# Public News in The Exchange Rate Market

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# Abstract

In this thesis, we tackle the question of how newly available public information is absorbed in the FX market. The existing literature uses a standardized news transformation on macroeconomic data before using it in time-series models, due to a link between the transformation and the rational expectations hypothesis. Our results challenge a *de facto* approach by highlighting that the choice of the news transformation has a significant effect on the results. In addition, we propose several methodological improvements to the popular time-series approach. However, combining low frequency macroeconomic indicators and high-frequency FX processes in time-series models creates an ill-structured problem. To shed new light on the popular existing methodology, we propose an innovative way of restructuring the problem so that less restrictive methods - such as scaling laws, dominance testing and probability metrics - can be applied. Our results show weak evidence for a widely reported observation that new information causes elevated levels of volatility in FX markets, and in fact the reverse is observed in some cases. Further investigation reveals that the only significant factor driving FX news shocks is an anticipation effect of the news release. Once we account for the anticipation effect, we observe that most releases have positive influence irrespective of the sign of the data indicator released.

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# Chapter 1

# Introduction

## 1.1 Motivation

Recent technology advances in collection and presentation of financial data created the possibility for researchers to analyze financial instruments at the fundamental level of price formation. An ability to observe the price formation at the tick frequency lead to the discovery of previously unexpected dynamics of periodicity and seasonality patterns at intraday levels. In this research project, we focus on the information absorption aspect in the high-frequency data.

The exchange rate market is one of the most heterogeneous and liquid markets in the world. Investors, traders, companies and speculators interact on a daily basis with various intentions from the control of the operation risk, to speculative objectives. The exchange rate market is an excellent place to study the absorption of new information, because there is no well formed model between FX rates and macroeconomic indicators.

A well-known failure of traditional international finance models to explain exchange rate dynamics, even when using daily frequency data, and the high complexity of the market in terms of inter-connectivity between countries and partial transparency due to its over-the-counter nature. Such setting provides excellent conditions to study how market agents with limited cognitive resources incorporate newly available information into the price.

The most common explanation to justify the failure of a specific model based on economic theory is often attributed to excessive speculation levels in the market. We propose to focus on periods when we are able to identify the driving force behind rate movements to some extent and study them. We expect that by understanding how information is absorbed in the market, we will be able to explain, and build upon limitations of the existing literature.

## 1.2 Contributions

Our research hypothesis is that publicly available[1] macroeconomic data is the main driver of market expectations and influences rate clearing levels. Therefore we need to account for most of available public quantitative macroeconomic data releases to accurately capture exchange rate dynamics. The deep complexity of the exchange rate market, and the limited cognitive resources of humans participating in it, create a market setting where rules-of-thumb and other oversimplifications such as technical analysis, are commonly employed (Oberlechner, 2001). The ideal approach should take into account human nature, and that there are only several possible sources of information to form speculative or other incentives, to engage in exchange rate trading. Therefore, these incentives will be derived from a common information source available to all market agents. The common information is defined as macroeconomic indicators that are publicly available and the definition is in-line with a semi-strong market efficiency. It must be noted that this research aims to use only publicly available information and is not similar to the market micro-structure approach (Lyons, 2006) where private information about order flows is used.

A novel aspect of our analysis is that we use the abundance of computational power available in recent years, to push the bounds of our model's complexity, and apply new methods of analysis. We mainly focus on applied econometric models, as no clear theory explaining the precise mapping of all available macroeconomic

[1] The data that is public to *all* market participants.

indicators to FX rate dynamics exists yet. The purpose of this thesis is to investigate the effect public news releases have on exchange rate dynamics measured on higher frequency intraday data. The impact of news releases has been only briefly investigated and is a major concern for all market agents: market makers are interesting in the precise impact as it would allow to maintain competitive spread levels; institutional agents are interested as it allows them to carefully moderate the volatility and stability of financial markets; individual parties are interested as it creates statistical arbitrage opportunities.

Speculation is a major force driving exchange rate movements in short- and mid-term time frames. We expect that these speculative incentives, or *animal spirits* as defined by Keynes (1936), can be captured at the fundamental level, by understanding how changes in a wide spectrum of macroeconomic indicators affect FX rate dynamics during rate formation periods.

A substantial amount of work (further explained in Chapter 2.3.1) has focused on a single process dynamics, using transformed macroeconomic data, but the interaction between high and low-frequency processes at the precise information shock points, has been only briefly explored. An example of an interaction between high and low frequency processes is someone trying to is model the effect of monthly released preliminary GDP figures on 5 minutes returns. The existing literature has focused on a technical representation of the shock component, where the difference between the expected and forecast values or a transformed version of the variable was used. Such representation is of little use to the majority of market agents, as we all have differing expectations that are derived in various ways. The relation between transformed macroeconomic data, and exchange rate dynamics, has been well-studied but the relation between the actual empirical macroeconomic data has not been explored at all. Therefore, this thesis first evaluates the strength of the insights provided by the most prevail way of modelling news impacts in the existing literature. The relation between news and exchange rate dynamics is further investigated using a different framework with a purpose of disentangling the precise effects empirical news data has on exchange rate dynamics.

## 1.3 Structure

We investigate new information absorption in FX markets by tackling the following milestones:

> An overview of the relevant literature relating to the exchange rate studies is provided in Chapter 2. This chapter identifies studies and theories investigating general exchange rate dynamics, and provides background information necessary to understand the reasoning in the theoretical work.
>
> An extensive study of the applied models from the literature is provided in Chapter 3 where the prevail methodology is evaluated and extensions allowing to improve it are identified. To provide a fresh perspective on the topic, we propose a model incorporating advances from the previous literature and our own augmentations. Results show that our proposed augmentations yield better results in terms of the quality of the fit obtained when compared to the popular approach in the existing literature. As a result, our alternative way of capturing short- and long-term components is shown to outperform the existing methodology in terms of the quality of the fit obtained. In addition, we evaluate three different news transformations (*de facto*, simplistic and our proposed transformation). Our findings reveal that it is possible to obtain different results regarding individual model components while maintaining a similar level of model fit regardless of the transformation used. Therefore, we contribute to the existing literature by: proposing a more parsimonious approach to capture short- and long-term news components; highlighting the influence news transformations have on results; identifying a lack of empirical support to use the popular news transformation when compared with alternative possible choices.

A new method to quantify news release shocks is proposed and evaluated in Chapter 4. Instead of following a traditional approach of using a time-series model, we propose a new framework of analysis. To strengthen our proposed framework, we evaluate the results of news influence on FX dynamics using scaling laws, stochastic dominances and probability metrics. Previous studies report that new information causes elevated levels of volatility.

In contrast, our results show that new information has a negligible influence because we are able to account for the anticipation[2] of releases. To the best of our knowledge, this is the first time that the anticipation of releases has been incorporated into an analysis of the news releases. Our contribution to the literature is: the proposal of an innovative way of restructuring data with an ability to account for the pre-release effect to investigate the influence of news on FX dynamics; an identification of a weak influence of new information on the volatility dynamics, contrary to the previous literature.

Chapter 5 presents results obtained by applying the most effective methodology from Chapter 4 and focusing on various external factors (time of the day, weekday and the sign of one of the three data points available at the announcement point: previous, forecast or released values). The most significant finding of all is that after accounting for the pre-release dynamics, we observe that all news releases cause a positive influence on the economy in questions. These findings are unique to the literature and we make the following contributions to the literature: investigate the influence weekdays have on reactions to news and observe that Thursday has a substantial influence and it has been previously overlooked; study the influence of the market liquidity on news reactions; analyze the effect signs of previous, forecast or released values have on FX dynamics after account for the pre-release dynamics; observe that most releases cause a positive influence on

[2]If a news release is expected - rational agents will engage in speculative activities based on their personal information sets and will cause an effect of news before the actual release.

the originating economy, but visible only after accounting for the pre-release dynamics.

# Chapter 2

# Background

## 2.1 Overview

The foreign exchange rate market is well-known for low entry barriers and to contain a substantial speculation component (Frankel, 2014). The main challenge in the empirical FX research is the explanation of the ambiguous nature of the effects of the macroeconomic indicators on nominal exchange rates. One of the possible causes for the ambiguity of how to model exchange rates could be attributed to the absence of a well-defined pricing model (for example as the Black-Scholes-Merton model is used for option pricing). In this chapter, we provide an extensive overview of alternative possible methodologies and theories used to analyse exchange rate dynamics. The purpose of this chapter is to identify and highlight possible approaches. In Chapters 3, 4, 5 a more detailed and concentrated literature review is provided at the beginning of each chapter. A brief overview of popular international finance models will be presented in Section 2.2. In general, these models are used to explain only low-frequency[1] dynamics and have various problems at a high-frequency[2] level. In the high-frequency time frame, theoretical models from international economics area are silent about the exchange rate determination and, often they tend to avoid such time-frames due to problems of

[1] Defined as a process with new observations that appear on weekly and lower frequencies.
[2] Defined as a process with new observations that appear on 5 minutes and higher frequencies.

combining low-frequency macroeconomic indicator processes with high-frequency rates data. We also focus on the literature using econometric models to disentangle causal links of macro news and exchange rates. Sections 2.3 and 2.4 will provide a detailed overview of advances and findings from the empirical literature. Section 2.4 will discuss a similar strand of literature, called order-flow analysis, that combines public and private nature information sets. To emphasise the difference from the micro-structure literature, this thesis aims to use only publicly available data that has virtually zero frictions to access, while order-flow studies rely on a private nature information. A relation between order-flows studies and econometric models studies will be discussed in this Section. Relevant literature is also revisited at the beginning of Chapters 3, 4 and 5.

## 2.2 Review of Economics Models for FX

In this section, an overview of two well-known approaches to determine exchange rates from international finance theory will be presented. Both approaches are used to explain exchange rate dynamics from the classic economics perspective in a medium to long-term time frames (from months to years). The main underlying idea in both approaches is based on the absence of arbitrage opportunities that in principle could be explained in short as: if there is a profitable opportunity, then it will be exploited until the risk level for the opportunity matches the return generated. A major limitation of both models due to the use of one low-frequency macroeconomic indicator in an attempt to explain exchange rate dynamics. As a result, often, estimated parameters are doubtful due to the serious limitation of small data samples and the possibility of structural changes in the underlying economy are often ignored. In the literature on international finance, it is generally agreed that when models are applied to the empirical data, they fail to explain the short-term dynamics of exchange rates, and are not superior to a random walk in the out-of-sample evaluation (Boothe and Glassman, 1987).

The following section is structured into three parts. An overview of the interest rate parity with empirical results will be presented first in Section 2.2.1. In Section 2.2.2, a law-of-one price will be applied to the context of international finance. The law-of-one price can be described as follows: a homogeneous good should have the same price across countries, due to the arbitrage principle as explained earlier.

### 2.2.1 Interest Rate Parity

The interest rate parity is known as a strong theoretical tool with a solid logic and is used to explained the dynamics of the floating exchange rates. In a perfect world, the parity identifies possible arbitrage opportunities that arise from the interest rate differentials between two homogeneous fixed income assets in the two countries in question. Many strong assumptions have to be made for such parity to hold, that are unrealistic in the world we live in. For example, an assumption of perfect information knowledge is essential for an elimination of arbitrage possibilities. However the assumption is highly unlikely to hold in the real world where agents have limited cognitive resources (Shleifer, 2000). Therefore, the parity is only valid for theoretical modeling. More detailed information on the parity can be found in works of Menzie and Chinn (2006), Chaboud and Wright (2005) and Batten and Szilagyi (2007). The parity is often presented in two different forms which we describe below:

In the first form of the parity known as the uncovered version (explained in a greater detail in later parts of this section) of the interest rate parity it uses future expectations of exchange rates that are unobservable in general. An assumption has to be made for a chosen indicator to proxy future expectations well before this flavour parity can be tested on the empirical data. As a result, a joint test of the parity and the expectations model is unavoidable. Similar as the market information efficiency tests that are based on a joint test of the information set and a market model. The functional definition following notation of Menzie and Chinn (2006) is:

$$\triangle s_{t,t+\triangle} \quad = \quad \left(i^d_{t,t+\triangle} - i^f_{t,t+\triangle}\right) - \eta_{t,t+\triangle} + \xi_{t,t+\triangle}, \tag{2.1}$$

where $i^d$ and $i^f$ denotes the domestic and foreign interest rate yielding assets for a period from $t$ to $t + \triangle$ and both assets are perfect substitutes, $\triangle s_{t,t+\triangle}$ denotes the expected spot exchange rate change from $t$ to $t + \triangle$, $\xi$ is the white noise component and $\eta$ is the risk premium. A common choice for the expectations proxy is the rational expectations[3] model. In the empirical works, the uncovered parity is weakly supported by empirical evidence. To be specific, a study by Chaboud and Wright (2005) analyzed the strength of the parity by using fixed-income instruments with up to 1 year maturity and found only weak evidence supporting the ability to explain FX dynamics using this parity. A significant variation in results was observed by varying a starting measurement point in calendar time. Such findings suggest the presence of parameter instability in the parity. The cause for parameter instability is argued to be due to the market convention for the interest payments for the overnight position to be paid at a specific daytime that varies between countries and dealers. The choice of the proxy for the interest rate measurement was noted to be unimportant, due to a high degree of correlation in short-term interest rate yielding assets.

In the second form of the parity, the covered version (explained in a greater detail in later parts of this section) of the parity replaces the expectations component with a forward price of the exchange rate. As a result such parity is based on the market evaluation of the future value of the exchange rate. The functional definition of the parity is:

$$1 + i_d = \frac{\acute{F}_{t,t+\Delta}}{\acute{S}_t}(1 + i_f), \tag{2.2}$$

where $\acute{F}_{t,t+\Delta}$ denotes a forward rate at time $t$ with a target date $t + \Delta$ and all

[3] Defined as a variable where the expected value of the future observation is the current value and reflects all available information.

other indicators are as defined earlier, while $\acute{S}$ denotes a spot rate of the exchange rate. Such specification of the parity implies a much stronger arbitrage condition between future, spot and interest rate markets. In the empirical analysis, Batten and Szilagyi (2007) found a strong evidence in favour of the covered interest rate parity, but deviations from the parity were observed during turbulent hours of the market. Results indicated that arbitrage conditions hold within transaction cost bounds for normal market times. Given the ambiguity behind the choice of the interest rate proxy and central banks influence on the overall fixed income term structure during the recent decade, parity is not considered in the empirical models of Chapter 3.

### 2.2.2 Purchasing Power Parity

The purchasing power parity idea is based on a classic economics approach of the law of one price[4]. In an efficient market, the law of one price argues that any misalignment's between prices of the same good, in two different countries will be removed by rational agents engaging in an arbitrage-enforcing behaviour. However, contrary to the theoretical world, transaction costs, geographic constrains, information and search costs, and other frictions make this law questionable. The parity is often defined and used in relative rather than absolute terms. The relative version of the parity is more appealing, as it has the ability to partially capture market frictions, and to preserve differences in price levels due to country-specific features. The parity can be defined using the notation of Serletis and Gogas (2004):

$$\ln(\acute{S}_t) = \alpha + \beta \ln(P_{d,t}) - \beta \ln(P_{f,t}), \tag{2.3}$$

where $\acute{S}_t$ is the nominal exchange rate at time $t$, $\alpha$ is an arbitrary constant, $P_{d,t}$ and $P_{f,t}$ denote the domestic and foreign price levels, respectively, and ln() is the

[4]Law of one price - the price for goods that are perfect substitutes in all countries should be the same.

natural logarithm transformation. In their empirical analysis, Zhou and Kutan (2011) argued that contradictory evidence against the parity were observed. An instability of the relation between the real (implied by the parity) and the nominal (observed in the market) exchange rate was argued to be the cause of the contradictory evidence. Taylor and Taylor (2004) concluded that in the long-run purchasing power parity holds and a movement towards the implied theoretical exchange rate level was observed. Therefore, parity is not considered in the empirical models of Chapter 3 due to limited relevance for the short- and intermediate term dynamics and a weak tendency for a reversion to the theoretical rate.

## 2.3 Literature on News Effects in FX

This section will provide a detailed description of findings from the existing exchange rate announcement literature using econometric models, and is primarily related to the research presented in Chapter 3. The discussion will start with an introduction of the most popular model specification (Section 2.3.1). We will then focus on several general research categories. Categories are selected to focus on the most important insights found by empirical studies analysing scheduled public news shocks in the exchange rate market. An asymmetric reaction to positive and negative news will be covered in greater detail at first (Section 2.3.2). Followed by a discussion of sluggish information processing speeds in the post-announcement period observed by various studies (Section 2.3.3) and overall relevance of to the whole thesis.

### 2.3.1 Origin

The efficient market hypothesis (EMH)[5] suggests an instantaneous price adjustment to new information in the market. If the EMH is assumed to hold, then the price process must have a martingale property:

[5] For further details, see Fama (1998).

$$E(P_{t+1}|\Omega_t) = P_t, \tag{2.4}$$

where $P_t$ is the expected price level at $t$ and $\Omega_t$ is the information set available at $t$. This property implies an immediate and symmetric reaction to new information content in the market, along with many other strong restrictions. The market efficiency hypothesis is an open topic for discussion, because any test of efficiency is a joint test of the model chosen to represent the theoretical efficient market and a proxy for the information set. Our research interest in Chapter 3 and partially in Chapters 4 and 5 is only on the effect of new information content. Specifically, the effect of on instantaneous and symmetric responses expected for the theoretical point of view. The symmetry of the response is defined as an equal magnitude reaction to positive and negative news.

An order-flow study by Evans and Lyons (2008), documented that around 30% of the intra-day price volatility[6] was observed around the time of information shocks. It was argued that the common belief of dealers quickly, or close to instantaneously, adjusting exchange rate quotes to new rate levels after the release was falsely justified. Results of Evans and Lyons (2008) indicated that dealers observed incoming trades and made subsequent adjustment, to quotes as a result of the information flow as oppose to estimating the new equilibrium rate and making an instantaneous adjustment. Furthermore, a study by Kim (1998) suggested that an increased volatility during announcement periods was a result of the market depth testing by traders to pin-point the expected impact level of the news content. The presence of the announcement, not the content, was argued to be the cause of such behaviour. Such behaviour indicates a lack of agreement on what effect macroeconomic data should have on exchange rate dynamics. Divergences from the instantaneous market response to news are challenged in various way by the existing literature and is explained in detailed in Section 2.3. Chapter 3 provides

[6] As defined by authors, the proportion of a price change per day that is attributed to trade intensity during the news release periods happening during that day.

in depth analysis of the existing literature and its flaws while Chapters 4 and 5 go further and disentangle the anticipation effect from the release impact.

We now shift our focus to the information sources used by market participants as the empirical literature identifies it to be an important factor. A survey study by Oberlechner and Hocking (2004) identified financial news wires to be the most important source of information for traders in the exchange rates market. They note that the credibility of the announcement content increased as it continuously reappeared on financial wires in different evaluation reports. The knowledge of the overall market interpretation of the news content was more important than an individual evaluation. These findings suggest a strong herding behaviour by market agents in attempt to discover the new equilibrium rate.

One of the common features of the branch of literature studied in this chapter is the use of the Money Market Survey (MMS) dataset as an information proxy. The MMS dataset contains forecasted values and as well as realized values of macroeconomic indicators. The MMS dataset will be further discussed in Section 2.3.2. A study by Andersen et al. (2003) argued that news information shocks must be explicitly accounted for empirical models to reduce the potential bias and noisiness of estimated results when modelling FX with time-series models. The study used a linear econometric model to analyze macroeconomic indicator effects for the high-frequency (5-min) exchange rate data combined with a MMS dataset used for the formation of the standardised news. Many subsequent studies used the same specification of the methodology and observed supporting findings. Surprisingly, over almost a decade, only Evans and Speight (2010a) suggested an innovative extension to the linear model and attempted to decompose the news impact shock, around the release by including leads and lags[7] of the news indicators. Their results indicated similar findings to other studies, that news announcements had a significant effect on the volatility level for several hours after the release but the extensive use of dummy variables cast doubt on the robustness

[7] The release point is surrounded by lagging or leading dummy variables to measure the average influence of the release at the specific time period FX return.

of results. Ehrmann and Fratzscher (2005) study has marginally extended the methodology of Andersen et al. (2003) by including dummies for calendar effects. Their results are comparable to previously mentioned studies and dummies for calendar effects were found to be statistically significant.

