ultra	0.05$
TMO	Thermo Fisher Scientific Inc.	0.05$
HCP	HCP Inc.	0.05$
SIAL	Sigma-Aldrich Corp.	0.05$
FLIR	FLIR Systems Inc.	0.05$
EL	Estee Lauder Companies	0.05$
AYE	Allegheny Energy Inc.	0.05$
CI	Cigna Corp.	0.05$
NFLX	Netflix Inc.	0.05$
CHRW	C.H. Robinson Worlwide Inc.	0.05$
GENZ	Genzyme Corp.	0.05$
DDR	DDR Corp.	0.05$
WFT	West Fraser Timber Co. Ltd.	0.05$
MHS	Medco Health Solutions Inc.	0.05$
DTE	DTE Energy Company	0.05$
TRV	The Travelers Companies	0.05$
NYX	NYSE Group IPO	0.05$
COF	Capital One Financial Corp.	0.06$
WLP	WellPoint Inc.	0.06$
TWC	TWC Entreprises Ltd.	0.06$
SWN	Southwestern Energy Co.	0.06$
NSC	Norfolk Southern Corp.	0.06$
CAM	Corporate Actions Middleware	0.06$
OXY	Occidental Petroleum Corp.	0.06$
FPL	First Trust New Opportunities	0.06$
ESRX	Express Scripts Holding Co.	0.06$
AIV	Apartment Investment Co.	0.06$
BHI	Boulevard Holdings Inc.	0.06$
FCX	Freeport-McMoRan Inc.	0.06$
APOL	Apollo Group Inc.	0.06$
SCG	Scentre Group Ltd.	0.06$
CB	Chubb Limited	0.06$
IBM	Int. Business Machines Corp.	0.06$
GME	GameStop Corp.	0.06$
DE	Deere & Company	0.06$
LNC	Lincoln National Corp.	0.06$
AVY	Avery Dennison Corp.	0.07$
MCK	McKesson Corp.	0.07$
PLD	Prologis Inc.	0.07$
DGX	Quest Diagnostics Inc.	0.07$
CERN	Cerner Corp.	0.07$
IRM	Irom Mountain Inc.	0.07$
COL	Rockwell Collins Inc.	0.07$
NU	NeutriSci International Inc.	0.07$
CVH	Coventry Health Care Inc.	0.07$
WFR	MEMC Electronic Materials	0.07$
AGN	Allergan PLC.	0.07$
GAS	GAS	0.07$
APH	Amphenol Corp.	0.07$
EXC	Exelon Corp.	0.07$
WEC	WEC Energy Group Inc.	0.07$
AFL	AFLAC Inc.	0.07$
NOV	National Oilwell Varco Inc.	0.07$
SUN	Sunoco LP	0.07$
BTU	Peabody Energy Corp.	0.07$
ROK	Rockwell Automation Inc.	0.07$

[1] Average spread from 9:40:00 to 15:50:00 New York time during 2008.

Table **A-5.**: Information of the stocks in Group 2 and 3.

Group 2

Symbol	Company	Spread[1]
GD	General Dynamics Corp.	0.07$
CSC	Computer Sciences Corp.	0.07$
FII	Federated Investors Inc.	0.07$
HIG	Hartford Fin. Services Group	0.07$
ITT	ITT Inc.	0.07$
TROW	T. Rowe Price Group Inc.	0.07$
MDP	Meredith Corp.	0.07$
GR	Goodrich Corp.	0.07$
AKS	AK Steel Holding Corp.	0.07$
PFG	Principal Financial Group	0.07$
HUM	Humana Inc.	0.07$
STI	SunTrust Banks Inc.	0.07$
CMI	Cummins Inc.	0.08$
STR	Questar Corp.	0.08$
ZMH	Zimmer Holdings Inc.	0.08$
FO	Fortune Brands Inc.	0.08$
SII	Sprott Inc.	0.08$
HRL	Hormel Foods Corp.	0.08$
OI	O-I Glass Inc.	0.08$
HCN	Welltower Inc.	0.08$
ANF	Abercrombie & Fitch Co.	0.08$
LM	Legg Mason Inc.	0.08$
FDX	FedEx Corp.	0.08$
PRU	Prudential Financial Inc.	0.08$
DHR	Danaher Corp.	0.08$
WY	Weyerhaeuser Company	0.08$
OKE	ONEOK Inc.	0.08$
SRCL	Stericycle Inc.	0.09$
LUK	Leucadia National Corp.	0.09$
BLL	Ball Corp.	0.09$
FE	FirstEnergy Corp.	0.09$
ATI	Allegheny Technologies Inc.	0.09$
ETN	Eaton Corp.	0.09$
VTR	Ventas Inc.	0.09$