### 2.3.2 Asymmetric Reactions

A symmetric reaction to positive and negative news is expected in an efficient market populated by rational traders.[8] In such market, new information is independent of any transformation of present and past information and directly relates to the martingale property. The martingale property implies unpredictability and symmetry in the news response. Dacorogna et al. (2001) and many others, documented a strong first-order negative serial correlation at the highest-frequency (lower than 5 minutes frequencies) exchange rate data. The correlation at the intra-day level data is an example case of the evidence against the martingale property implied by the EMH[9]. Many other empirically observed contradictions to the rationality lead to the development of the field of behavioural finance (For more details Schmidt, 2006). The strength of the asymmetry is often analyzed from a magnitude and sign perspectives. An example would be the effect of a loss aversion[10]. If a long losing position is held longer than a profitable one, then a price response due to such activity would be asymmetric. However, the explanation for the observed asymmetry provided in the literature, varies from study to study, and no-one has pinpointed the precise cause. Instead of focusing on failures and ambiguities of theoretical and applied models to explain observed market dynamics, we shift our focus on the overall effect that news have on FX dynamics and re-validate asymmetric reaction claims.

Pearce and Solakoglu (2007) found a symmetric reaction of volatility to news shocks, using a 5 minutes frequency dataset from 1986 to 1996. Results indicated

[8] For further details of a rational agent, see von Neumann and Morgenstern (1992).

[9] EMH - Efficient Market Hypothesis implies instantaneously information processing speed

[10] Investors hold negative positions longer than profitable ones. For further details, see Amonlirdviman and Carvalho (2010).

that news effects were not observed at lower frequencies, and at longer than 6 hours time-frame the economic importance of macroeconomic indicators was too insignificant to be detected. A more interesting result was no evidence of an asymmetric response. On the other hand, a study by Aggarwal and Schirm (1998) used a similar time frame dataset, but a slightly different methodology of news, and found results in favour of the asymmetric response depending on the sign. An asymmetric reaction was detected by a study by Kim (1998) that used a GARCH type model. Results showed an asymmetric reaction to news in the volatility that lasted for several hours after the release. A great importance of US macroeconomic indicators for exchange rate dynamics explanation was noted. Many other studies using various methodologies found evidence in favor of an asymmetric impact effect, such as: news analytics approach by Prast and de Vor (2005), a quoting activity study by Omrane and Heinen (2009), an order placement study by Savaser (2011) and a rolling regression study by Galati and Ho (2003). Galati and Ho (2003) has also observed a variation in the strength of the asymmetry over time. The most interesting observation of this rolling regression study was the variation of the estimated effects of news over time. A study by Savaser (2011) argued for an asymmetric response to be due to the result of stop-loss order triggering.

### 2.3.3 Information Processing Speed

Many models in finance assume an instantaneous adjustment to new information content, but the imperfect world we live in shows a sluggish adjustment speed when empirical data is studied. Evans and Lyons (2005) separated a new information impact effect into two stages: an initial adjustment period with a wide bid-ask spread and a strong response, and a gradual movement towards the equilibrium after the spread has contracted. Christie-David and Chaudhry (2000) argued for an elevated level of volatility to be a sign of the disagreement in the market, and the persistence of volatility indicated a sluggish adjustment to new information. A strong initial reaction with a gradual decay was found by Hautsch et al.

(2011). An observed volatility behaviour was an indication of new information processing as previously argued. Evans and Lyons (2005) noted that information processing lasted up to several days after the initial impact when studied using an order-flow data. The persistent levels of volatility with varying lengths were documented in many other studies: Kim et al. (2004), Oberlechner and Hocking (2004), Hogan and Batten (2005), Pearce and Solakoglu (2007), Omrane and Heinen (2010), Hashimoto and Ito (2010), Evans and Speight (2010a), Evans and Speight (2010b), Rosa (2011) and Fischer and Ranaldo (2011). A study by Hogan and Batten (2005) focused on the value of the private information, and argued that the private information economic gains were maximized only from 2 to 5 ticks after the initial news release, and the total economic gain from the private information was lost after just 20 ticks after the release. Omrane and Heinen (2010) suggested that the volatility persistence was a result of a "hot potato" effect.[11] In general, a gradual decay to previous levels of volatility were observed after the initial news release impact, from over a period of several hours and different studies argue for the effect to last even up to several days.

### 2.3.4 Areas For Improvement

The literature covered in this section indicated that it is essential to account for information shocks in empirical models aimed to explain exchange rates behaviour at the high-frequency scale. Many studies focused on datasets with data up to 2007, and failed to recognize the effect suggested by Álvaro Cartea and Jaimungal (2010) called as "a rise of algorithmic trading". The effect could be explained as the growth of popularity and ease of development of algorithmic trading in the recent decade. Therefore, most of the previously observed effects in older datasets might not be observable in newer ones. The stylized facts that were observed several years ago might not be present in the current data at all. Andersen and Bollerslev (1997) argued that an ability to observe data at a higher frequency does

[11] For further details, see Lyons (2006).

not provide more information about the mean of the process, and only about the variance. We show that the decay rate of information value is severely affected, and to measure the precise effect we move from using a 5 minutes data in Chapter 3, to using 5 seconds data in Chapters 4 and 5. The abundance of the computational power changed the market structure greatly, and most of the trading in the exchange rate market is now done by algorithms. This thesis first focuses on re-applying existing models to a new dataset with sample period from 2007 till 2012, in an attempt to verify if previously documented effects are still relevant for today's microchip market, in Chapter 3. In Chapters 4 and 5, we provide a detailed investigation of the information shock dynamics at a frequency of five seconds and ticks.

## 2.4 Alternative Empirical Models

The following section provides an overview of other possible empirical approaches to study exchange rate dynamics. A market micro-structure based approach will be discussed in Section 2.4.1. A strong reliance on the private nature of the source of information in the micro-structure approach, makes it of a secondary interest for this thesis. Section 2.4.2 will focus on reviewing all other approaches for exchange rate dynamics modeling. The literature reviewed in this section is of secondary importance and is provided for the overall consistency of the topic.

### 2.4.1 Announcement Effect Studies

The market micro-structure approach (Lyons, 2006) is based on a microeconomics theory where dealers are rational agents facing an inventory, and an information management problem. The information management problem comes from the inability to identify the source of the incoming trade, either from an uninformed or informed trader. Trading with informed traders is undesirable due to the information asymmetry between both parties. The inventory management problem arises from the accumulation of positions due to trading events with clients[12]. An economic rent is required by dealers to provide liquidity in such market setting, and as a result the bid-ask spread arises. The unique characteristic of the approach is an ability to observe useful information in the event if no trades are observed. In a classic time-series framework, absence of data points provides no information about the data generating process but in this case it identifies lack of need to adjust positions of market agents and an effect on the liquidity level. The empirical application of the approach commonly relies on econometric methods. For example, a empirical application study by Evans and Lyons (2005) used a VAR specification to investigate the effect of released news on order-flows of exchange rate pairs. The source of the private data required for the analysis is the main drawback of the approach, when compared to the research in this thesis. The order-flow data is available only at an individual dealer level, and an overall market order-flows cannot be observed due to over-the-counter market structure in the exchange rate market. The data used for order-flow studies is of a private nature and if an incremental explanatory power is observed then conclusions are in line with the EMH predictions of private information having some explanatory power. An additional assumption of the observed dataset to be a representative sample of the market is often made in the background when using order-flows data.

The news analytics approach is based on innovations in the natural language processing field (Mitra and Mitra, 2011). The idea of the approach is to convert highly qualitative financial (e.g. Monetary Policy Committee minutes by Bank of England) data to quantitative indicators. The empirical application of the approach showed an incremental explanatory power on older datasets and a weak statistical evidence on newer datasets. If viewed from the behaviour finance perspective, this approach attempts to overcome cognitive limitations of

[12]A market maker taking the opposite position due to the order from a client received and causing the prevailing market price of the instrument to change due to the change of his inventory is defined as a trading event in this thesis.

market agents and to increase the overall level of "rationality", according to the von Neumann and Morgenstern (1992) axioms of rational behaviour.[13]

The most common econometric specification of the announcement impact analysis on the volatility relies on the GARCH class of models (Lundbergh and Terasvirta, 2002) with various extensions to account for market periodicities, and other market structure effects. The original GARCH specification was studied by Engle and Ng (1993), and was found to be unable to account for news shocks accurately. It was noted that an asymmetric version[14] of GARCH provides a better fit. More recent studies combine multiple models to account for the intra-day and other calendar effects; Ehrmann and Fratzscher (2005) included dummies for the day of the week effect; Evans and Speight (2010a) used a spline function; Evans and Speight (2010c), Andersen et al. (2003) used a sinusoidal functions for intra-day periodicities; Evans and Speight (2010c) compared splines and sinusoidal methods, and their results indicated the spline method to have a better fit in terms of ability to pinpoint precise time of impact. We believe for the necessity to model the mean and the variance of the processes simultaneously and need to focus on the short- and long-run components to adequately capture news effects.

### 2.4.2 FX Dynamics Models

Continuous-time models are often used in financial time-series analysis, due to proclaimed ability to approximate process dynamics more accurately, and overcome the asynchronicity problem. The asynchronicity problem is caused when two observed data series have non-overlapping time points. To overcome the asynchronicity problem a model is specified in a continuous-time, and the most common specification used is by Krugman (1991). A generic shape using the notation of Trede and Wilfling (2007) is defined as:

[13] For further details, see Groß-Klußmann and Hautsch (2011), Prast and de Vor (2005).

[14] A version of the model where positive shocks have a different effect when compared to negative shocks.

$$x\left(t\right)=k\left(t\right)+\dot{\alpha}\frac{E\left[dx\left(t\right)|\phi\left(t\right)\right]}{dt}, \tag{2.5}$$

where $x\left(t\right)$ is the logarithmic spot exchange rate, $dx\left(t\right)$ is the change in $x\left(t\right)$, $k\left(t\right)$ represents the sum of macroeconomic components that affect prevailing logarithmic spot exchange rate, $\phi\left(t\right)$ is the information set at $t$, $E[\cdot|\cdot]$ is the expectation operator at time $t$ conditional on the prevailing information set $\phi\left(t\right)$, $\dot{\alpha}$ is a positive mixing parameter and $\frac{E[dx(t)|\phi(t)]}{dt}$ represents the speculative component of the exchange rate. The model was extended for the event study analysis by Wilfling and Maennig (2001), Trede and Wilfling (2007) and Naszodi (2011) to analyze the movement from floating to fixed exchange rate regimes. Lack of justification for the need to introduce this model complexity is the reason this approach is not used in later chapters.

An interesting branch of Markov-regime switching models was introduced by Hamilton (1989). This approach adds several randomly varying states to the model to capture possible structural changes in the data generating process. The state space is assumed to be discrete, and different functional specifications can be used for models in each state. The model was successfully applied to tackle various problems encountered in modeling economic processes with state shifts. Exchange rate returns are commonly used in such approaches as stated by Wilfling (2009), and are defined as: $R_t = 100 \times \left[log\left(x_t\right) - log\left(x_{t-1}\right)\right]$, where $x_t$ denotes the nominal spot exchange rate at time $t$. A successful empirical application of the model relies on *a priori* identification of all possible states $S_t$ that are assumed to be unobservable, and significantly effect the dynamics of the process. A study by Wilfling (2009) analyzed volatility dynamics, and their results indicated significant changes in volatility dynamics when an underlying state has changed. Studies by Syllignakis and Kouretas (2011) and Yuan (2011) augmented the approach with an error correction mechanism to study processes using rate levels instead of returns. It was also noted that statistical testing issues were encountered, when the model was used. In general, empirical results of previously mentioned studies that used regime switching components for discrete-time models indicated a much better forecasting power when compared with the theoretical exchange rate models. The estimated empirical transition probabilities often corresponded to *a posteriori* events observed in the data.

Another approach to investigate FX dynamics is the power law application (or scaling law) that does not require one to specify a data generating process in order to analyze the dynamics of the process. Mandelbrot and Hudson (2005) suggested to move away from a simple and commonly used Gaussian distribution, due to its well documented inabilities to capture statistical, fractal and other properties of financial asset dynamics. The existence of scaling laws in finance was well-documented by Glattfelder et al. (2011), but the reason for the existence was noted to be not well understood. The power law was defined as:

$$\langle|\triangle X|\rangle_p = \left(\frac{\triangle t}{C_x(p)}\right)^{E_x(p)}, \tag{2.6}$$

where $\triangle t = t_i - t_{i-1}$ is the time interval of interest,

$$\triangle X = X_i - X_{i-1} \tag{2.7}$$

$$X_t = \frac{(ln(bid_t) + ln(ask_t))}{2} \tag{2.8}$$

$$\langle x\rangle_p = \left(\frac{1}{n}\sum_{j=1}^{n} x_j^p\right), \tag{2.9}$$

with $p \in \{1,2\}$ and $E_x(p)$ with $C_x(p)$ are scaling parameters. As argued by Müller et al. (1990), power laws allow to capture stable properties of the data generating process. Their results support the claim and show stable scaling laws holding across various nominal exchange rate pairs.

An interesting and relevant twist to the approach was taken by Siokis (2012) who used the Omori law[15] to analyze the decay rate of shocks around the event

[15] Defined as the decay rate per unit of time of the number of shocks that follow the power law defined as: $n(t) \propto t^{-p}$.

of interest in financial time series. The law studied was noted to hold only after large magnitude shocks. A variation of this methodology is used in Chapters 4 as a benchmark tool.

The duration analysis approach is similar to a traditional GARCH approach, but instead focuses on modeling durations between changes of the process of interest. The idea is related to the micro-structure framework, where the duration between two quotes provides information about the market pace. For example, a study by Bauwens and Hautsch (2008) identified strong similarities with the volatility and duration process. It was noted that a variation in the estimated parameters of the process could create an illusion of a long-memory feature in the data. The most common model used in the duration analysis is the Autoregressive Conditional Duration (ACD) model. Durations are defined as $x_i = \frac{t_i - t_{i-1}}{s(t_i)}$, where $s\left(t_i\right)$ is the seasonality component of the process. The seasonal component is specified *a priori* and a cubic spline function is often used. Bauwens and Hautsch (2008) noted that the most common specification of the model is ACD(1,1) with a similar structure to GARCH(1,1) process:

$$\phi_i = \omega + \alpha x_{i-1} + \beta \phi_{i-1} \tag{2.10}$$

and usual GARCH(1,1) stationarity conditions apply, $\phi_i$ is the conditional duration at point $i$ and $x_i$ is the empirical duration at point $i$. A study by Engle (2000) augmented the GARCH specification with a duration component, and provided a way to incorporating the duration information to the volatility process model. Results indicated a positive correlation between the inverse duration and the volatility process. Hautsch and Jeleskovic (2008) generalized this approach. This thesis ignores the joint nature of returns, durations and volatility with a goal of keeping the analysis tractable and implementable within given time constrains.

### 2.4.3 Common Limitations

A variety of different approaches attempt to explain exchange rate behaviour with different exogenous variables. The most important common feature of all of them is an inability to explain exchange rate dynamics in high-frequency data. In addition, if an out-of-sample forecasting criteria is used to evaluate the fit of the model, a general approach is to use lagged coefficients in an attempt to improve the performance, even when there is no serial correlation in the variable being lagged (often referred as an information criterion maximization). Furthermore, to the best of our knowledge, no model currently exists that would use all available macroeconomic variables to explain exchange rate dynamics. Accordingly, we focus on measuring empirical links of the almost all publicly available macroeconomic indicators and high-frequency exchange rates. We first assess limitations and possible improvements of the existing literature using time-series models in Chapter 3 before discussing information impact analysis in Chapter 4 and 5.

# Chapter 3

# Importance of News Definition in FX Market

In this chapter, we investigate the relevance and limitations of the time-series approach discussed in Section 2.3.4 in Chapter 2. Fundamental macroeconomic data is commonly transformed before it is used in empirical models. This chapter highlights the main problem with the existing studies that used transformed macroeconomic news. Results obtained using different news transformations are observed to be transformation-dependent. As a result, any interpretations of results are conditional on the selected news transformation. We first propose an alternative way of transforming news with superior characteristics compared to the existing approaches. Our results highlight the importance of simultaneously modelling short and long-run components to fully capture news shocks that is commonly overlooked in the existing literature. The comparison of different sample periods shows the strong influence of the financial mood on conditional residuals and test statistics. In addition, we highlight alternative news transformations that yield comparable results to the common approach in the existing literature. We observe that the news definition causes a substantial influence on the results, suggesting that the results from the existing literature are dependent on the news transformation used.

The remainder of the chapter is structured as follows. Section 3.1 highlights the relevant literature for ideas studied in the chapter. Section 3.2 describes the methodology. Section 4.3 presents the empirical data and the results. Section 4.4 concludes.

## 3.1 Literature Review

Economic theory tends to focus on a narrow set of macroeconomic indicators to uncover relations to structural models (Bacchetta and van Wincoop, 2013). Empirical studies, however, focus on a wider set of available indicators and their impact on exchange rates without imposing a structural model. Many studies focus on the impact dynamics in the exchange rate market using level one market data (e.g. Kim (1998), Galati and Ho (2003), Andersen et al. (2003), Ehrmann and Fratzscher (2005), Evans and Speight (2010a), Fatum et al. (2012), Laakkonen and Lanne (2013)).

Balduzzi et al. (2001) proposes the use of standardised news transformation as a more compact representation of the macroeconomic data. The transformation is later adapted in other studies but the difference between the transformed and actual data is never emphasised. Andersen et al. (2003) observe a strong and statistically significant link between the selected macroeconomic data releases, and exchange rates with the standardised news transformation used as information shock proxy. Evans and Speight (2010a) adapt the approach of Andersen et al. (2003) to study the short-run impact by surrounding the news shock points with leads and lags of the transformed news indicators. Their results support the findings of previous literature, but a more detailed treatment of the shock dynamics is not explored. This transformation still remains the *de facto* approach in newer studies aiming to quantify news impact (Gilbert et al., 2015), despite a valid criticism by Rigobon (2006); Kurov et al. (2015) and proposal for a need of alternative potential approaches by Rigobon (2006).

Similar findings are observed in a more recent study by Laakkonen and Lanne

(2013) that focuses on the importance of the announcement and subsequent revisions of the announcement on the exchange rate volatility dynamics, using transformed news. Each quantitative macroeconomic news release on financial news wires commonly has three distinct data points: the previous, current and forecast values along with commentary about the details of the release. The popular standardised news transformation uses only the forecast and current values of the macroeconomic indicator to represent the news shock along with other limitations. A simple difference between current and previous values was used before the introduction of the standardised news (e.g. Galati and Ho, 2003).

Galati and Ho (2003) note that estimated news parameters vary over different time horizons, a finding that so far only Evans and Speight (2010a) have noted but not addressed. In this thesis, we consider a dataset of high-frequency FX rates sampled from 2007 to 2012. The macroeconomic dataset is similar with respect to indicators set to the one used by Andersen et al. (2003) The dataset consists of 41 most important global indicators from U.S. and Germany. We divide our dataset into four subsets where each subset is similar in size to the datasets used by Evans and Speight (2010a) and Galati and Ho (2003). Each subset has a distinct economic outlook. We are able to quantify the impact of the mood on the results by estimating our models on each individual subset. We observe that economic prospects have a substantial effect on the model quality fit as well as hypothesis tests. We extend the findings of Galati and Ho (2003) by identifying a possible cause of variation in the estimated parameters to be due to financial mood changes.

A popular approach when studying news release impacts in the empirical literature is to focus either on the volatility (e.g. Laakkonen, 2013), the short-run effect (e.g. Fatum et al., 2012), or a longer time frame effect (e.g. Andersen et al., 2003). In this chapter, we propose to combine the short and long-run components into a single model, based on ideas from the market microstructure literature (Lyons (2006), Evans and Lyons (2008)). Our alternative approach captures the short-run news in a complex form and still promotes model parsimony. We investigate the impact of news transformation, by varying the transformation used for the short and long-run components and their subsequent effects that, to our best knowledge, have not been explored in the existing literature before. In addition, we observe that the impact due to the news transformation used for the short-run component is affected by the long-run component transformation. In summary, we extend the literature by highlighting the importance of using two separate components to capture long and short run effects and the impact that different news transformations have on results.

Our first contribution is the measurement of the impact that news transformation have on results. We propose an alternative news transformation, and use it along with the popular standardised and the actual difference news transformations, to evaluate the impact the choice of transformation has on the results. Our results extend the existing literature by indicating that different news transformations have a substantial impact on results. In addition, our proposed news transformation improves on the limitations of the popular standardised news transformation approach.

The second contribution is a compact and parsimonious approach to capture short and long-run news components. Hypothesis tests reveal our proposed approach is superior compared to the model by Andersen et al. (2003). In addition, we are able to highlight the importance of using both short and long-run components to fully reflect news release impact, as both components are found to be inter-related. Our results indicate potential limitations of the analysis by Laakkonen and Lanne (2013), Laakkonen (2013), Fatum et al. (2012), Evans and Speight (2010a), Andersen et al. (2003) and others, as these studies solely focus on just one of the two impact components.

The third contribution is the extension of results of Galati and Ho (2003) to investigate the stability of innovation statistics overlooked in the recent literature. In our analysis, we are able to show that this instability is mainly caused by financial market mood variation.

Our findings indicate that the choice of transformation has a strong influence on the analysis results. We highlight that transformed news must not be confused with actual empirical news data, as commonly done in the literature.

## 3.2 Methodology

In Section 3.2.1, we first describe the existing approach to transform macroeconomic data to an indicator, and then introduce our new magnitude impact news transformation. In Section 3.2.2, we review a selection of common model specifications popular in the literature and propose our augmented model. In Section 3.2.3, we explain our tests and diagnostics procedure.

### 3.2.1 News Transformations

Let $A_t$ denote the value of a news indicator at time $t$ that represents a transformed version of news data available at time $t$. All of the transformation explained here are applied on individual series of each macroeconomic indicator. The natural approach when computing the news release impact is to take the difference of the previous and the current indicator value:

$$D_t = A_{t-1} - A_t \ . \tag{3.1}$$

Balduzzi et al. (2001) suggest transforming three public macroeconomic news data points (previous, current and expected indicator values) to a single point value and allow it to reflect the unexpected shock level of the release. This transformation has been used by Laakkonen and Lanne (2013), Laakkonen (2013), Fatum et al. (2012), Evans and Speight (2010a), Andersen et al. (2003) and others. Let $E_{t-1}(A_t) = E\left(A_t|\Omega_{t-1}\right)$ denote the conditional expectation of $A_t$ at time $t-1$ given the available filtration of the information set $\Omega$, until time $t-1$. The standardised news transformation is defined as:

$$S_t = \frac{A_t - E_{t-1}(A_t)}{\sqrt{Var\left(A_t - E_{t-1}(A_t)\right)}} \ . \tag{3.2}$$

The expected value is commonly replaced by a Money Market Survey dataset median forecast value (Andersen et al., 2003; Evans and Speight, 2010a). The division by the standard deviation allows a comparison of different indicators. The standard deviation is estimated on the difference of $A_t - E_{t-1}(A_t)$ series. It should be noted, however, that the variance is not known at time $t$ and can only be computed ex post. Consequently, $S_t$ cannot be calculated at time $t$, casting doubt on its usefulness for practical implementations such as forecasts for event arbitrage in high-frequency trading. The transformation is based on the rational expectations hypothesis, but recent studies by Leitner and Schmidt (2007), Branch (2007) and others, observed ample amounts of evidence against the hypothesis. In addition, market expectations are unobservable and therefore a proxy variable is required in the standardised news transformation to capture expectations ($E_{t-t}(A_t)$) with an empirical variate. Survey results are often used as a proxy but they do not correspond to the expectation of the market as results are often not based on actual financial positions, but only on expressions of opinion. Therefore, the captured news information shock component is reflecting the shock relevant to a limited part of the market, if at all.

We address these problems by suggesting an alternative transformation that can be computed at time $t$. Furthermore, it should be noted that the information about the previous value of the macroeconomic indicator $A_{t-1}$ is considered redundant in the standardised news transformation. The difference between the expected levels of the indicator, the previous and the realised value contain information about the level of surprise and are omitted as well. To correct these drawbacks we suggest to use a magnitude impact news transformation $M_t$ defined as:

$$M_t = M_t^A + M_t^B \tag{3.3}$$

where

$$\begin{aligned} M_t^A &= Direction \times (\{A_t - E_{t-1}(A_t)\} \times \{E_{t-1}(A_t) - A_{t-1}\}) \\ M_t^B &= Direction \times \left(A_t - \frac{E_{t-1}(A_t) + A_{t-1}}{2}\right) \end{aligned}$$

with $Direction = Indicator\ Impact \times \operatorname{sign}(A_t - A_{t-1})$. The *Indicator Impact* takes a value of either $+1$ or $-1$ to capture the expected effect of the macroeconomic indicator. For example, an *increase* in the GDP growth rate ($+1$) should not have the same direction of the effect as an *increase* in the unemployment rate ($-1$), because otherwise a positive indicator value for the unemployment figure would have the same directional effect as a positive value for the GDP figure. The first component of the transformation ($M_t^A$) captures the degree of surprise in the market, by measuring the distances between previous, current and expected values of the indicator. A substantial disruption is expected in the market if the expected value is far away from the previous and current values of the indicator at the time of the release. The second component ($M_t^B$) aims to capture gradual adjustment, the behavioural framing effect (e.g. Freling et al., 2014) or other effects of slow absorption of the indicator. In addition, it captures the actual information impact ignored in the standardised news transformation.

If the expected value $E_{t-1}(A_t)$ were equal to the released value $A_t$, the standardised news transformation would result in a value equal to zero. However, our proposed transformation is able to capture the fundamental impact in the second component $M_t^B$.

In general, the magnitude news transformation has the desired property of incorporating the difference between all three information points. For example, if the distance between expected and previous values is substantial, while the current realisation is a similar level as the expectation was, then the first term $M_t^A$ will dominate the second one, indicating a reasonable shock in the market. The effect would be barely observable using the standardised news transformation.

A standardised news transformation would reflect only a marginal effect. The magnitude impact news transformation focuses more on the short-term horizon, as it incorporates previous expectations that become irrelevant after the information shock component has been absorbed, and serves as an alternative measure to the standardised news transformation.

As proposed by Hafex and Xie (2013), the news indicator transformation is extended with a decaying effect. In our model, a transformed indicator is discounted with the time passed since the previous indicator change at time $j$ (news release point) is defined as:

$$N_t^{SR} = \frac{N_j}{t - j + 1} \ , \tag{3.4}$$

where $N_j$ is the news indicator at time $j$ as defined in either eq. (3.2), eq. (3.3) or eq. (3.1). The transformation is used for a short-run ($SR$) impact modelling, while the long-run ($LR$) component is modelled by using a corresponding news transformation without a decay factor in the denominator.

### 3.2.2 News Impact Models

In this subsection, we first review popular models from the existing literature. We start by specifying a linear null model without macroeconomic effects discussed in Section 3.2.2.1. In Section 3.2.2.2, the null model is extended with transformed news variables. We also consider an alternative specification to a popular approach used in the literature, and include decaying effects in the short-run component and a separate component for the long-run impact effect. Our suggested augmentations are not limited by a fixed time window (e.g Evans and Speight, 2010a) and allow to accommodate a slower impact decay rate with fewer parameters, compared to the popular approach by Andersen et al. (2003) and others. In addition, we combine (a) the short-run component studied in isolation by Fatum et al. (2012), Evans and Speight (2010a), Laakkonen (2013), Laakkonen and Lanne (2013) and (b) the long-run component studied by Andersen et al. (2003). The combination of two effects allow us to evaluate the precise nature of the news impact and impact dynamics that, to our best knowledge, have not been jointly addressed in the literature.

#### 3.2.2.1 Linear Model

A linear model without any news components is used as the null model to evaluate gains from additional components in the subsequent models. Returns of exchange rates are computed as $R_t = \log(P_t) - \log(P_{t-1})$, where $P_t = \sqrt{bid_t \times ask_t}$ (Dacorogna et al., 2001). The general form mean equation from the existing literature is defined as:

$$R_{LIN,t} = c + \sum_{i=1}^{I} \varrho_i R_{t-i} + \sum_{l=1}^{L} \pi_l \epsilon_{t-l} + \delta^{Mon} D_{Mon} + \delta^{Fri} D_{Fri} + \epsilon_t, \quad (3.5)$$

where $c$ is a constant term, $R_{t-i}$ and $\epsilon_{t-l}$ are the $i$-th and $l$-th lags of the series $R_t$ and $\epsilon_t$ respectively, $\epsilon_t$ is the residual defined as $\epsilon_t = R_t - \hat{R}_t$, $\varrho_i$ is the $i$th order auto-regressive component parameter, $D_{Mon,Fri}$ is a dummy variable for either Monday or Friday and $\delta^{Mon,Fri}$ are dummy parameters. The variance equation is defined as:

$$\sigma^2_{LIN,t} = const_2 + \sum_{b=1}^{B} \theta_b \sigma^2_{t-b} + \sum_{g=1}^{G} \vartheta_g \epsilon^2_{t-g} + \psi \frac{\hat{\sigma}_{d(t)}}{\sqrt{288}} + \left( \sum_{q=1}^{Q} \left( \zeta_q cos\left(\frac{q2\pi t}{288}\right) + \varphi_q sin\left(\frac{q2\pi t}{288}\right) \right) \right), \quad (3.6)$$

where $\hat{\sigma}_{d(t)}$ is the expected daily level of volatility forecast by a GARCH(1,1) model that is optimised on the data series; $\epsilon^2_{t-g}$ is the squared error term from the mean equation; the last term contains trigonometric variables of length $q$

used to capture intraday periodicities of the series. The lag lengths $I$, $L$, $B$, $G$ and $Q$ are determined using Bayesian Information Criterion. The mean equation contains necessary components to obtain consistent estimates in a compact form and to capture structural effects of weekday influences identified by the previous existing literature. The variance equation facilitates enough flexibility to capture daily structures in the absolute returns by using a mixture of sinusoidal functions; approximates the autocorrelation of absolute returns in a compact GARCH(B,G) form and contains a forecast of expected volatility of the day implied by GARCH(1,1) model. All parameters are estimated by Quasi Maximum Likelihood (QML). The methodology used in the previous literature depends on the normality of the innovations (Andersen et al., 2003; Ehrmann and Fratzscher, 2005; Evans and Speight, 2010a). In this chapter, the standardised innovations component (the error of the mean equation that is scaled by the expected standard deviation) is assumed to originate from a skewed Student-$t$ distribution (Hansen, 1994), which nests as the limiting case of the Gaussian distribution, while being flexible to capture the stylised fact of leptokurtosis of returns adequately. Parameters $\nu$ and $\rho$ are used to characterize thickness of tails and skewness of the distribution respectively as defined by (Hansen, 1994).

Parameters are estimated by minimizing our defined loss function in an incremental fashion starting with global search algorithms, followed by heuristic algorithms and using simplex algorithm at the very end. All of the estimation is done using Matlab optimization library toolboxes.

#### 3.2.2.2 Model Extensions

One of the first econometric models in the literature that documented exchange rate reactions to news shocks in the conditional mean and variance was specified by Andersen et al. (2003). Their analysis was implemented on a dataset considering only the data points from news release to news release[1], while our analysis focuses

[1] The return of the exchange rate that occured from the previous news release to the next one is regressed on various exogenous factors.

on 5 minute frequency data. We consider the model by Andersen et al. (2003) as the base model with extensions from Ehrmann and Fratzscher (2005) and Evans and Speight (2010a).

The mean equation of the base model is defined as:

$$R_{BASE,t}(N) \quad = \quad R_{LIN,t} + \sum_{f=1}^{F}\sum_{c=1}^{C} \beta_{c,t-f} N_{c,t-f}, \tag{3.7}$$

where $R_{LIN,t}$ is defined in eq. (3.5), and $N_{c,t} = S_t \times Indicator\ Impact$. The variance equation is modelled as:

$$\sigma^2_{BASE,t}(N) \quad = \quad \sigma^2_{LIN,t} + \sum_{b=1}^{B}\sum_{w=1}^{W} \beta_{w,t-b} Dummy_{w,t-b}(N_{w,t-b}), \tag{3.8}$$

where $\sigma^2_{LIN,t}$ is defined in eq. (3.6), and $Dummy_{w,t}$ is the dummy variable taking value of one if a news release of macroeconomic indicator $w$ has changed at time $t-b$, and zero otherwise. Variables $C$, $W$ and $M$, $J$, $Z$ in eq. 3.9, 3.10, 3.11 and 3.12, are of the same length equal to the macroeconomic indicator set but are identified using a different notation for the explanatory convenience of the testing structure presented in Section 3.2.3. The macroeconomic indicator set consists of 41 transformed variable observed on the 5 minutes data frequency.

Both the linear null model and the base model are used as benchmark models to test whether our proposed augmentations yield any improvements. In particular, we consider model extensions suggested by Laakkonen and Lanne (2013) and Evans and Speight (2010a), and therefore implement the analysis at the 5-minute high frequency grid. We generalise the approach by using an explicit impact function to a flexible one-step procedure similar to Laakkonen (2013). Our main contribution is the separation of the short-term impact and the longer term effects as postulated in the microstructure literature (Lyons, 2006). The augmented model consists of the short-term impact component with a simple decay transformation (eq. (3.4)) and the long-term component. The decay of the short-term component is necessary to capture the deterioration of the information value after the release, while the long-run component is required to preserve the fundamental impact on the exchange rate. In addition, our proposed approach of capturing news impacts is more flexible and parsimonious in terms of parameter use, when compared with popular approaches with respect to the parameter use. We are assuming that $F+C > 2$ which would represent the most minimal specification and in case $F+C = 2$ our methodology is comparable in terms of parameters use. The approach pioneered by Andersen et al. (2003) and identfied as a base approach in this section requires $F \times C$ parameters in the mean equation (eq. (3.7)) and $B \times U$ parameters in the variance equation (eq. (3.8)) where $U = C$ and $F, B \geq 1$, while our proposed approach of capturing news requires only $M + J$ (eq. (3.9)) and $Z$ (eq. (3.11)) parameters. In particular, we specify:

$$R_{AUG,t}(N^{SR}, N^{LR}) = R_{BASE,t}(N_t^{LR}) + \sum_{m=1}^{M} \beta_m N_{m,t-1}^{SR} + \sum_{j=1}^{J} \beta_j N_{j,t-1}^{LR} \quad (3.9)$$

$$\sigma^2_{AUG,t}(N^{SR}, N^{LR}) = \sigma^2_{BASE,t}(N_t^{LR}) + \sum_{z=1}^{Z} \beta_z |N_{z,t-1}^{SR}| \quad (3.10)$$

where $R_{BASE,t}$ and $\sigma^2_{BASE,t}$ are defined in eq. (3.7) and (3.8), and $N_{o,t}^{SR}$ is the transformed news indicator $o$ at time $t$ with the decay effect aiming to capture the short-term impact effect and the $N_{o,t}^{LR}$ is the corresponding long-run part being either $D_t$, $S_t$ or $M_t$. The short-term impact component is always transformed with eq. (3.4) and is reflected by $N_{o,t}^{SR}$.

### 3.2.3 Model Diagnostics

To evaluate the quality of the model fit we focus on the residual analysis from the in- and out-of-sample data. In particular, we divide the dataset into four sequential subsets in order to verify the quality of the model performance in different economic conditions. The estimated model parameters from the previous subset are used as inputs to obtain out-of-sample innovations on the following subset. Tests of normality, Durbin's $m$ test for the serial correlation as proposed by Dezhbakhsh (1990), and all four moments of the residuals statistics are used for assessment. We also use the sample size corrected critical values when considering the hypothesis tests results, because the classic critical value tables have limited power in larger datasets (Leamer, 1978). The mean squared error (MSE) is computed for the predicted values that are compared to the observed ones. We further decompose MSE to the variance and the bias levels. These metrics allow us to assess the quality of the fit more accurately, and complement information from residuals statistics.

We consider a set of likelihood ratio tests for our hypothesis tests and use our saturated model that nests extensions used in the literature. The saturated model

| Test | Reasoning | $H_0$ |
|---|---|---|
| *1* | The constrained model $R_{LIN,t}$,$\sigma^2_{LIN,t}$ is used to measure importance of using macroeconomic indicators. | $\beta_c = \beta_m = \beta_j = \beta_k = \beta_z = 0$ |
| *2* | The significance of the benchmark model from the literature $R_{BASE,t}$,$\sigma^2_{BASE,t}$ is tested with the normality assumption. | $\beta_j = \beta_m = \beta_z = 0$, $\nu = 100$, $\rho = 0$ |
| *3* | The adequacy of using only the benchmark model from the literature $R_{BASE,t}$,$\sigma^2_{BASE,t}$ is measured. | $\beta_m = \beta_j = \beta_z = 0$ |
| *4* | The explanatory power of the corresponding model without the long-run component is tested. | $\beta_j = 0$ |
| *5* | The importance of the short-run component in the corresponding model is tested. | $\beta_m = \beta_z = 0$ |
| *6* | The adequacy of the normality assumption in our extended model is tested. | $\nu = 100, \rho = 0$ |
| *7* | The significance of the extended model without the benchmark specification from the literature ($R_{BASE,t}$,$\sigma^2_{BASE,t}$) is tested. | $\beta_c = \beta_k = 0$ |

Table 3.2.1: Likelihood ratio tests descriptions and corresponding null hypotheses.

is defined as:

$$\begin{aligned} R_{AUG,t}(N^{SR}, N^{LR}) &= const_1 + \sum_{i=1}^{I} \varrho_i R_{t-i} + \sum_{l=1}^{L} \pi_l \epsilon_{t-l} + \delta^{Mon} D_{Mon} \\ &+ \delta^{Fri} D_{Fri} + \sum_{f=2}^{F} \sum_{c=1}^{C} \beta_{c,t-f} N^{LR}_{c,t-f}, + \sum_{m=1}^{M} \beta_m N^{SR}_{m,t} \\ &+ \sum_{j=1}^{J} \beta_j N^{LR}_{j,t} + \epsilon_t \qquad (3.11) \\ \sigma^2_{AUG,t}(N^{SR}, N^{LR}) &= const_2 + \sum_{b=1}^{B} \theta_b \sigma^2_{t-b} + \sum_{g=1}^{G} \vartheta_g \epsilon^2_{t-g} + \psi \frac{\hat{\sigma}_{d(t)}}{\sqrt{288}} \\ &+ \sum_{q=1}^{Q} (\zeta_q cos(\frac{q2\pi t}{288}) + \varphi_q sin(\frac{q2\pi t}{288})) \\ &+ \sum_{b=1}^{B} \sum_{k=1}^{K} \beta_k Dummy_{k,t-b} N^{LR}_{k,t-b} + \sum_{z=1}^{Z} \beta_z |N^{SR}_{z,t}| \qquad (3.12) \end{aligned}$$

Table 3.2.1 provides an overview of the null hypothesis in the individual likelihood ratio tests along with the constrained parameters. The testing procedure is designed to check the validity of the common methodology in the literature with tests *1, 2* and *7*. The benchmark approach from the literature is nested and tested from two perspectives, of under the null, and under the alternative, to support the power of results in tests *2, 3* and *6*. The individual explanatory power of each proposed extension is measured by tests *4* and *5*, and the assumed improvements by using macroeconomic variates, is tested in test *1*.

## 3.3 Results

### 3.3.1 Data

The data set in the analysis, provided by Olsen Ltd. consists of the exchange rate pairs EUR/USD, EUR/JPY, EUR/GBP, GBP/USD and USD/JPY observed in the period 2007 - 2012 at 5 minute sampling frequency. The dataset is further divided into four subsets of similar lengths, which are also similar to the sample period length in the study of Evans and Speight (2010a) and Galati and Ho (2003).

The macroeconomic data is extracted from publicly available sources [2] and only releases containing previous, forecast and released values are used.

The first subperiod (*Sub1*) from 1*st* of January 2007 to 25*th* of April 2008 is characterised as a financial distress period with high levels of uncertainty. The second subperiod (*Sub2*) from 25*th* of April 2008 to 19*th* of August 2009, features news announcements with high levels of pessimism about the economy. The third subperiod (*Sub3*) from 19*th* of August 2009 to 12*th* of December 2010, contains various attempts by the U.S. government to restore the confidence in the economy after the stressful period. The fourth subperiod (*Sub4*) from 12*th* of December 2010 to 30*th* of March 2012, is dominated by the economic recovery and U.S. quantitative easing policy. The subsets structure will be utilised for out-of-sample analysis and to check the stability of the residual statistics in a rolling window approach.

Table 3.3.1 displays the sample descriptives statistics of the FX rate returns. These indicate substantial variation in all four moments of each subset. Results for the full length series indicate a slight skewness and exceptionally high kurtosis levels compared to the study in Evans and Speight (2010a). We also conduct the Jarque-Bera and Kolmogorov-Smirnov tests for normality, and find strong evidence against the null hypothesis of the empirical data originating from a normal distribution. Also, serial correlation is found in the raw data using Durbin's $m$-test (Dezhbakhsh, 1990) with adjusted critical values to account for the large sample sizes (Leamer, 1978).