Group 3

Symbol	Company	Spread[1]
HAR	Harman Int. Industries Inc.	0.10$
NFX	Nasdaq Futures	0.10$
EQT	EQT Corp.	0.10$
HRS	Harris Corp.	0.10$
COG	Cabot Oil & Gas Corp.	0.10$
PPG	PPG Industries Inc.	0.10$
MEE	Massey Energy Company	0.10$
HP	Helmerich & Payne Inc.	0.10$
DVN	Devon Energy Corp.	0.10$
IFF	Int. Flavors & Fragrances	0.10$
LH	Laboratory Corp.	0.10$
UNP	Union Pacific Corp.	0.10$
EW	Edwards Lifesciences Corp.	0.10$
STT	State Street Corp.	0.10$
RRC	Range Resources Corp.	0.10$
SJM	J. M. Smucker Company	0.10$
SNA	Snap-On Inc.	0.11$
PNC	PNC Fin. Services Group	0.11$
CEG	Constellation Energy Group	0.11$
LMT	Lockheed Martin Corp.	0.11$
FTI	TechnipFMC PLC	0.11$
CNX	CNX Resources Corp.	0.11$
ARG	Amerigo Resources Ltd.	0.11$
DVA	DaVita Inc.	0.11$
GS	Goldman Sachs Group Inc.	0.11$
TMK	Torchmark Corp.	0.12$
EMN	Eastman Chemical Co.	0.12$
MUR	Murphy Oil Corp.	0.13$
ROP	Roper Technologies Inc.	0.13$
JEC	Jura Energy Corp.	0.13$
HES	Hess Corp.	0.13$
ETR	Entergy Corp.	0.13$
MON	Monsanto Company	0.14$
DV	Dolly Varden Silver Corp.	0.14$
VFC	V.F. Corp.	0.14$
GWW	W. W. Grainger Inc.	0.14$
WHR	Whirlpool Corp.	0.15$
MOS	Mosaic Company	0.15$
SPG	Simon Property Group	0.15$
EOG	EOG Resources Inc.	0.15$
VMC	Vulcan Materials Co	0.16$
X	United States Steel Corp.	0.16$
SHLD	Sears Holding	0.16$
LLL	L3 Technologies Inc.	0.17$
WYNN	Wynn Resorts Ltd.	0.17$
BXP	Boston Properties Inc.	0.17$
PSA	Public Storaga	0.17$
PCP	Precision Castparts Corp.	0.18$
VNO	Vornado Realty	0.18$
DNB	Dun & Bradstreet Corp.	0.19$
CLF	Cleveland-Cliffs Inc.	0.19$
FLR	Fluor Corp.	0.20$
PCLN	Priceline Group Inc.	0.20$
MTB	M&T Banc Corp.	0.20$
AVB	AvalonBay Comm. Inc.	0.21$
BEN	Franklin Resources Inc.	0.21$
DO	Diamond Offshore Drilling	0.23$
CF	CF Industries Holdings	0.24$
AZO	AutoZone Inc.	0.25$

[1] Average spread from 9:40:00 to 15:50:00 New York time during 2008.

B. Foreign exchange pairs used to analyze the bid-ask spread impact

We analyze the bid-ask spread impact in the price response functions for 46 foreign exchange pairs in the foreign exchange market for the years 2011, 2015 and 2019. In Tables **B-1** and **B-2**, we list the pairs in their corresponding pip bid-ask spread groups.

Table **B-1**.: Foreign exchange pairs used in Sect. 4.5.

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

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

Table **B-2**.: Foreign exchange pairs used in Sect. 4.5.

Symbol	Pair	Category	Scaling factor	2011	2015	2019
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.

List of Figures

List of Tables

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