### 3.3.2 Empirical Findings

We first focus our analysis on the in-sample residual statistics. Table 3.3.2 presents the FX pair EUR/USD statistics of the in-sample innovations obtained from estimating the saturated model (nesting the benchmark model and our proposed extensions). Results for the other FX pairs are shown in Tables A.1.2 to A.1.4

[2]For example http://www.forexfactory.com/.

| FX Pair | | Total Sample | Subperiods *Sub*1 | *Sub*2 | *Sub*3 | *Sub*4 |
|---|---|---|---|---|---|---|
| **EUR/USD** | Mean | 0.2E-9 | 1.3E-8 | -7.8E-9 | -4.9E-9 | 0.4E-9 |
| | St. Dev. | 3.7E-6 | 2.4E-6 | 4.8E-6 | 3.5E-6 | 3.6E-06 |
| | Skewness | 0.0003 | -0.0234 | 0.0015 | 0.0016 | 0.0030 |
| | Kurtosis | 0.3515 | 2.5257 | 0.2126 | 0.1709 | 0.2067 |
| **EUR/GBP** | Mean | 3.9E-7 | 1.2E-6 | 5.3E-7 | -1.5E-7 | -7.5E-8 |
| | St. Dev. | 0.0003 | 0.0002 | 0.0004 | 0.0003 | 0.0003 |
| | Skewness | 0.4477 | 0.9058 | 0.3681 | 0.3690 | 0.3848 |
| | Kurtosis | 30.6545 | 97.4174 | 20.1617 | 22.9766 | 22.8614 |
| **EUR/JPY** | Mean | -6.4E-9 | 3.1E-9 | -1.4E-8 | -1.4E-8 | -0.1E-9 |
| | St. Dev. | 5.2E-6 | 3.6E-6 | 7.2E-6 | 4.9E-6 | 4.3E-6 |
| | Skewness | 0.0012 | -0.0008 | 0.0015 | -0.0052 | 0.0098 |
| | Kurtosis | 0.6930 | 0.2641 | 0.4439 | 0.3551 | 1.6481 |
| **GBP/USD** | Mean | -3.7E-7 | 7.4E-8 | -1.3E-6 | -3.3E-7 | 1.2E-7 |
| | St. Dev. | 0.0004 | 0.0002 | 0.0006 | 0.0004 | 0.0003 |
| | Skewness | -0.1699 | 0.0532 | -0.1603 | -0.1216 | -0.1834 |
| | Kurtosis | 31.8059 | 19.4842 | 22.1350 | 20.4808 | 23.0809 |
| **USD/JPY** | Mean | -6.6E-9 | -9.9E-9 | -6.5E-9 | -9.3E-9 | -0.6E-9 |
| | St. Dev. | 4.0E-6 | 3.6E-6 | 5.4E-6 | 3.7E-6 | 3.2E-6 |
| | Skewness | -0.0002 | -0.0018 | -0.0056 | -0.0061 | 0.0377 |
| | Kurtosis | 1.2588 | 0.3425 | 0.5844 | 0.4992 | 6.8632 |

Table 3.3.1: Descriptive Statistics of 5 minute FX rate returns.

in the appendix. The actual difference and the standardised news transformation were considered for the long-run component, as the magnitude transformation mainly focuses on the short-term effect as explained in Section 3.2.1. All in-sample results reject the Jarque-Bera test for normality at 5% error level and exhibit independent residuals with respect to the Durbin's $m$ test for the serial-correlation with sample size corrected to critical values at 5% error level. The non-normality of the data does not affect the quality of estimates as we are using a flexible distribution with thicker than Gaussian distribution tails.

We investigate the impact different news transformations have on the MSE, kurtosis, and skewness values on the in-sample residual statistics. We start by focusing on specifications with the standardised news transformation used for the long-run component $(\cdot, S_t)$, and investigate effects on results by comparing

| Components $(SR, LR)$ | | In-Sample *Sub 1* | *Sub 2* | *Sub 3* | Out-of-Sample *Sub 2* | *Sub 3* | *Sub 4* |
|---|---|---|---|---|---|---|---|
| $(D_t, D_t)$ | Mean | 0.1488 | 0.0817 | -0.4245 | -0.3965 | -0.0569 | -0.0999 |
| | St.D. | 1.1338 | 0.3996 | 0.7721 | 1.5402 | 0.3801 | 1.0788 |
| | Skew. | -0.1978 | -0.0106 | 0.2497 | 0.7325 | 0.0921 | 0.2733 |
| | Kurt. | 1.6047 | 11.0239 | 2.8048 | 2.4588 | 6.8079 | 2.1815 |
| | MSE | 0.4487 | 0.0340 | 0.2352 | 2.2050 | 0.0296 | 0.3782 |
| | Bias | 0.4487 | 0.0340 | 0.2352 | 2.2048 | 0.0296 | 0.3782 |
| $(S_t, D_t)$ | Mean | 0.1529 | 0.2657 | -0.3222 | 0.2226 | -0.1914 | -0.0897 |
| | St.D. | 1.1782 | 1.0852 | 1.1120 | 1.2597 | 1.0186 | 1.1330 |
| | Skew. | -0.2980 | 0.5350 | 0.1336 | 0.4445 | 0.3449 | 0.2348 |
| | Kurt. | 18.9018 | 9.4712 | 6.9246 | 11.1696 | 5.4325 | 8.0246 |
| | MSE | 0.0320 | 0.0444 | 0.0246 | 0.0343 | 0.0378 | 0.0232 |
| | Bias | 0.0320 | 0.0444 | 0.0246 | 0.0343 | 0.0378 | 0.0232 |
| $(M_t, D_t)$ | Mean | 0.1527 | 0.2656 | -0.3220 | 0.2225 | -0.1913 | -0.0895 |
| | St.D. | 1.1774 | 1.0848 | 1.1108 | 1.2585 | 1.0183 | 1.1320 |
| | Skew. | -0.2995 | 0.5358 | 0.1335 | 0.4466 | 0.3444 | 0.2361 |
| | Kurt. | 18.9458 | 9.4753 | 6.9131 | 11.1968 | 5.4293 | 8.0232 |
| | MSE | 0.0417 | 0.0478 | 0.0284 | 0.0363 | 0.0412 | 0.0248 |
| | Bias | 0.0417 | 0.0478 | 0.0284 | 0.0363 | 0.0412 | 0.0248 |
| $(D_t, S_t)$ | Mean | -0.0313 | 0.1058 | 0.0318 | -0.0639 | 0.0974 | 0.0444 |
| | St.D. | 0.7668 | 0.9883 | 1.0371 | 1.2601 | 1.0518 | 0.8463 |
| | Skew. | -2.8057 | 0.2992 | -0.0741 | 0.1771 | -0.0278 | 0.1876 |
| | Kurt. | 308.2154 | 8.9463 | 5.6132 | 15.9775 | 4.2004 | 10.9897 |
| | MSE | 0.0061 | 0.0405 | 0.0297 | 0.0251 | 0.0462 | 0.0192 |
| | Bias | 0.0061 | 0.0405 | 0.0297 | 0.0251 | 0.0462 | 0.0192 |
| $(S_t, S_t)$ | Mean | 0.2185 | 0.1054 | -0.0315 | 0.0871 | 0.0959 | 0.0272 |
| | St.D. | 1.0706 | 1.0237 | 1.0570 | 1.2020 | 1.0759 | 1.0064 |
| | Skew. | -0.5980 | 0.2937 | -0.1033 | 0.3121 | -0.0452 | 0.2438 |
| | Kurt. | 28.2428 | 9.3886 | 7.8787 | 12.9618 | 4.5018 | 11.8777 |
| | MSE | 0.0252 | 0.0394 | 0.0202 | 0.0295 | 0.0436 | 0.0180 |
| | Bias | 0.0252 | 0.0394 | 0.0202 | 0.0295 | 0.0436 | 0.0180 |
| $(M_t, S_t)$ | Mean | -0.0334 | 0.0062 | -0.0231 | -0.0376 | 0.0069 | -0.0216 |
| | St.D. | 0.8021 | 0.8947 | 0.8015 | 1.1279 | 0.6583 | 0.8216 |
| | Skew. | -9.9147 | 0.1227 | 0.1350 | 0.1440 | 0.1634 | 0.2555 |
| | Kurt. | 1250.8960 | 20.2098 | 15.7891 | 21.9856 | 17.1692 | 18.6254 |
| | MSE | 0.0058 | 0.0234 | 0.0122 | 0.0236 | 0.0122 | 0.0128 |
| | Bias | 0.0058 | 0.0234 | 0.0122 | 0.0236 | 0.0122 | 0.0128 |

Table 3.3.2: Descriptive statistics of the innovations of the augmented model $R_{AUG,t}(N_t^{SR}, N_t^{LR})$ for the EUR/USD FX pair.

different subsets. Table 3.3.2 (*In-Sample* columns), shows that there significant differences between cases when the short-run component is modelled with either standardised or actual difference news (see results of $(S_t, S_t)$ or $(D_t, S_t)$ models in Table 3.3.2), and a trade-off is observable between lower MSE values and superior residual statistics in terms of kurtosis values closer to 3 or close to zero skewness values. Similar findings can be seen for other FX pairs in Tables A.1.2 to A.1.4. An irregular variation pattern is observed by changing news specifications for the short and long-run components. For example, if we focus on cases where the actual difference news are used for the long-run component ($(D_t, D_t)$, $(S_t, D_t)$, and $(M_t, D_t)$ specifications in Table 3.3.2), we observe values of skewness, kurtosis and MSE, to follow a different pattern of variation over subsets (visible on signs and magnitudes of statistics). Similar features are present when focusing on cases where the standardised news are used for the long-run component ($(D_t, S_t)$, $(S_t, S_t)$ and $(M_t, D_t)$), or varying the news transformation of the short-run component. We did not identify the superior or inferior combination of news transformations, based on the in-sample residual statistics alone. The irregular variation pattern is further addressed in the out-of-sample residual analysis and hypothesis tests. The effect caused by different news transformations on the long and short-run components is not independent.

In the next step, we focus on measuring the stability of the out-of-sample innovation statistics. We mainly focus here on Table 3.3.2 (*Out-of-Sample* columns), as similar findings are observable across all other FX pairs considered in Tables A.1.2 to A.1.4. Models with the actual difference or standardised news for the long-run component ($(\cdot, D_t)$ or $(\cdot, S_t)$), show similar results as we have observed in the in-sample innovation statistics. The variation of the short-run component only, and focusing on corresponding specifications ($(D_t, \cdot)$, $(S_t, \cdot)$ and $(M_t, \cdot)$) yields similar results of comparable performance between different specifications. The superior news combination cannot be determined, based on the in- or out-of-sample residual statistics. The variation of the exchange rate pair and news specification has an observable effect on the in- and out-of-sample residual statistics. Most of the variation is due to the change in the time period of data (for example, compare results of *Sub 1*, *Sub 2* and *Sub 3* for *In-Sample* or *Out-of-Sample columns* sections in Table 3.3.2). We attribute it to the economic climate and the mood of financial markets. In general, as long as in-sample economic outlook is similar to the out-of-sample one, residual statistics are observed to be at similar values as seen by focusing on the in-sample *Sub3* results, and comparing MSE and kurtosis values to out-of-sample *Sub4* results, irrespective of the news transformation.

Residual statistics do not identify any abnormalities in the quality of fits obtained for all of the specifications considered. A pattern of improvement in the quality of fits based on MSE and kurtosis values is observed when older subsets are compared with the more recent ones (for example, see statistics from subsets *Sub1* to *Sub3* in Table 3.3.2). To the best of our knowledge, this effect has not been identified in the previous literature. In addition, the level of kurtosis of the conditional innovations decreases in the same pattern with the exception for exchange rate pairs related to the Japanese Yen. The effect of estimates variation has been explored by Galati and Ho (2003) but the cause was not identified, and we argue that the cause of the instability is due to the market sentiment variation.

In general, we observe for the definition, or transformation, of the fundamental macroeconomic data to have a substantial effect on the model quality of fit, data patterns and effects on results. These findings have not been addressed in the literature and have a profound effect for results in the works of Galati and Ho (2003), Andersen et al. (2003), Fatum et al. (2012), Evans and Speight (2010a), Laakkonen (2013), Laakkonen and Lanne (2013), Evans and Speight (2010c) and others. The claimed relation between the fundamental data and exchange rates must not be confused with the relation between transformed macroeconomic data and exchange rates. In addition, conclusions drawn from a model omitting one of the components will be misleading, if either the long or the short-run components are overlooked.

| | | $R_{AUG,t}(D_t, S_t)$ | | | $R_{AUG,t}(D_t, D_t)$ | | | Critic. |
|---|---|---|---|---|---|---|---|---|
| FX Pair | Test | *Sub 1* | *Sub 2* | *Sub 3* | *Sub 1* | *Sub 2* | *Sub 3* | values |
| **EUR/ USD** | *1* | 15.3165 | 8.9856 | 8.6139 | 18.5995 | 11.5296 | 12.1822 | *1.9761* |
| | *2* | 14.5524 | 5.9681 | 6.1381 | 17.6818 | 7.8826 | 9.6593 | *1.0176* |
| | *3* | 15.2077 | 8.9107 | 8.5150 | 18.4910 | 11.4561 | 12.0804 | *0.9939* |
| | *4* | 14.3095 | 7.9751 | 7.8282 | 17.6045 | 10.7095 | 11.3973 | *0.3313* |
| | *5* | 0.0257 | 0.0233 | 0.0481 | 0.1422 | 0.2456 | 0.3114 | *0.6626* |
| | *6* | 0.1361 | 1.0589 | 0.9589 | 0.2325 | 1.1101 | 0.6246 | *0.0237* |
| | *7* | 0.0357 | 0.0281 | 0.0342 | 0.0340 | 0.0282 | 0.0350 | *0.9939* |
| **EUR/ JPY** | *1* | 5.4201 | 5.3903 | 6.7182 | 8.0641 | 7.1763 | 9.5090 | *1.9761* |
| | *2* | 0.5578 | 0.2419 | 2.6084 | 3.1811 | 1.1051 | 5.3614 | *1.0176* |
| | *3* | 5.3519 | 5.3528 | 6.6509 | 7.9959 | 7.1425 | 9.4411 | *0.9939* |
| | *4* | 5.2547 | 5.3034 | 6.5611 | 7.8992 | 7.0668 | 9.3520 | *0.3313* |
| | *5* | 0.0290 | 0.0368 | 0.0384 | 0.0017 | 0.0182 | 0.0208 | *0.6626* |
| | *6* | 2.8430 | 3.2254 | 1.8679 | 2.0164 | 3.1249 | 1.0138 | *0.0237* |
| | *7* | 0.0297 | 0.0208 | 0.0281 | 0.0299 | 0.0206 | 0.0293 | *0.9939* |
| **EUR/ GBP** | *1* | 9.9745 | 9.0981 | 10.3215 | 16.0345 | 13.1210 | 15.0764 | *1.9761* |
| | *2* | 7.1438 | 6.4735 | 8.4196 | 13.1396 | 10.4516 | 13.3135 | *1.0176* |
| | *3* | 9.9265 | 9.0083 | 10.2194 | 15.9850 | 13.0285 | 14.9670 | *0.9939* |
| | *4* | 9.7529 | 8.7815 | 9.3188 | 15.8109 | 12.8027 | 12.7881 | *0.3313* |
| | *5* | 0.0649 | 0.0339 | 0.0309 | 0.0410 | 0.0348 | 0.8763 | *0.6626* |
| | *6* | 1.4126 | 0.9350 | 0.4923 | 0.5916 | 0.9306 | 0.3732 | *0.0237* |
| | *7* | 0.0171 | 0.0309 | 0.0370 | 0.0166 | 0.0324 | 0.0364 | *0.9939* |
| **GBP/ USD** | *1* | 12.3419 | 8.0945 | 9.8422 | 15.5993 | 11.4372 | 13.0781 | *1.9761* |
| | *2* | 12.0439 | 3.9628 | 8.0641 | 15.2440 | 7.2714 | 11.4725 | *1.0176* |
| | *3* | 12.2485 | 8.0289 | 9.7450 | 15.5060 | 11.3708 | 12.9792 | *0.9939* |
| | *4* | 11.8100 | 7.5504 | 9.3529 | 15.0649 | 10.8936 | 12.0813 | *0.3313* |
| | *5* | 0.0009 | 0.0130 | 0.0362 | 0.0726 | 0.1839 | 0.2321 | *0.6626* |
| | *6* | 0.2134 | 1.6427 | 0.4233 | 0.2575 | 1.3264 | 0.3598 | *0.0237* |
| | *7* | 0.0378 | 0.0263 | 0.0332 | 0.0357 | 0.0273 | 0.0345 | *0.9939* |
| **USD/ JPY** | *1* | 4.4674 | 8.5997 | 8.2932 | 0.7573 | 1.1069 | 1.1280 | *1.9761* |
| | *2* | 0.2488 | 5.3958 | 5.0830 | 0.2830 | 0.7058 | 0.7972 | *1.0176* |
| | *3* | 4.4038 | 8.5278 | 8.2157 | 0.7509 | 1.1001 | 1.1201 | *0.9939* |
| | *4* | 4.3370 | 8.2418 | 8.1738 | 0.7442 | 1.0810 | 1.1159 | *0.3313* |
| | *5* | 0.0398 | 0.0231 | 0.0385 | 0.0028 | 0.0016 | 0.0038 | *0.6626* |
| | *6* | 3.4615 | 1.2865 | 1.2308 | 0.2654 | 0.1466 | 0.0918 | *0.0237* |
| | *7* | 0.0299 | 0.0274 | 0.0313 | 0.0031 | 0.0029 | 0.0033 | *0.9939* |

Table 3.3.3: Hypothesis testing results of the augmented model with standardised ($R_{AUG,t}(D_t, S_t)$) or actual difference news ($R_{AUG,t}(D_t, D_t)$) in the long-run component.

| | | $R_{AUG,t}(S_t, S_t)$ | | | $R_{AUG,t}(S_t, D_t)$ | | | Critic. |
|---|---|---|---|---|---|---|---|---|
| FX Pair | Test | *Sub 1* | *Sub 2* | *Sub 3* | *Sub 1* | *Sub 2* | *Sub 3* | values |
| **EUR/ USD** | *1* | 8.0883 | 6.5219 | 9.7078 | 18.6699 | 11.6078 | 12.2562 | *1.9761* |
| | *2* | 2.8364 | 2.4791 | 7.3672 | 17.7521 | 7.9608 | 9.7333 | *1.0176* |
| | *3* | 7.9702 | 6.4543 | 9.6067 | 18.5614 | 11.5343 | 12.1544 | *0.9939* |
| | *4* | 7.8182 | 6.2722 | 8.4830 | 17.5866 | 10.7071 | 11.3883 | *0.3313* |
| | *5* | 0.1426 | 0.1171 | 0.0254 | 0.0718 | 0.1673 | 0.2374 | *0.6626* |
| | *6* | 2.5815 | 1.9176 | 0.8125 | 0.2312 | 1.1100 | 0.6186 | *0.0237* |
| | *7* | 0.0054 | 0.0093 | 0.0111 | 0.0122 | 0.0098 | 0.0125 | *0.9939* |
| **EUR/ JPY** | *1* | 0.1289 | 5.7525 | 6.2198 | 8.1391 | 7.2516 | 9.5854 | *1.9761* |
| | *2* | 24.8710 | 0.3712 | 2.1876 | 3.2561 | 1.1804 | 5.4378 | *1.0176* |
| | *3* | 0.1460 | 5.7184 | 6.1553 | 8.0709 | 7.2178 | 9.5174 | *0.9939* |
| | *4* | 0.1730 | 5.1039 | 5.5853 | 7.8958 | 7.0649 | 9.3466 | *0.3313* |
| | *5* | 0.0644 | 0.1021 | 0.0426 | 0.0734 | 0.0936 | 0.0971 | *0.6626* |
| | *6* | 28.1846 | 3.4505 | 2.2027 | 2.0140 | 3.1266 | 1.0130 | *0.0237* |
| | *7* | 0.0015 | 0.0080 | 0.0093 | 0.0104 | 0.0086 | 0.0110 | *0.9939* |
| **EUR/ GBP** | *1* | 10.9874 | 8.1577 | 10.8211 | 16.1266 | 13.1968 | 15.1512 | *1.9761* |
| | *2* | 9.2278 | 3.9418 | 9.3597 | 13.2317 | 10.5275 | 13.3883 | *1.0176* |
| | *3* | 10.8504 | 8.0774 | 10.7138 | 16.0771 | 13.1043 | 15.0418 | *0.9939* |
| | *4* | 10.5531 | 7.5038 | 10.5804 | 15.7980 | 12.7977 | 12.7738 | *0.3313* |
| | *5* | 0.0955 | 0.1266 | 0.1168 | 0.1330 | 0.0411 | 0.8015 | *0.6626* |
| | *6* | 0.6939 | 1.6081 | 0.2577 | 0.5903 | 0.9284 | 0.3699 | *0.0237* |
| | *7* | 0.0413 | 0.0121 | 0.0130 | 0.0080 | 0.0135 | 0.0127 | *0.9939* |
| **GBP/ USD** | *1* | 11.6787 | 8.0716 | 9.7218 | 15.6706 | 11.5163 | 13.1547 | *1.9761* |
| | *2* | 10.8468 | 2.6323 | 7.4225 | 15.3154 | 7.3504 | 11.5490 | *1.0176* |
| | *3* | 11.5557 | 8.0147 | 9.6288 | 15.5774 | 11.4499 | 13.0557 | *0.9939* |
| | *4* | 11.0820 | 6.7511 | 8.2737 | 15.0537 | 10.8923 | 12.0699 | *0.3313* |
| | *5* | 0.0831 | 0.5409 | 0.1943 | 0.0013 | 0.1048 | 0.1556 | *0.6626* |
| | *6* | 0.3234 | 2.2286 | 0.7232 | 0.2573 | 1.3260 | 0.3566 | *0.0237* |
| | *7* | 0.0152 | 0.0085 | 0.0112 | 0.0154 | 0.0101 | 0.0113 | *0.9939* |
| **USD/ JPY** | *1* | 6.9655 | 8.7821 | 10.1614 | 0.7629 | 1.1148 | 1.1356 | *1.9761* |
| | *2* | 1.8539 | 5.3154 | 7.8334 | 0.2886 | 0.7137 | 0.8048 | *1.0176* |
| | *3* | 6.9045 | 8.7118 | 10.0705 | 0.7564 | 1.1079 | 1.1276 | *0.9939* |
| | *4* | 6.7833 | 8.2026 | 9.6652 | 0.7436 | 1.0807 | 1.1150 | *0.3313* |
| | *5* | 0.0959 | 0.1091 | 0.1133 | 0.0084 | 0.0063 | 0.0113 | *0.6626* |
| | *6* | 3.8542 | 1.3058 | 0.8162 | 0.2629 | 0.1467 | 0.0917 | *0.0237* |
| | *7* | 0.0091 | 0.0102 | 0.0108 | 0.0010 | 0.0013 | 0.0012 | *0.9939* |

Table 3.3.4: Hypothesis testing results of the augmented model with standardised ($R_{AUG,t}(S_t, S_t)$) or actual difference news ($R_{AUG,t}(S_t, D_t)$) in the long-run component.

| | | $R_{AUG,t}(M_t, S_t)$ | | | $R_{AUG,t}(M_t, D_t)$ | | | Critic. |
|---|---|---|---|---|---|---|---|---|
| FX Pair | Test | *Sub 1* | *Sub 2* | *Sub 3* | *Sub 1* | *Sub 2* | *Sub 3* | values |
| **EUR/ USD** | *1* | 3.0106 | 8.4226 | 10.5589 | 27.7337 | 8.3885 | 14.6478 | *1.9761* |
| | *2* | 5.2629 | 5.3132 | 8.9463 | 31.0477 | 10.1843 | 15.3497 | *1.0176* |
| | *3* | 2.9453 | 8.3467 | 10.4550 | 27.5551 | 8.3183 | 14.5932 | *0.9939* |
| | *4* | 2.7475 | 8.0263 | 10.2555 | 27.5076 | 8.3044 | 10.6103 | *0.3313* |
| | *5* | 0.0940 | 0.0417 | 0.0433 | 0.0131 | 0.0108 | 0.3210 | *0.6626* |
| | *6* | 6.6660 | 0.9644 | 0.3819 | 0.5494 | 12.2234 | 0.9555 | *0.0237* |
| | *7* | 0.0501 | 0.0255 | 0.0303 | 0.0498 | 0.0413 | 0.0285 | *0.9939* |
| **EUR/ JPY** | *1* | 5.5494 | 5.1903 | 8.0313 | 14.2891 | 8.0351 | 20.3616 | *1.9761* |
| | *2* | 0.6248 | 0.6133 | 3.9629 | 15.4272 | 5.8861 | 20.5766 | *1.0176* |
| | *3* | 5.4794 | 5.1547 | 7.9667 | 14.1441 | 7.9270 | 20.2123 | *0.9939* |
| | *4* | 5.1933 | 5.0147 | 6.5517 | 14.1302 | 7.8557 | 19.9063 | *0.3313* |
| | *5* | 0.0095 | 0.0228 | 0.2141 | 0.0044 | 0.0332 | 0.0226 | *0.6626* |
| | *6* | 2.7892 | 3.4734 | 1.8901 | 0.1838 | 0.7038 | 0.2066 | *0.0237* |
| | *7* | 0.0265 | 0.0201 | 0.0256 | 0.0609 | 0.0604 | 0.0711 | *0.9939* |
| **EUR/ GBP** | *1* | 7.0911 | 9.0249 | 11.4139 | 13.7201 | 2.7503 | 12.0097 | *1.9761* |
| | *2* | 8.7536 | 6.1680 | 10.1860 | 3.6911 | 18.4746 | 11.3845 | *1.0176* |
| | *3* | 7.0707 | 8.9378 | 11.3089 | 13.5758 | 2.6575 | 11.8267 | *0.9939* |
| | *4* | 6.2730 | 8.6055 | 11.2604 | 12.7368 | 2.6178 | 11.5556 | *0.3313* |
| | *5* | 0.0579 | 0.0372 | 0.0448 | 0.9757 | 0.0276 | 0.0218 | *0.6626* |
| | *6* | 11.9459 | 1.0340 | 0.2362 | 1.4527 | 19.0321 | 0.3775 | *0.0237* |
| | *7* | 0.0112 | 0.0284 | 0.0323 | 0.0512 | 0.0243 | 0.0823 | *0.9939* |
| **GBP/ USD** | *1* | 11.8483 | 5.2588 | 11.6126 | 27.6761 | 17.2402 | 13.4904 | *1.9761* |
| | *2* | 10.7449 | 0.7796 | 10.2431 | 27.9682 | 16.0069 | 13.5854 | *1.0176* |
| | *3* | 11.7193 | 5.2090 | 11.5149 | 27.4523 | 17.2219 | 13.4067 | *0.9939* |
| | *4* | 10.9951 | 5.1056 | 10.5547 | 24.5916 | 17.2160 | 13.2111 | *0.3313* |
| | *5* | 0.0174 | 0.0319 | 0.0615 | 0.0587 | 0.0176 | 0.0442 | *0.6626* |
| | *6* | 0.3778 | 3.5376 | 0.2840 | 0.0959 | 8.0166 | 0.5442 | *0.0237* |
| | *7* | 0.0378 | 0.0226 | 0.0290 | 0.0809 | 0.0160 | 0.0223 | *0.9939* |
| **USD/ JPY** | *1* | 2.6546 | 7.5060 | 8.1025 | 34.1061 | 15.0387 | 15.4784 | *1.9761* |
| | *2* | 2.6677 | 2.9792 | 5.1477 | 34.8110 | 15.7829 | 15.4186 | *1.0176* |
| | *3* | 2.6069 | 7.4413 | 8.0271 | 33.9535 | 14.7909 | 15.3499 | *0.9939* |
| | *4* | 2.5600 | 7.1458 | 7.8410 | 33.9128 | 14.4097 | 15.2693 | *0.3313* |
| | *5* | 0.0427 | 0.0366 | 0.0412 | 0.0188 | 0.0161 | 0.0342 | *0.6626* |
| | *6* | 4.1244 | 1.9186 | 1.3353 | 0.2180 | 0.4129 | 0.0337 | *0.0237* |
| | *7* | 0.0231 | 0.0249 | 0.0280 | 0.0405 | 0.0626 | 0.0410 | *0.9939* |

Table 3.3.5: Hypothesis testing results of the augmented model with standardised ($R_{AUG,t}(M_t, S_t)$) or actual difference news ($R_{AUG,t}(M_t, D_t)$) in the long-run component.

Tables 3.3.3, 3.3.4 and 3.3.5 present test statistic values of the hypothesis tests results obtained using the likelihood ratio test. In test *1*, we test the relevance of all transformed macroeconomic data to explain exchange rate 5 minute returns. The test indicates if there are any gains for using macroeconomic data when modelling exchange rate returns. In all of the cases considered, we observe all of the macroeconomic components to be important for capturing the exchange rate dynamics, with the exception of USD/JPY pair where the actual difference news were used for the long-run, and the same transformation or the standardised news transformation, are used for the short-run component ($(S_t, D_t)$ and $(D_t, D_t)$ specifications). It must be noted that this combination of news is one of the two combinations with a different pattern of variation as referred in the in- and out-of-sample results. We observe the in-sample quality fit to substantially effect hypotheses testing results. Irrespective of the way macroeconomic data is transformed, it is still jointly relevant to explaining exchange rate dynamics.

In test *2*, we measure the joint explanatory power of the base model (the model combining proposed extensions by Andersen et al. (2003), Fatum et al. (2012) and Ehrmann and Fratzscher (2005). The rationale of the test is to check whether all of the proposed extensions are important. The base model was found to be unable to fully explain exchange rate dynamics on all subsets considered, irrespective of the specifications (as observed in test *2*). Results indicated space for the improvement from the popular model specification that we addressed by our suggested modifications.

In tests *4* and *5*, we test the relevance of the short-run and the long-run components of our proposed extensions. The test measures the contribution of our proposed approaches to modelling both components in explaining exchange rate dynamics. In our saturated model, we suggested to include two new components to represent the long-run and the short-run effects. The long-run component is found to explain a significant proportion of exchange rate dynamics as seen in test *4*. The short-run component studied by Andersen et al. (2003), Evans and

Speight (2010a), Fatum et al. (2012), Laakkonen (2013) and Laakkonen and Lanne (2013), is found to be insignificant in most of the cases, irrespective of the news transformation considered as seen in the test *5* results. Therefore, we observe an interesting feature: when both components are modelled jointly, the long-run component explains most of the information, while the short-run component is irrelevant, suggesting the macroeconomic data is relevant only for longer periods, and it indicates overlooked effects in the existing literature (Andersen et al. (2003), Evans and Speight (2010a), Fatum et al. (2012), Laakkonen (2013) and Laakkonen and Lanne (2013)).

In tests *3* and *7* we further investigate the plausibility of using the popular specification in the existing literature (Andersen et al. (2003), Fatum et al. (2012), Ehrmann and Fratzscher (2005)), with skewed $t$-distribution residuals. In test *3*, we check if, when the popular specification is modelled with a skewed $t$-distribution and we observe it to be unable to achieve the same explanatory power level as with our proposed extensions. We change the perspective of the problem by considering the explanatory power, gained due to adding the popular approach of capturing news in the saturated model, as shown in test *7* and find it to be irrelevant. Results indicate strong evidence in favour of our modifications to capture the relevance of the macroeconomic data in a more compact setting, as opposed to the approach used by Andersen et al. (2003), Fatum et al. (2012), Ehrmann and Fratzscher (2005).

Irrespective of the subset, currency or model specification considered, the base model lacks explanatory power when compared to our more parsimonious specification. The choice of news transformation yields a substantial effect on the results, the model significance and the explanatory power of individual components, as seen in Tables 3.3.3, 3.3.4 and 3.3.5, especially on the USD/JPY pair. The choice of news transformation affects the in- and out-of-sample residuals and these effects are passed to the hypothesis tests. Previous studies (Andersen et al. (2003), Fatum et al. (2012), Ehrmann and Fratzscher (2005), Evans and Speight (2010a), Laakkonen (2013), Laakkonen and Lanne (2013)), have overlooked the importance of the choice of transformation on results, and claimed to have observed and measured effects on the relation between fundamental data and exchange rates. While, in light of our findings, we see previously published results to be only conditionally valid on the choice of transformation. On another note, the actual difference news transformation ($A_t$) produced the most consistent results when applied to the long-run component, as observed in test statistics value for test *4* and compared across subsets or FX pairs.

## 3.4 Discussion

We have provided an empirical analysis of the exchange rate dynamics around public macroeconomic indicator shocks, on selected major FX currency pairs using a set of macroeconomic indicators similar to that of Andersen et al. (2003).

Our first contribution is that we found that our approach is better able to explain exchange rate dynamics than the commonly-adopted ones (Galati and Ho (2003), Andersen et al. (2003), Fatum et al. (2012), Evans and Speight (2010a), Laakkonen (2013), Laakkonen and Lanne (2013), Evans and Speight (2010c)). Moreover, it is superior in terms of parameter use, by requiring fewer parameters in the model to capture news components. Our results are robust with respect to the exchange rate pair, news transformation, data subset, residuals distribution or the formulation of the test hypothesis. We observed that short and long-run components must be modelled jointly to fully measure news impact, as opposed to focusing either on the short, long-run or only on the variance individually (Andersen et al. (2003), Fatum et al. (2012), Evans and Speight (2010a), Laakkonen (2013), Laakkonen and Lanne (2013)). Only when both components were used is the long-run component found to be relevant, while the short-run component contribution is observed to be insignificant in explaining exchange rate dynamics with appropriate critical values. Therefore, the literature has overlooked the importance of the *combined* impact of both components, and focused only on the variance or either the short or long-run components separately.

Our second contribution is that the use of various news transformations in this chapter allowed us to show that the definition of the fundamental news must not be confused with the actual news transformation itself. The most popular news transformation in the literature is the standardised news transformation used by Laakkonen (2013), Laakkonen and Lanne (2013), Fatum et al. (2012), Gilbert et al. (2015), Kurov et al. (2015) and others. In general, we observe that the choice of the news transformation affects the in- and out-of-sample residual statistics and even the results of the hypothesis tests. A clear distinction must be made between empirical macroeconomic data and the transformed version of the data. We demonstrated that transforming macroeconomic data has a profound impact on residuals, and tests statistics. In similar spirit as Rigobon (2006) shown a substantial influence of the transformation on the short-term component only. In general, the popular standardised news transformation, based on rational expectations hypothesis, was shown to be weakly supported by empirical evidence (Leitner and Schmidt (2007), Branch (2007) and others).

Our third contribution is that the comparison of various news transformations in multiple model specifications allows us to quantify the importance of the macroeconomic news transformations in different economic conditions. In general, the macroeconomic data alone is unable to capture the economic mood variation, as strong effects on the in- and out-of-sample residual and test statistics are observed in different data subsets. The issue has previously been studied by Galati and Ho (2003), Laakkonen and Lanne (2013) and partially addressed by Evans and Speight (2010a). Comparing data subsets with a different market mood, we observe that the variation in the quality of fit is caused by changes in market sentiment. In our future research we will further investigate these effects in order to obtain a stable quality of fit, by including exogenous market sentiment information into the modelling framework.

In this chapter, we have observed that neither of the studied news transformations were able to provide a superior explanatory power, despite having totally different approaches and logic. As a result, before using transformed variables in time-series models, we should understand the nature of the impact caused due to variables. Therefore, in the following chapter (Chapter 4), we will outline and investigate alternative methods of analysis, focusing only on the information impact in FX markets.

# Chapter 4

# Observer's Effect in FX Market Financial News

In this chapter, we evaluate different methodologies for studying information absorption in FX markets and focus on empirical news impact shock dynamics. In the spirit of Kurov et al. (2015), we investigate effects of scheduled news releases in FX markets and focus on disentangling a news content[1] effect from the pre-release reaction. However, instead of using a parametric model, we apply probability metrics to investigate the problem, and compare our approach with the the scaling law framework and stochastic dominance[2] tests. We also consider a calendar time[3] as well as a event time[4] setting, and are able to extract a pure information impact effect for observed news release shocks in both settings. Contrary to the existing literature, our results show a limited response to news releases compared with a zero information state[5]. We only observe the strong impact reported in the lit-

[1]The news content effect is measured by comparing releases with positive versus negative signs of corresponding macroeconomics variables of interest (previous, currently released or expected values of the indicator).

[2]Stochastic dominance of $X$ over $Y$ is defined as a random variable $X$ showing superior statistical features when compared to $Y$ in this thesis. First and second order dominances are explained in greater detail in this chapter.

[3]Calendar time is defined as a time-series data setting where observations are measured based on a fixed amount of time that has elapsed between observations (i.e. 5 minutes, 10 minutes).

[4]Event time is defined as a time-series data setting where observations are measured based on a number of price changes that have happened (i.e. 5 price changes, 10 price changes).

[5]Zero information state is defined as an environment when there is no new information that would affect price changes. All of the observed price changes are due to random nature of the price.

erature if we restrict attention to the *post-release* returns. The main contrast to the existing literature is that after accounting for the pre-release dynamics, we do not observe the strong influence of news either on returns or the volatility of the process. Therefore, the commonly observed influence in the existing literature is documenting the presence effect as oppose to the news content effect.

Our contributions in this chapter are: (a) proposal of an innovative way of restructuring the news shock impact analysis problem to a setting with fewer assumptions and ability to account for the pre-release dynamics; (b) an evaluation of the most suitable methodology for our proposed approach and an application of the previous two to investigate new information influence on FX volatility. We observe contradicting evidence to the previous literature and new information causes a limited influence on the post-release volatility dynamics. We are able to identify that previous literature observed a response to the pre-release reaction when focusing solely on the post-release dynamics as oppose to a response to new information.

The remainder of this chapter is structured as follows: Section 4.1 highlights the relevant literature in the remaining chapter; in Section 4.2 we introduce our methodology. We start by describing the application of probability metrics. The research hypotheses to investigate the economic impact are then discussed. We also outline the scaling law approach and the stochastic dominance tests, which we consider as benchmark models in this chapter. In Section 4.3 we investigate our findings of proposed probability metrics and evaluate evidence against our proposed hypotheses. Section 4.4 concludes.

## 4.1 Introduction

A general approach in the literature when studying news announcements is to estimate news effects and validate the importance of each of the news components using test statistics (Laakkonen, 2013; Laakkonen and Lanne, 2013; Fatum et al., 2012; Evans and Speight, 2010a; Andersen et al., 2003). The existing literature measured news impact of the release by focusing on returns in the post-release period. A more recent study by Evans and Speight (2010a) suggested surrounding the impact point with lead and lag dummy variables around the release point to capture the news shock impact structure. Analysis was based on a restrictive time-series model, along with a structured framework, where a low-frequency macroeconomic process was compared against a high-frequency trading process. News release impacts were investigated only in a calendar time grid, neglecting possible effects in event-time, a common perspective in econophysics (Bouchaud, 2002).

In this chapter we propose a less restrictive approach to determine whether there is an effect of macroeconomic news release on exchange rate dynamics. The advantage of our proposed application is the ability to incorporate traditional ideas from the existing literature, and extend them to be able to observe news shock effects on the overall probability distribution function. We are not required to impose any structure on the data to measure the effect of news releases, contrary to existing studies (Laakkonen, 2013; Laakkonen and Lanne, 2013; Fatum et al., 2012; Evans and Speight, 2010a; Andersen et al., 2003). We tackle the problem by proposing a new application of probability metrics. In addition, we verify the robustness of our results using two well-known methods: stochastic dominance tests from income inequality studies (Davidson and Duclos, 2000), and scaling laws from high-frequency FX rate studies (e.g. Müller et al., 1990, among others).

It is plausible that market participants react to scheduled news announcements due to speculative or hedging purposes, and this is a central assumption of this chapter. If the news release in question does not reveal any new information, then only by taking into account the pre-release dynamics, and using them as a base behaviour against which we compare post-release dynamics, will we be able to distinguish if we observe an impact (or no impact in this case) of the news release content, or just a correction due to the pre-release activity. Otherwise, we will observe a combined impact, reflecting new information released and adjustment of the financial positions taken right before the news release. Therefore, measurements based solely on post-release rates (e.g. Laakkonen and Lanne, 2013; Evans and Speight, 2010a) are likely to be confounding the effect of the expectation of the release with the impact of the actual content. We study the effects of news releases by focusing on: (a) the pre-release period to investigate the anticipation effect, (b) the post-release period to measure the combined effect as done in the existing literature, and (c) a combined approach to extract the pure information shock. Our analysis is implemented on event and calendar time grids.

Our first contribution is a new application of probability metrics to quantify the information shock in FX markets. Our suggested approach does not require *a priori* assumption of the model, and is able to uncover the information shock dynamics on the high-frequency rates. Our suggested approach considers results on the overall distribution function, as opposed to focusing on individual moments as done by Laakkonen (2013), Evans and Speight (2010a), Andersen et al. (2003) and others.

Our second contribution is the identification of the *news content effect* as opposed to the confounded overall news impact effect. By accounting for the pre-release rates, we are able to extract the true information shock of the release. We present a clear depiction of the news release effect due to new information, and look at the pre-release and post-release effects individually as done by Laakkonen and Lanne (2013), Fatum et al. (2012), Evans and Speight (2010a), Andersen et al. (2003) and others.

## 4.2 Methodology

In the following, we first introduce the proposed probability metrics in Section 4.2.1. Section 4.2.2 presents a description of the rationale of hypotheses aimed to investigate impacts of news releases. In the last two sections we outline our benchmark analysis methods: Section 4.2.3.1 presents scaling laws application to measure the effect of news releases on the exchange rate volatility and Section 4.2.3.2 presents stochastic dominance tests.

We consider the standard notation $FXA/FXB$ to define the foreign exchange (FX) rate involving the base currency $FXA$ and the quote currency $FXB$ (e.g. EUR/USD). Let $t_1, t_2, ..., T$ denote a series of timestamps and $\{R\}_{t=1}^{T}$ the corresponding time series of the FX rate. Each observation corresponds to a new rate change with its arrival time being stochastic. Furthermore, let $t_0^i$ represent the time of the $i$-th announcement containing information related to either $FXA$ or $FXB$, or both. To study the effects of announcements on the FX rate in a high-frequency setting, we extract each news release with a window with width $\Delta t$ of up to six hours before and after the release point $t_0^i$ and define the subset of $\{R\}_{t=1}^{T}$ within this window $[t_0^i - \Delta t; t_0^i + \Delta t]$ as $\{R\}_i = \{R\}_{t=t_0^i-\Delta t}^{t_0^i+\Delta t}$. We also implement our analysis in an event-time setting to compare and evaluate the robustness of our results. We assess the sensitivity of our findings to the measurement grid, in which case we consider a window of up to $j$ observations before and after the announcement, and we use the notation $[t_{0-j}^i; t_{0+j}^i]$ to define a data set consisting of two series plus minus $j$ observations since the release. Also, in order to be able to make comparisons across time and currency rates, we normalise the series of $\{R\}_i$ such that $R_{t_0^i} \equiv 1$ for all release points $i = 1, ..., n$. Figure 4.1 illustrates an example of the EUR/GBP rate, comparing all $\{R\}_i$ with respect to their corresponding news release points $t_0^i$ and also showing the obtained (gross) return distribution at $t_0^i - 3h$ (top left panel) and $t_0^i + 3h$ (top right panel). In subsequent sections, return distributions always refers to the normalised exchange rate series.

### 4.2.1 Probability Metrics

Probability distances allow us to quantify differences between two random variable distributions. In this chapter, we focus on Kantorovich and Lévy quasi-semi distances and their corresponding dual values (the value obtained by swapping the arguments $X$ and $Y$ when computing the distance). Quasi-semidistances are an extension of the common probability semidistances and allow us to assess the

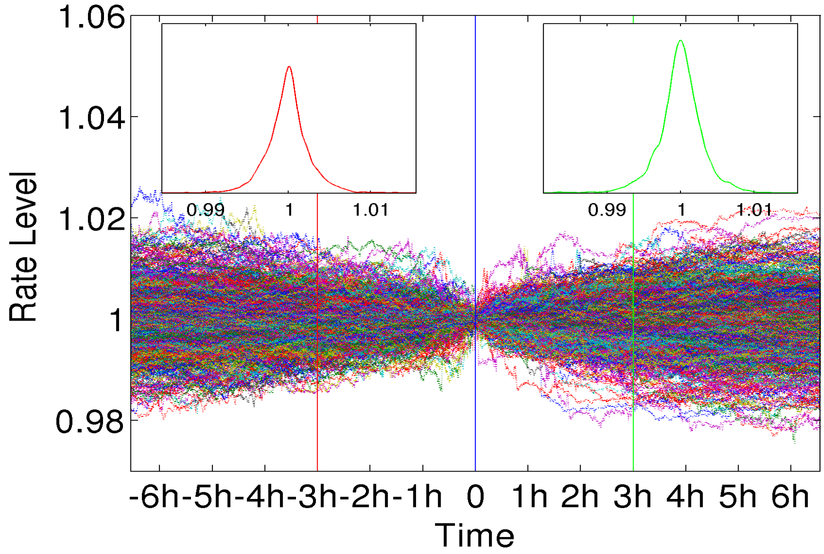


Figure 4.1: Subsets of EUR/GBP rates rescaled to 1 at news release point and the corresponding kernel densities of returns 3 hours before ($t_0^i - 3h$, top left panel) and after ($t_0^i + 3h$, top right panel) the announcement for all publicly available indicators originating from Europe and Great Britain. Sampling frequency is 5 seconds.

degree of violation of the stochastic dominance relation. In addition, we also focus on the difference between the quasi-semi distance and its dual.

Let $X$ and $Y$ denote the normalised FX rate at $t_0^i - \Delta t$ and $t_0^i + \Delta t$, respectively. $F_X$ and $F_Y$ represents their corresponding cumulative distribution functions (CDF). Technically, Kantorovich quasi-semi distance allows us to measure the area of by how much one CDF overlaps with another one. The distance $\kappa$ and its dual $\kappa_D$ are defined as (e.g. Rachev et al., 2011, p. 329):

$$\kappa(X,Y) = \int_{\mathbb{R}} \left(F_Y(x) - F_X(x)\right)_+ dx \tag{4.1}$$

$$\kappa_D(X,Y) = \kappa(Y,X) \tag{4.2}$$

describing the positive area between the CDFs of $X$ and $Y$ (see Figure 4.2, bottom panels). To obtain the estimates of the distances, we use empirical distribution functions $N$ being the number of observations in the sample $x$, later defined as:

$$\hat{F}(x) = \frac{1}{N} \sum_{i=1}^{N} \mathbf{1}(X_i \leq x) \ . \tag{4.3}$$

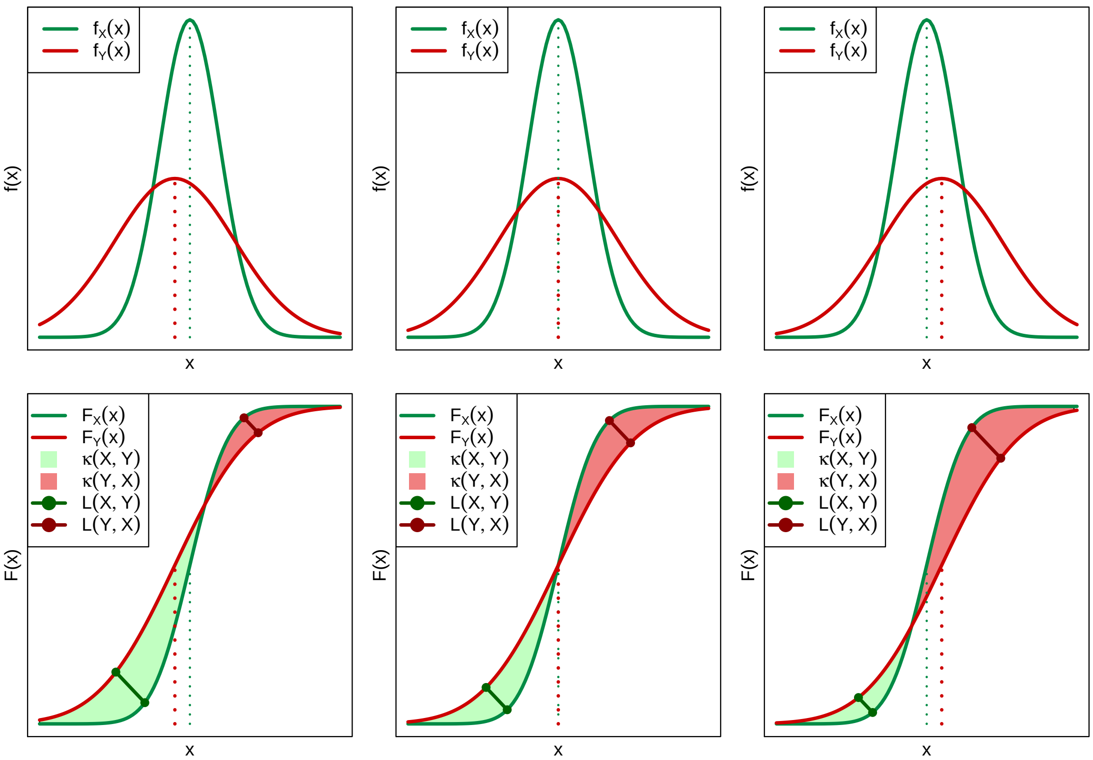


Figure 4.2: Illustrations of the quasi-semidistances ($\kappa\,(X,Y)$ and $L(X,Y)$) and their duals ($\kappa\,(Y,X)$ and $L(Y,X)$) resulting from different comparisons of $F_X$ and $F_Y$ with $Var(X) < Var(Y)$ where: $E(X) > E(Y)$ (left), $E(X) = E(Y)$ (centre), or $E(X) < E(Y)$ (right). .

For illustration, consider two financial return distributions $F_X$ and $F_Y$ where $Var(X) < Var(Y)$ (see Figure 4.2). If $E(X) > E(Y)$ (left panels), the value of Kantorovich quasi-semidistance $\kappa\,(X,Y)$ is greater than its dual $\kappa_D$ and we have $\Delta\kappa > 0$. $\Delta\kappa$ is defined as a difference between the metric and its dual. Similarly, for the scenarios $E(X) = E(Y)$ (middle panels) and $E(X) < E(Y)$ (right panels), we obtain $\Delta\kappa = 0$ and $\Delta\kappa < 0$, respectively. The quasi-semi distance can be interpreted as the expected value of the difference between two distributions as it is a probability weighted area. Therefore by taking a difference between the dual and its quasi-semi distance we obtain the value proportional to the expected absolute value difference between two outcomes.

The second quasi-semi distance we consider in this chapter is the Lévy quasi-semi distance defined as (Rachev et al., 2011, p. 315):

$$\begin{aligned} L_\lambda(X,Y) &= \sup_{x\epsilon\mathbb{R}}\inf_{y\epsilon\mathbb{R}} \max\left[\frac{1}{\lambda}|x-y|, (F_X(x)-F_Y(y))_+\right] \qquad (4.4) \\ &= \inf\left\{\epsilon>0 : (F_X(x)-F_Y(x+\lambda\epsilon))_+ < \epsilon, \forall x\in\mathbb{R}\right\} \\ L_{D,\lambda}(X,Y) &= L_\lambda(Y,X) \qquad (4.5) \end{aligned}$$

where in our application the parameter $\lambda$ is set to 1 as discussed by Rachev et al. (2011), in which case we are measuring the maximum distance obtained between two CDFs on the 45° line (see Figure 4.2, bottom panels).

Lèvy distance is used as an alternative measure to Kantorovich distance. As mentioned above, we focus on the differences of the metric and its dual. Lèvy metric allows to quantify the effect of news release on the asymmetry of the distribution, that could be otherwise overlooked by $\Delta\kappa$. For example, let $X$ follow a $\mathcal{N}(\mu,\sigma^2)$ distribution while $Y$ has a $\chi^2$ distribution with the same expected value as $X$. $\Delta\kappa$ would indicate that both financial asset distributions are identical, however $\Delta L$ would indicate them to be different with respect to symmetry as the distance along the 45° line is not the same of the metric and the dual while the area is. As a results, Lèvy distance allows to quantify effects on the asymmetry of the distribution, namely the skewness. Kantorovich distance allows to quantify effects on the mass of the difference, namely the variance and kurtosis.

To measure the statistical significance of the estimated probability metrics, we adapt ideas by Davidson and Duclosb (2013) to obtain distributions of the metric, dual and their difference, similar to approaches of Berrenderoa and Cárcamoa (2011) and Barrett and Donald (2003). To achieve that, we propose a combined bootstrapping algorithm that is applied by the authors that we augment with an inner loop to account for our observed limitations of points estimates (the averaging out of the value around the point of interest). The overall bootstrap procedure to obtain empirical estimates is outlined in Algorithm 1. For more details, we refer the reader to the original works of Davidson and Duclosb (2013), Berrenderoa and Cárcamoa (2011) and Barrett and Donald (2003).

**Algorithm 1:** Bootstrap procedure

**Data**: Transformed data of the exchange rate pair of interest.

**Result**: The empirical value and the $p$-value of the metric, its dual and the difference $\bar{M}_\tau, \bar{M}_{D,\tau}, \Delta\bar{M}_\tau$, for $M \in \{\kappa, L\}$. For calendar time application $\tau \in \{5min, 10min, 30min, 1h, 3h, 6h\}$ while for event time $\tau \in \{500, 2500, 5000, 10000, 15000, 20000\}$ data points before and after the release.

**for** *each* $\tau$ **do**
- **for** *each* $t \in \{\tau * 0.975, ..., \tau * 1.025\}$ **do**
  - Estimate the empirical quasi-semi distance, the dual and the difference between two (corresponding to variables $M_t^{emp}, M_{D,t}^{emp}, \Delta M_t^{emp}$) of the metric for $X$ and $Y$;
  - Combine $X$ and $Y$ to form the set $Z$;
  - **for** *number of iterations* $i = 1$ **to** 1000 **do**
    - Draw samples $\dot{X}$ and $\dot{Y}$ from the set $Z$ with replacement;
    - Calculate the quasi-semi distance, its dual and their difference (corresponding to variables $M_t^{sim}, M_{D,t}^{sim}, \Delta M_t^{sim}$) for $\dot{X}$ and $\dot{Y}$; (see also Davidson and Duclosb, 2013)
  - **end**
  - Obtain probabilities of the quasi-semi distance, its dual and their difference as $prob_t^M = \frac{1}{1000} \sum_{i=1}^{1000} \mathbf{1}\left(M_t^{emp} \leq M_t^{sim}\right)$
- **end**
- Obtain $\overline{prob_\tau^M} = \frac{1}{length(t)} \sum_t prob_t^M$;
- Obtain $\overline{M}_\tau = \frac{1}{length(t)} \sum_t M_t$;

**end**

Obtain $p$-value of a two-side test where under the null estimate is equal to zero for each $\tau$ of $M_\tau, M_{D,\tau}, \Delta M_\tau$ as $p = \overline{prob_\tau^M} * 2$ if $\overline{prob_\tau^M} \leq 0.5$ else $p = (1 - \overline{prob_\tau^M}) * 2$ ;

Estimates obtain from selected $\Delta t$ values can introduce a problem of a high-frequency noise due to data being irregularly spaced in physical time, with possibly delayed time-stamping of announcements and subsequent reactions. To account for the noise effect, we consider data points approximately $\pm 5\%$ (of $\Delta t$, or number of events) around the time point of interest. For example, if we are interested in the effect of a news announcement on a FX rate at $\Delta t = 60$ minutes after its release, we would consider all time points of interest in the window $[t_i + 58.5min; t_i + 61.5min]$. The event-time analysis is adjusted in similar structure. The effect of the high-frequency noise on measurement values is illustrated in Figure 4.3, where the blue line represents the metric at the precise point of interest while red shows the smoothed value as calculated in Algorithm 1. Algorithm 1 variables are defined as follows: $\tau$ defines the time point of interest (i.e. 1 hour after the release); $t$ indicates all time points of interest around $\tau$ (i.e. time points in a range from 58.5 to 61.5 minutes) increased till the next available observation point (i.e. if we start with a point of 58.5 and a point of 58.6 is not available then we move to the next available one of 58.7); $M_t^{emp}, M_{D,t}^{emp}, \Delta M_t^{emp}$ defines corresponding metrics obtained by using only the data for a time point $t$; $M_t^{sim}, M_{D,t}^{sim}, \Delta M_t^{sim}$ defines corresponding metrics obtained by using a perturbated data for a time point $t$; $p$-values are computed for a two-side test with a $H_0$ being of the estimated parameter being equal to zero. The outlined local perturbations allows to account for the sensitivity of results and improves the robustness of the analysis (comparison of red and green lines). To our best knowledge, this aspect of measurement noise has not been addressed in the literature so far. If ignored, the starting point and the step size of the time grid imposed on the raw data would cause a substantial influence on estimated metrics.

To account for the increasing variance as we move to higher $\Delta t$ values when using proposed probability metrics, we consistently scale them down by $\sqrt{\Delta t}$ (we will see later that the estimated $\alpha_{pre,post}$ parameters of the scaling law proposed in Section 4.2.3.1 and results in Section 4.3.3.1 are close to the values expected from a random walk) Figure 4.3 presents an example of the smoothed, scaled and unscaled metric values (red, green and blue lines correspondingly). The unscaled metric value increases as we move to higher $\Delta t$ since the release, but the scaled metric displays a stable level irrespective of the $\Delta t$ value.

### 4.2.2 Hypothesis Tests

News releases have been documented to cause a statistically significant impact on the exchange rate dynamics in the existing literature (Laakkonen and Lanne, 2013; Fatum et al., 2012; Evans and Speight, 2010a; Andersen et al., 2003). In this chapter, we evaluate the impact news caused on the exchange rate dynamics

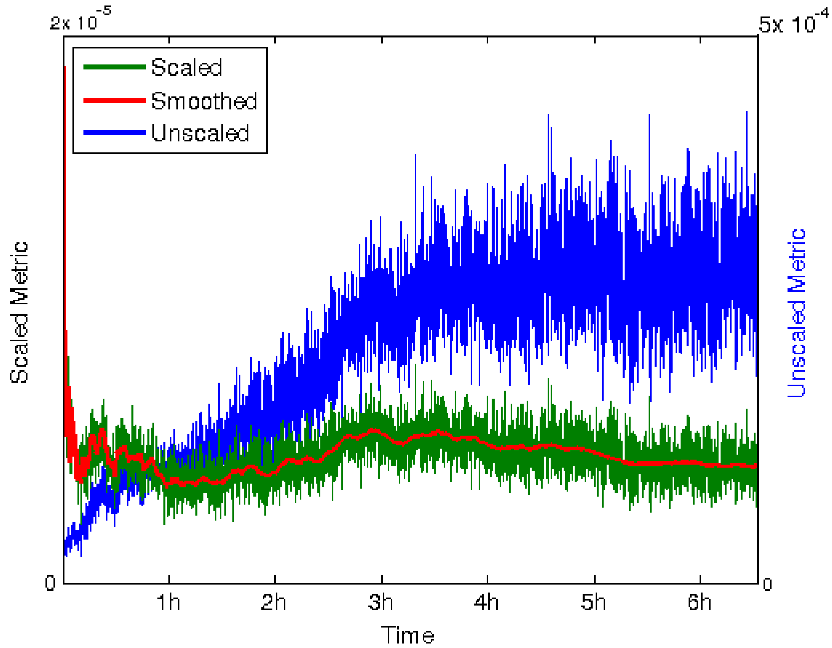


Figure 4.3: This figure shows the unscaled, scaled and smoothed Kantorovich metric obtained by comparing post-release returns of the EUR/GBP pair quote economy news to a theoretical normal distribution for a randomly selected one European news release. The blue line indicates the unscaled Kantorovich metric, green line represents the scaled and the red line displays the smoothed metric. Smoothening is implemented as shown in Algorithm 1 to account for the increasing measurement noise over time.

in a model-free setting in three ways, by measuring the effect on the post-release return distribution, and comparing it to the pre-release return distribution at the corresponding $\Delta t$ (and $j$) time grid. A normally distributed $\mathcal{N}(0, \sigma^2_{t_0^i \pm \Delta t})$ (and $\mathcal{N}(0, \sigma^2_{t^i_{0\pm j}})$ in event time) represents the null model of a zero information state. The choice of the density used for simulations does not affect results as long as it is symmetric. Put simply, the pre-release effect on FX rates at $t_0^i - \Delta t$ is measured by comparing it against a $\mathcal{N}(0, \hat{\sigma^2}_{t_0^i - \Delta t})$ distribution; similarly, the effect due to the presence of news release is measured by comparing the empirical rates observed at $t_0^i - \Delta t$ against a $\mathcal{N}(0, \hat{\sigma^2}_{t_0^i + \Delta t})$ distribution. The following research hypotheses are tackled by investigating the results of the selected quasi-semidistances:

**4.1** "*News announcements cause no effect on the post-release ($t_0^i + \Delta t$ or $t^i_{0+j}$) exchange rate dynamics when compared to a state with no information.*"

This hypothesis follows ideas behind the works of Laakkonen and Lanne

(2013), Evans and Speight (2010a), Andersen et al. (2003) and others, and is aiming to test the effect of news on the post-release ($t_0^i + \Delta t$ or $t_0^i + j$) FX rates as commonly studied in the literature. A symmetric zero mean normally distributed variate with the empirical sample volatility $\sigma_{t_0^i+\Delta t}$ or $\sigma_{t_{0+j}^i}$ is used to represent the case corresponding to a time-series model using a dummy variate taking value of 1 at the $\Delta t$ time point and 0 otherwise to capture the news release effect. In the dummy variable case, the effect is assumed to be zero mean normally distributed under the $H_0$ hypothesis. The average quantified effect is depicted as the average vertical difference between points C and B in Figure 4.4 (across all releases).

**4.2** "*Expected news releases cause no effect on the pre-release ($t_0^i - \Delta t$ or $t_{0-j}^i$) FX rates when compared to a state with no information.*" It is natural to expect market agents to react and take financial actions before the scheduled news release. To measure the strength of the anticipation effect, we compare a normally distributed variable with the pre-release FX rates at time $t_0^i - \Delta t$ (or $t_{0-j}^i$), in a similar way as in Hypothesis 4.1. The hypothesis measures the average vertical difference between points A and B in Figure 4.4 versus the zero mean Gaussian density as done in Hypothesis 4.1. The idea behind the hypothesis has been inspired by Evans and Speight (2010a), but their results showed a reaction only to several of the macroeconomic indicator considered.

**4.3** "*News cause no effect on the post-release ($t_0^i + \Delta t$ or $t_{0+j}^i$) FX rates when compared to the pre-release ($t_0^i - \Delta t$ or $t_{0-j}^i$) if the effect of the news anticipation is accounted for.*" We extend the idea of Hypothesis 4.2 and measure the true effect caused by the new information release by comparing the pre-release return distribution at $t_0^i + \Delta t$ (or $t_{0+j}^i$) against the post-release distribution at $t_0^i - \Delta t$ (or $t_{0-j}^i$) rates (instead of comparing to the zero mean Gaussian density as commonly done in the existing literature and Hypothesis 4.1). The effect measured compares the average vertical difference

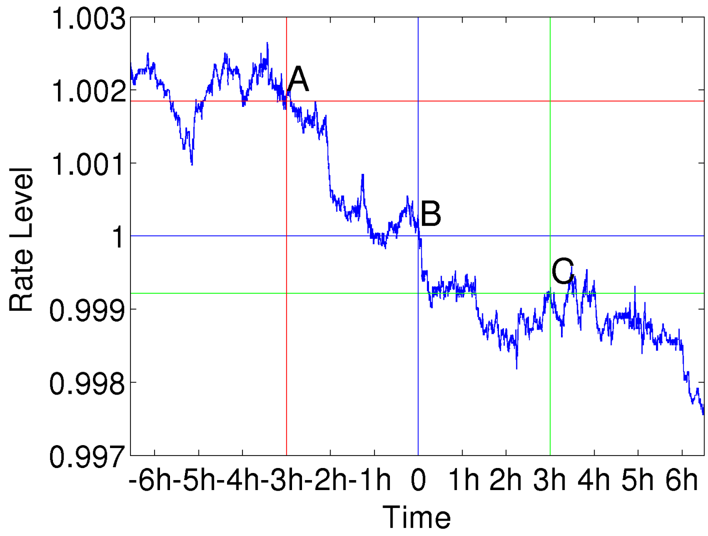


Figure 4.4: A selected EUR/GBP rate path to illustrate the tested effects in our hypotheses.

between points A to B and B to C in Figure 4.4.

To summarise, by testing these hypotheses we are able to separate the true nature of the news shock instead of looking at confounded effects as reported in the literature (e.g. Laakkonen and Lanne, 2013; Fatum et al., 2012; Andersen et al., 2003; Laakkonen, 2013, and others).

### 4.2.3 Benchmark Approaches

In this section, we briefly discuss the alternative approaches used. We first introduce the scaling laws method to capture news effect on the volatility (Section 4.2.3.1) and then the stochastic dominance tests to compare the pre- and post-release returns distributions (Section4.2.3.2).

#### 4.2.3.1 Scaling Volatility

A common approach in the literature, especially mathematical finance and econophysics, is to measure the volatility as a function of time using the scaling law method (e.g. Glattfelder et al., 2011). In the most prominent example of the random walk often used as the null model, it is well-known that the standard deviation of the process is proportional to the square root of time. In a similar spirit as done by Ormerod and Mounfield (2001), Savoiu (2013, p. 49-66), we apply a volatility scaling law to use as a first method for robustness analysis, to measure the impact of news on the variance of FX returns. The scaling law approach allows to aggregate vast amounts of information to a compact and simple to represent relations between variables of interest. In our case we are able to represent the relation between the volatility levels and time since the release. The major drawback of the approach for the problem we study, when compared to selected probability metrics features, is the averaging of the impact that prevents us from uncovering the effect of news releases at precise $\Delta t$ values.

Let $\tau \in \{t_0^i - \Delta t; t_0^i + \Delta t\}$ denote a certain point in time before or after the news release and $\sigma_\tau$ the standard deviation of the return distribution at time $\tau$. To quantify the influence of news on the volatility of the exchange rate dynamics, we estimate the following scaling law $\sigma_\tau = A\tau^{\alpha_{pre,post}}$ as:

$$\log(\sigma_\tau) = \log(A) + \alpha_{pre,post} \log(\tau)$$

(see also Bouchaud, 2001, 2002). The estimated volatility will be utilised in our hypothesis tests described above in Section 4.2.2.

The application of the scaling law to the pre-release FX rates $(t_0^i - \Delta t)$ and (separately) to the post-release rates $(t_0^i + \Delta t)$ allows us to compare the estimated scaling parameter $\alpha$ and test the hypothesis $H_0 : \alpha_{pre} = \alpha_{post}$. In the empirical section, we will choose $\tau \in \{t_0^i + 5secs, t_0^i + 10secs, t_0^i + 15secs, ..., t_0^i + 6hours,\}$ to estimate $\alpha_{post}$, and $\tau \in \{t_0^i - 5secs, t_0^i - 10secs, t_0^i - 15secs, ..., t_0^i - 6hours,\}$ to estimate $\alpha_{pre}$. Similarly, the corresponding event time setting we consider $\tau_j \in \{t_5^i, t_{10}^i, t_{15}^i, ..., t_{20000}^i\}$ and $\tau_j \in \{t_{-5}^i, t_{-10}^i, t_{-15}^i, ..., t_{-20000}^i\}$ accordingly. The raw data in this chapter consists of unique new ticks with a timestamp accuracy of seconds. As a result, by imposing the structure of matching seconds-to-ticks, we expect to observe findings to be similar in the event and calendar time measured on 5 second and 5 ticks grids respectively, if market remains highly liquid (one or more unique ticks per second) for the whole period of interest.

Previous studies by Laakkonen (2013), Laakkonen and Lanne (2013) and Fatum et al. (2012) suggested higher volatility levels in the post-release period ($t_0^i + \Delta t$ or $t_{0+j}^i$). We expect the following relation to hold between the selected probability distances in Section 4.2.1 and the proposed scaling law: if the difference of the estimated $\alpha_{pre}$ and $\alpha_{post}$ parameters is statistically significant, then the volatility at higher $\Delta t$ or $j$ values before or after the release point should lead to higher Kantorovich metric values (while the difference between the metric and the dual would be insignificant).

#### 4.2.3.2 Stochastic Dominance Tests

Stochastic dominance is a well-established concept that allows us to quantify the difference between two distributions of interest and is commonly used in income inequality (Davidson and Duclos, 2000) or financial studies (Leana et al., 2010; Meskarian et al., 2012; Olmoa and Sanso-Navarro, 2012; Dupacová and Kopa, 2014). In this chapter, stochastic dominance tests are used to quantify the impact of news on the post-release returns when compared to the pre-release returns. Relations between certain probability distances and stochastic dominance orders exist (for details, see Rachev et al., 2011). Stochastic dominance tests are used as a benchmark approach to compare to results of the probability metrics. In addition, to establish a second order dominance we would first need to test and remove the possibility of the first order dominance, resulting in a loss of the power of the test. Let the random variables $X$ and $Y$ represent the return on two risky investment strategies with $E(X) \geq E(Y)$ and $Var(X) = Var(Y)$. If an investor does not prefer strategy $Y$ to strategy $X$, $X$ is said to dominate $Y$ with respect to the first-order stochastic dominance (FSD), $X \succeq_{FSD} Y$, in which case we would have $F_X(x) \leq F_Y(x)$, $\forall x \in \mathbb{R}$ (for an illustration see Figure 4.5, left panels). However, if $E(X) = E(Y)$ and $Var(X) \leq Var(Y)$ such that a risk-averse investor does not prefer $Y$ to $X$, then $X$ dominates $Y$ in terms of the second-order stochastic

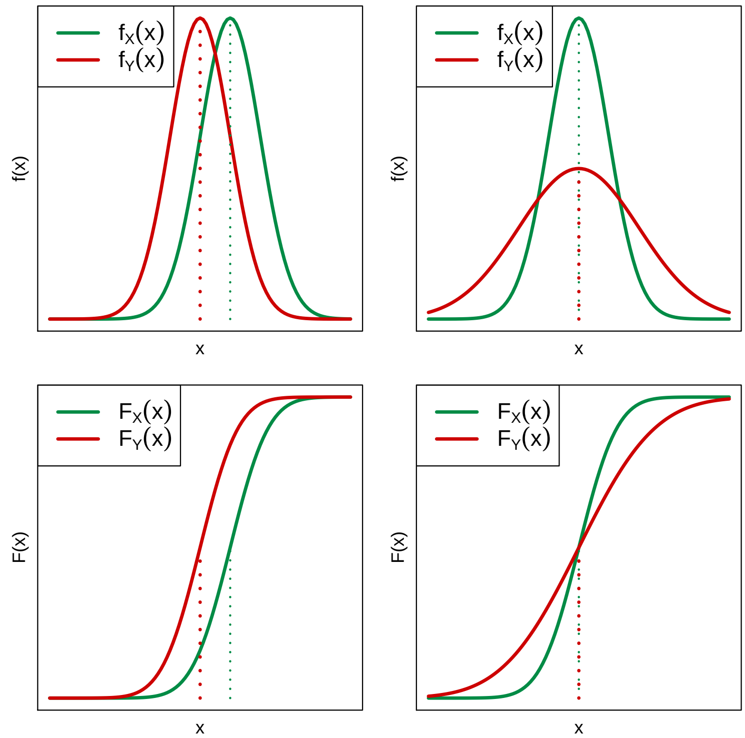


Figure 4.5: Illustration of the concepts of first order stochastic dominance (FSD, left panels) and second order stochastic dominance (SSD, right panels) for two distributions $F_X$ and $F_Y$ (the dotted lines indicate the positions of their respective means).

dominance (SSD), $X \succeq_{SSD} Y$, which is equivalent to:

$$\int_{-\infty}^{x} F_X(z)dz \leq \int_{-\infty}^{x} F_Y(z)dz \qquad \forall x \in \mathbb{R}$$

(see Figure 4.5, right panels).

As mentioned above, $X$ and $Y$ correspond to returns distributions at $t_0^i - \Delta t$ and $t_0^i + \Delta t$, respectively, and $F_X$ and $F_Y$ denote their corresponding cumulative distribution functions (for an illustration of their probability densities, $\Delta t = 3h$, see Figure 4.1). In particular, we focus on testing the stochastic dominance of the first and second orders of $X$ and $Y$. For example, if news releases generally have a positive impact on the FX rate after the announcement, then we expect $Y \succeq_{FSD} X$. Similarly, if news releases tend to depreciate the FX rate, then we expect the relation $X \succeq_{FSD} Y$ to hold. If, however, the FX rate after the announcement is at similar level as in the pre-release but has a lower volatility, then we would expect $Y \succeq_{SSD} X$; vice versa, if the FX rate is generally more stable before the announcement, but tends to fluctuate radically afterwards, then we would have $X \succeq_{SSD} Y$. The main hypothesis of interest is: $H_0 : F_X \preceq_{FSD,SSD} F_Y$.

Existing literature (e.g Fatum et al., 2012) reports that news releases tend to cause a substantial impact on the exchange rate dynamics. It must be noted that the null hypothesis allows both random variables to be equal (Davidson and Duclosb, 2013). Therefore, we also consider a reversed version of the test ($H_0 : F_Y \preceq_{FSD,SSD} F_X$) to establish if two variables are equal. In a trading context, the latter would help the investor to identify whether reversing the trading strategy (e.g. volatility arbitrage, speculating on the anticipation effect) yields a higher profit. Additionally, the comparison of a number of simultaneous rejections of the null hypothesis in the main and reversed tests, allows to assess the robustness of tests in our application.

To implement the test of the first order dominance, we follow the methodology of Barrett and Donald (2003). The second order stochastic dominance is tested following the approach by Berrenderoa and Cárcamoa (2011). Davidson and Duclosb (2013), indicated that the choice of methodology of the first order test has no impact on results, as test statistics follow a standard normal distribution. Tests of higher order than the first order dominance rely on numerical methods to obtain probability values. The second order dominance tests relies on bootstrapping tests statistics. Therefore, we use the generalized approach by Barrett and Donald (2003) to test the second order dominance (below referred to as the main test) and verify results with the methodology of Berrenderoa and Cárcamoa (2011) (below referred as the alternative test).

We are able to establish a relation between the proposed scaling law and stochastic dominance tests results as follows: if the scaling parameter $\alpha_{t_0^i-\Delta t} < \alpha_{t_0^i+\Delta t}$ ($\alpha_{t_0^i-\Delta t}$ and $\alpha_{t_0^i+\Delta t}$ corresponding to $\alpha_{pre}$ and $\alpha_{post}$) and is statistically significant, then as $\Delta t$ increases the difference between the volatility of the $t_0^i - \Delta t$ and $t_0^i + \Delta t$ will increase as well, leading to the second order stochastic dominance of the pre-release exchange rates over the post-release rates (assuming both outcomes have the same expected value as illustrated in Figure 4.2 in Section 4.2.1, middle plot). This relation allows to compare results from all three methods used in this chapter.

## 4.3 Results

We study scheduled macroeconomics news releases on five major foreign exchange rate pairs (EUR/USD, EUR/JPY, EUR/GBP, GBP/USD and USD/JPY). Public releases from the Eurozone, Japan, U.S and Great Britain are considered in the period from 2007 to 2012. We implement the study on the high-frequency time frame of 5 seconds for calendar time and 5 ticks grid for event time. We use two different time transformations to measure the sensitivity of our results depending on the chosen time grid. We first discuss the results of the application of the proposed probability metric in Section 4.3.1 and then test our research hypotheses in Section 4.3.2. Metrics are only compared at symmetric time points $\pm\Delta t$ or $\pm j$. It is assumed that responses are symmetric in nature to maintain the thesis tractable and implementable given time constrains and available resources.

### 4.3.1 Probability Metric Bootstrap

Table 4.3.1 presents Kantorovich metrics obtained by comparing the post-release $(t_0^i + \Delta t)$ and pre-release $(t_0^i - \Delta t)$ FX rates in calendar time. The metric, its dual, their difference and corresponding $p$-values are bootstrapped for each $\Delta t$ time value and averaged values are presented. Values in bold indicate statistically significant results at 5% significance level as otherwise bootstrap numeric standard errors would be dominating obtained estimates.

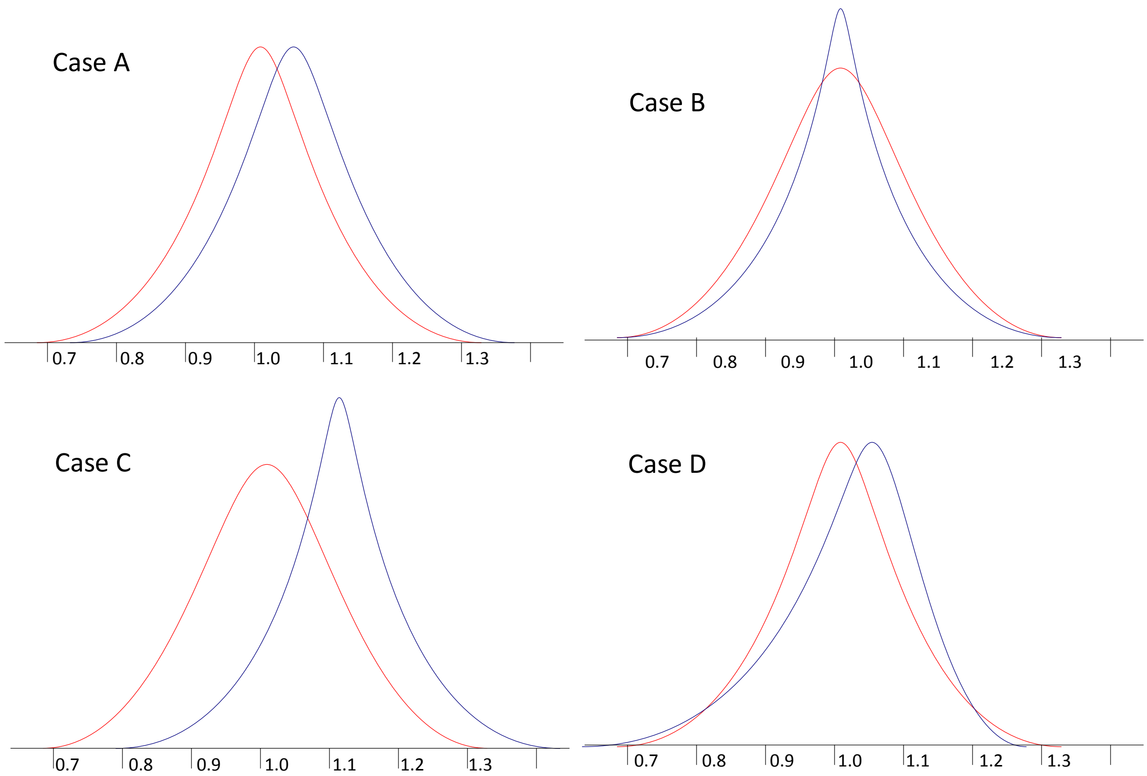


Figure 4.6: Example cases for the probability metric interpretation. Case A: Same variances but different means; Case B: Same means but different variances; Case C: Different mean and variance levels; Case D: Same means and variances but different skewness levels

We interpret Kantorovich metric results with the following reasoning: values of Kantorovich metric difference being significantly different from zero indicate a difference in the means of the two FX return distributions (as presented in Case A in Figure 4.6). On the other hand, if Kantorovich metric and its dual difference is not different from zero but individual components are, then one sample has a higher volatility than the other, implying SSD (as presented in Case B in Figure 4.6). For example, Table 4.3.1 shows that for the base economy of the USD/JPY FX rate the metric and dual have statistically significant values at 1 hour time window, but the difference between the two is not significant. Therefore, we are able to conclude that at 1 hour mark after and before the release, the volatility level is not equal when the USD/JPY pair base economy news are released. Lèvy metric results in Table 4.3.2 show an effect on the asymmetry of two returns distribution.

A significant Lèvy metric difference identifies an effect on the asymmetry between two outcomes compared (as presented in Case C in Figure 4.6). However, only a combination of Kantrovich and Lèvy results allows to distinguish the effect on the asymmetry. A comparison of Case C and Case D only based on Lèvy results in Figure 4.6 would yield indistinguishable results. A similar outcome would be observed when comparing Case B and Case D in Figure 4.6 based on Kantorovich metric results. The USD/JPY pair base economy news at 1 hour before and after the release have a difference in the asymmetry, because Lèvy metric value is significant, but neither the dual nor the difference is statistically significant. It must be noted, that the effect on asymmetry is not strong enough to cause an impact on means of two cases compared. As a result, Kantorovich metric difference is not statistically significant at 5% error level.

The existing literature (e.g. Laakkonen and Lanne, 2013; Fatum et al., 2012) has identified a strong response in the variance of only post-release data due to news releases. Calendar results in Table 4.3.1 and event time results in Table A.2.5 identify a presence of the effect, but do not display a consistent pattern across exchange rate pairs. We observe multiple news subsets in Kantorovich metric results where the metric and the dual is significant, and the difference between two is not (e.g. USD/JPY $1, 2, 3$ hours base news subset or GBP/USD $1, 2, 3$ hours quote news subset in Table 4.3.1). We argue that Lèvy metric results in Tables 4.3.2 and A.2.6 indicate that news cause an effect on the skewness or kurtosis in terms of extreme observations, because we only observe few cases of the metric difference to be statistically significant, and only for EUR/GBP pair in calendar time (Table 4.3.2). A higher number of statistically significant differences is observed for various FX pairs in event time (Table A.2.6). Therefore, we conclude that only a limited impact on the volatility level can be observed, due to news irrespective of the time transformation, contrary to the existing studies focusing only on the post-release returns in calendar time only (e.g Laakkonen, 2013; Laakkonen and Lanne, 2013; Fatum et al., 2012; Evans and Speight, 2010a).

However, we do observe an impact on the shape of the overall distribution function.

| | | Base | | | Quote | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\kappa$ | $\kappa_D$ | $\Delta\kappa$ | $\kappa$ | $\kappa_D$ | $\Delta\kappa$ |
| USD/JPY | 5min | **0.413** | 0.053 | **0.360** | **0.103** | 0.158 | -0.054 |
| | 10min | **0.123** | 0.078 | 0.046 | **0.382** | 0.037 | **0.345** |
| | 30min | 0.269 | **0.268** | 0.001 | **0.506** | **0.101** | 0.405 |
| | 1h | **0.335** | **0.363** | -0.029 | **0.888** | 0.071 | **0.818** |
| | 3h | **0.789** | **0.964** | -0.180 | **1.103** | 0.042 | **1.061** |
| | 6h | **0.825** | **0.972** | -0.147 | **0.825** | 0.059 | **0.766** |
| GBP/USD | 5min | **0.255** | 0.387 | -0.131 | **0.100** | 0.316 | -0.216 |
| | 10min | 0.070 | **0.492** | -0.422 | 0.052 | 0.257 | -0.204 |
| | 30min | 0.059 | 0.271 | -0.212 | 0.110 | **0.244** | -0.134 |
| | 1h | **0.291** | 0.178 | 0.113 | **0.290** | **0.369** | -0.078 |
| | 3h | **0.810** | 0.207 | **0.601** | **0.650** | **0.874** | -0.229 |
| | 6h | **0.688** | 0.009 | **0.679** | **0.784** | **1.106** | -0.321 |
| GBP/JPY | 5min | **0.512** | 0.379 | 0.133 | **0.163** | 0.193 | -0.030 |
| | 10min | **0.265** | 0.143 | 0.122 | **0.446** | 0.067 | 0.379 |
| | 30min | 0.145 | **0.234** | -0.089 | 0.271 | **0.133** | 0.138 |
| | 1h | **0.308** | 0.058 | 0.251 | **0.909** | 0.047 | **0.862** |
| | 3h | **0.655** | 0.197 | 0.453 | **1.120** | 0.010 | **1.103** |
| | 6h | **0.742** | 0.006 | **0.736** | **1.210** | 0.225 | **0.985** |
| EUR/USD | 5min | **0.251** | 0.218 | 0.033 | **0.242** | **0.358** | -0.115 |
| | 10min | **0.155** | 0.063 | 0.092 | **0.085** | 0.189 | -0.104 |
| | 30min | 0.210 | **0.031** | 0.179 | 0.280 | **0.110** | 0.171 |
| | 1h | **0.361** | 0.030 | **0.330** | **0.342** | 0.267 | 0.075 |
| | 3h | **0.328** | 0.021 | 0.302 | **0.804** | **0.864** | -0.065 |
| | 6h | **0.528** | 0.188 | **0.340** | **0.872** | **0.861** | 0.012 |
| EUR/JPY | 5min | **0.329** | 0.457 | -0.128 | **0.135** | 0.233 | -0.098 |
| | 10min | **0.181** | 0.185 | -0.004 | **0.132** | 0.207 | -0.076 |
| | 30min | 0.257 | **0.062** | 0.195 | 0.040 | 0.369 | -0.329 |
| | 1h | **0.492** | 0.018 | **0.474** | **0.661** | 0.121 | **0.540** |
| | 3h | **0.373** | 0.246 | 0.121 | **0.723** | 0.017 | **0.702** |
| | 6h | **0.619** | 0.266 | 0.354 | **0.775** | 0.195 | **0.580** |
| EUR/GBP | 5min | **0.410** | 0.023 | **0.387** | **0.230** | 0.130 | 0.100 |
| | 10min | **0.489** | 0.022 | **0.467** | **0.412** | **0.068** | **0.344** |
| | 30min | **0.376** | **0.030** | 0.347 | **0.620** | **0.044** | 0.576 |
| | 1h | **0.513** | 0.087 | **0.425** | **0.298** | 0.125 | 0.172 |
| | 3h | **0.387** | **0.508** | -0.119 | **0.436** | **0.717** | -0.277 |
| | 6h | **0.161** | 0.080 | 0.080 | **0.074** | **0.490** | -0.417 |

Table 4.3.1: Results of Kantorovich metric obtained by comparing the post-release $(t_0^i + \Delta t)$ and pre-release $(t_0^i - \Delta t)$ rate in calendar time. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the time gap before or after the release.

| | | Base | | | Quote | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $L$ | $L_D$ | $\Delta L$ | $L$ | $L_D$ | $\Delta L$ |
| USD/JPY | 5min | **15.470** | 54.422 | -38.952 | 11.790 | 70.051 | -58.261 |
| | 10min | 4.739 | 19.041 | -14.303 | 7.245 | 21.022 | -13.778 |
| | 30min | 10.379 | **7.220** | 3.158 | 5.281 | **7.301** | -2.020 |
| | 1h | **7.164** | 5.901 | 1.263 | **4.723** | 8.236 | -3.513 |
| | 3h | **9.424** | **8.258** | 1.188 | 1.809 | **9.791** | -8.023 |
| | 6h | **5.762** | **6.661** | -0.899 | 2.995 | 4.548 | -1.553 |
| GBP/USD | 5min | **28.714** | 44.714 | -16.000 | 20.587 | 16.164 | 4.423 |
| | 10min | 12.389 | 13.428 | -1.039 | 9.451 | 10.937 | -1.486 |
| | 30min | 6.712 | **3.277** | 3.435 | 3.862 | 7.476 | -3.614 |
| | 1h | 4.080 | 8.995 | -4.915 | 3.642 | 8.281 | -4.639 |
| | 3h | **2.839** | 5.949 | -3.081 | **7.290** | 5.587 | 1.654 |
| | 6h | 0.584 | 5.939 | -5.355 | **8.030** | **5.816** | 2.214 |
| GBP/JPY | 5min | **23.340** | 23.585 | -0.245 | **29.106** | 8.338 | 20.768 |
| | 10min | 11.081 | 16.783 | -5.703 | **14.201** | 9.391 | 4.810 |
| | 30min | 6.638 | **10.090** | -3.452 | 4.780 | 12.303 | -7.523 |
| | 1h | 3.875 | 9.698 | -5.823 | 2.949 | 7.798 | -4.849 |
| | 3h | **3.082** | 4.950 | -1.889 | 1.469 | 8.174 | -6.777 |
| | 6h | 1.631 | **8.572** | -6.940 | **4.968** | **8.307** | -3.338 |
| EUR/USD | 5min | 13.568 | 21.601 | -8.033 | **10.384** | 18.398 | -8.014 |
| | 10min | 11.968 | 9.164 | 2.804 | **14.082** | 5.034 | 9.048 |
| | 30min | 3.759 | 4.418 | -0.659 | 4.634 | 5.655 | -1.021 |
| | 1h | 4.025 | 4.334 | -0.309 | 3.659 | 5.286 | -1.627 |
| | 3h | 2.254 | 3.339 | -1.140 | **8.262** | **8.547** | -0.319 |
| | 6h | **4.216** | **6.564** | -2.349 | **7.908** | **6.096** | 1.812 |
| EUR/JPY | 5min | **29.307** | 23.407 | 5.900 | 17.028 | 25.583 | -8.555 |
| | 10min | 7.324 | 8.893 | -1.569 | **13.774** | 8.188 | 5.586 |
| | 30min | 4.720 | 7.061 | -2.341 | 6.776 | **6.014** | 0.762 |
| | 1h | 1.630 | 8.654 | -7.023 | 3.351 | 11.536 | -8.185 |
| | 3h | 1.607 | **7.654** | -6.046 | 1.420 | 9.115 | -7.714 |
| | 6h | 1.575 | **10.133** | -8.558 | 2.151 | 7.447 | -5.297 |
| EUR/GBP | 5min | 5.466 | 42.907 | -37.441 | 13.632 | 27.508 | -13.876 |
| | 10min | 17.135 | 16.072 | 1.063 | **14.260** | 13.760 | 0.500 |
| | 30min | 5.188 | 8.787 | -3.600 | 6.048 | **10.558** | -4.510 |
| | 1h | **9.097** | 4.141 | 4.956 | **9.169** | 4.865 | 4.304 |
| | 3h | **9.334** | 2.908 | **6.465** | **9.119** | 3.658 | **5.472** |
| | 6h | **3.863** | 1.695 | 2.168 | **6.591** | 0.899 | **5.692** |

Table 4.3.2: Results of the Lévy metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) rate in calendar time. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the time gap before or after the release.

### 4.3.2 Hypothesis Tests

To investigate our research hypotheses, we first focus on Kantorovich metric difference to infer the effect on the first moment; if it is found to be insignificant we focus on the metric and the dual significance, to infer the effect on the second moment (or variance and kurtosis if the metric and the dual are significant). To further investigate the effect on higher moments we move to Lèvy metric results where (a) significant differences show strong evidence of effects on asymmetry or (b) an insignificant difference but a significant metric and dual support Kantorovich metric results on the variance.

We start by focusing on Hypthesis 4.1 ("*News announcements cause no effect on the post-release* ($t_0^i + \Delta t$ *or* $t_0^i + j$) *exchange rate dynamics when compared to a state with no information.*"). To evaluate the evidence against the hypothesis, we focus on the difference between the metric and its dual of selected probability metrics that compare the post-release rates to the simulated Gaussian data in Tables 4.3.3, 4.3.4 with calendar results ( A.2.7, A.2.8 presents event time results). A similar hypothesis is investigated in the existing literature by Laakkonen and Lanne (2013), Fatum et al. (2012), Evans and Speight (2010a) and others. Calendar time results show a substantial reaction on the symmetry of the post-release exchange rates as Kantorovich metrics and duals in Table 4.3.3 are significant and similar in magnitude in many cases while the difference between the two is rarely significant. Similar to the existing literature, we observe an impact on the variance of the post-release returns when compared to the state of no information. Lèvy results show a limited impact on the mean return as the difference is rarely significant (see Table 4.3.4). On the other hand, event time results show a one-sided reaction where only the metric or the dual are significant (see Tables A.2.7 and A.2.8). We observe only a few cases where the difference between the two is significant, suggesting limited impact of news on the average post-release FX rate. *A priori*, we expected to observe no rejections of the null as news releases were not considered by the content. Therefore, on average, exchange rate dynamics before and after the release are expected to be equal with respect to the first moment. Kantorovich metric results show findings in favour of the hypothesis as the difference is rarely significant, but suggests reaction in the higher moments as the metric or the dual are significant. Further investigation of the individual metrics and duals as well as Lèvy metric results support the claim that most of the reaction is observed in the variance or higher moments of FX rate distributions that are compared. In general, we observe strong evidence against the hypothesis, and reaction is observable in the variance, if compared against the state of no information. To summarise, we observe similar findings to Laakkonen (2013); Laakkonen and Lanne (2013) when comparing the post-release returns to a state of no information.

| | | Base | | | Quote | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\kappa$ | $\kappa_D$ | $\Delta\kappa$ | $\kappa$ | $\kappa_D$ | $\Delta\kappa$ |
| USD/JPY | 5min | **0.962** | 0.640 | 0.322 | **0.728** | 0.492 | 0.236 |
| | 10min | **1.010** | **0.753** | 0.257 | **0.621** | 0.454 | 0.167 |
| | 30min | 0.764 | **0.607** | **0.157** | 1.118 | **0.911** | **0.207** |
| | 1h | **0.767** | **0.702** | 0.065 | **0.959** | 0.406 | 0.554 |
| | 3h | **0.672** | **0.669** | -0.002 | **0.808** | 0.268 | 0.541 |
| | 6h | **0.669** | **0.632** | 0.037 | **0.592** | 0.279 | 0.313 |
| GBP/USD | 5min | **0.932** | **0.842** | 0.091 | **0.814** | **0.967** | -0.153 |
| | 10min | **0.605** | **0.675** | -0.071 | **0.691** | **0.709** | -0.019 |
| | 30min | 0.697 | **0.576** | **0.121** | 0.679 | **0.770** | **-0.091** |
| | 1h | **0.730** | **0.630** | 0.100 | **0.812** | **0.882** | -0.070 |
| | 3h | **0.710** | 0.515 | 0.192 | **0.542** | **0.704** | -0.164 |
| | 6h | **0.636** | 0.446 | 0.190 | **0.441** | **0.689** | -0.249 |
| GBP/JPY | 5min | **1.276** | **1.167** | 0.110 | **1.123** | **1.006** | 0.117 |
| | 10min | **1.125** | 0.780 | 0.345 | **1.004** | **0.945** | 0.059 |
| | 30min | 1.014 | **0.681** | 0.333 | 1.299 | **1.133** | **0.166** |
| | 1h | **0.931** | 0.661 | 0.270 | **1.323** | 0.705 | 0.618 |
| | 3h | **0.950** | **0.789** | 0.155 | **1.074** | 0.643 | 0.431 |
| | 6h | **0.946** | 0.730 | 0.217 | **0.948** | 0.486 | 0.462 |
| EUR/USD | 5min | **0.675** | **0.757** | -0.082 | **0.741** | **0.818** | -0.077 |
| | 10min | **0.523** | **0.570** | -0.047 | **0.689** | **0.617** | 0.072 |
| | 30min | 0.504 | **0.480** | **0.024** | 0.669 | **0.510** | **0.158** |
| | 1h | **0.614** | 0.434 | 0.179 | **0.688** | **0.632** | 0.055 |
| | 3h | **0.522** | 0.434 | 0.085 | **0.499** | **0.531** | -0.034 |
| | 6h | **0.495** | 0.366 | 0.129 | **0.425** | **0.559** | -0.134 |
| EUR/JPY | 5min | **1.222** | **1.296** | -0.074 | **1.013** | 0.769 | 0.243 |
| | 10min | **1.133** | **1.212** | -0.079 | **0.840** | **0.819** | 0.021 |
| | 30min | 0.951 | **0.954** | **-0.003** | 0.993 | **1.103** | **-0.110** |
| | 1h | **1.078** | 0.804 | 0.274 | **0.983** | 0.661 | 0.322 |
| | 3h | **0.751** | **0.728** | 0.017 | **0.813** | 0.579 | 0.230 |
| | 6h | **0.819** | **0.732** | 0.087 | **0.684** | 0.447 | 0.237 |
| EUR/GBP | 5min | **0.807** | **0.650** | 0.157 | **0.848** | **0.744** | 0.105 |
| | 10min | **0.937** | **0.706** | 0.231 | **0.517** | **0.520** | -0.003 |
| | 30min | 0.837 | **0.594** | 0.243 | 0.488 | **0.420** | 0.068 |
| | 1h | **0.768** | 0.426 | 0.342 | **0.485** | **0.543** | -0.058 |
| | 3h | **0.452** | 0.315 | 0.133 | **0.498** | 0.433 | 0.065 |
| | 6h | **0.541** | 0.191 | 0.350 | **0.406** | **0.436** | -0.029 |

Table 4.3.3: Results of Kantorovich metric obtained by comparing the post-release ($t_0^i + \Delta t$) and simulated Gaussian ($\mathcal{N}(0, \sigma^2_{t_0^i+\Delta t})$) rates in calendar time. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i + \Delta t$ value used.

| | | Base | | | Quote | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $L$ | $L_D$ | $\Delta L$ | $L$ | $L_D$ | $\Delta L$ |
| USD/JPY | 5min | **52.159** | 24.815 | 27.344 | **81.770** | 13.905 | **67.866** |
| | 10min | **21.908** | 19.629 | 2.279 | **19.371** | 16.172 | 3.198 |
| | 30min | 13.138 | **11.205** | 1.933 | 6.128 | **7.002** | -0.874 |
| | 1h | **9.349** | **10.278** | -0.929 | **6.003** | 4.650 | 1.353 |
| | 3h | **7.764** | **10.866** | -3.121 | **3.626** | 7.866 | -4.272 |
| | 6h | **5.992** | **7.917** | -1.925 | **4.141** | 5.976 | -1.834 |
| GBP/USD | 5min | **43.998** | 19.376 | 24.622 | **51.495** | 31.642 | 19.853 |
| | 10min | **16.689** | 13.560 | 3.129 | **17.236** | **20.493** | -3.257 |
| | 30min | 13.420 | **13.260** | 0.160 | 10.481 | **16.306** | **-5.825** |
| | 1h | **9.556** | **16.303** | -6.748 | **11.127** | **16.190** | -5.062 |
| | 3h | **8.960** | 8.481 | 0.493 | **7.530** | **9.281** | -1.799 |
| | 6h | **4.862** | **7.074** | -2.212 | **7.581** | **7.867** | -0.286 |
| GBP/JPY | 5min | **30.414** | 33.348 | -2.934 | **31.075** | 15.593 | 15.482 |
| | 10min | **14.276** | 22.378 | -8.102 | **25.572** | 21.998 | 3.573 |
| | 30min | 12.490 | **17.692** | **-5.202** | 8.636 | **16.792** | -8.156 |
| | 1h | **9.122** | **16.372** | -7.251 | **10.023** | 14.726 | -4.703 |
| | 3h | **12.096** | 8.695 | 3.402 | **8.525** | 12.021 | -3.525 |
| | 6h | **6.812** | **11.127** | -4.315 | **7.012** | **10.050** | -3.038 |
| EUR/USD | 5min | **50.343** | 21.881 | 28.462 | **54.456** | 21.827 | 32.630 |
| | 10min | **16.001** | 14.585 | 1.416 | **16.469** | **22.187** | -5.718 |
| | 30min | 9.572 | **10.649** | -1.077 | 9.973 | **14.926** | **-4.953** |
| | 1h | **8.941** | 10.598 | -1.657 | **7.439** | **12.139** | -4.701 |
| | 3h | **7.279** | 6.798 | 0.490 | **6.038** | **6.581** | -0.606 |
| | 6h | **4.901** | **6.122** | -1.221 | **7.307** | 4.460 | 2.846 |
| EUR/JPY | 5min | **38.126** | 32.511 | 5.615 | **36.037** | 25.961 | 10.076 |
| | 10min | **17.678** | 20.532 | -2.854 | **23.250** | 15.271 | 7.979 |
| | 30min | 16.276 | **15.537** | 0.739 | 10.604 | **12.112** | -1.509 |
| | 1h | **11.244** | **14.529** | -3.285 | **10.350** | 10.108 | 0.243 |
| | 3h | **6.295** | **10.044** | -3.763 | **6.825** | 10.612 | -3.775 |
| | 6h | **5.595** | **9.470** | -3.875 | **5.245** | **8.973** | -3.728 |
| EUR/GBP | 5min | **60.736** | 24.710 | 36.026 | **63.662** | 17.399 | 46.263 |
| | 10min | **18.165** | 21.816 | -3.650 | **19.544** | 9.399 | 10.145 |
| | 30min | 9.647 | **18.332** | **-8.685** | 12.624 | **8.891** | 3.733 |
| | 1h | **10.466** | 12.017 | -1.552 | **14.536** | 6.032 | 8.504 |
| | 3h | **6.248** | 6.116 | 0.120 | **9.263** | 4.524 | 4.703 |
| | 6h | **5.178** | 5.468 | -0.290 | **7.349** | 4.200 | 3.149 |

Table 4.3.4: Results of Lèvy metric obtained by comparing the post-release ($t_0^i + \Delta t$) and simulated Gaussian ($\mathcal{N}(0, \sigma^2_{t_0^i+\Delta t})$) rates in calendar time. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i + \Delta t$ value used.

We move to the second hypothesis comparing simulated and empirical rates, and focus on Hypothesis 4.2 ("*News release presence causes no effect on the pre-release* ($t_0^i - \Delta t$ *or* $t_0^i - j$) *FX rates when compared to a state with no information.*"). The hypothesis has been tackled by Evans and Speight (2010a) where the pre-release reaction was observed on several indicators, but a general conclusion of no consistent pre-release impact (over all macroeconomic indicators considered) was drawn. Calendar time results in Tables 4.3.5, 4.3.6 and event time results in Tables A.2.9, A.2.10 show similar structure findings as in the previous hypothesis. Calendar time results indicate reaction mainly in the variance, and the kurtosis, of the pre-release exchange rates, while event time results show a substantial reaction on the asymmetry of the pre-release exchange rates. Therefore, we reject the null hypothesis, the pre-release reaction tends to be similar in magnitude to the post-release reaction and, contrary to Evans and Speight (2010a), we observe a consistent reaction to news before the release.

| | | Base | | | Quote | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\kappa$ | $\kappa_D$ | $\Delta\kappa$ | $\kappa$ | $\kappa_D$ | $\Delta\kappa$ |
| USD/JPY | 5min | **0.914** | **0.791** | 0.123 | **0.424** | **0.647** | -0.223 |
| | 10min | **0.646** | **0.817** | -0.172 | **0.590** | 0.420 | 0.169 |
| | 30min | 0.731 | **0.863** | **-0.132** | 0.557 | **0.287** | 0.270 |
| | 1h | **0.740** | **0.830** | -0.090 | **0.605** | 0.305 | 0.300 |
| | 3h | **0.573** | **0.747** | -0.175 | **0.787** | 0.268 | 0.518 |
| | 6h | **0.396** | **0.569** | -0.173 | **0.713** | 0.268 | 0.445 |
| GBP/USD | 5min | **0.403** | **0.596** | -0.194 | **0.657** | **0.748** | -0.091 |
| | 10min | **0.383** | **0.788** | -0.405 | **0.618** | **0.773** | -0.154 |
| | 30min | 0.359 | **0.721** | **-0.362** | 0.654 | **0.714** | **-0.059** |
| | 1h | **0.632** | **0.633** | -0.001 | **0.691** | **0.709** | -0.018 |
| | 3h | **0.746** | 0.349 | 0.393 | **0.600** | **0.654** | -0.056 |
| | 6h | **0.725** | 0.250 | 0.475 | **0.501** | **0.556** | -0.055 |
| GBP/JPY | 5min | **0.734** | **0.869** | -0.135 | **0.774** | **0.906** | -0.133 |
| | 10min | **0.701** | **0.943** | -0.242 | **0.916** | 0.702 | 0.214 |
| | 30min | 0.539 | **0.942** | **-0.403** | 0.754 | **0.788** | **-0.034** |
| | 1h | **0.777** | **0.811** | -0.035 | **0.876** | 0.670 | 0.206 |
| | 3h | **0.935** | 0.616 | 0.312 | **1.201** | 0.486 | 0.710 |
| | 6h | **0.966** | 0.426 | 0.540 | **0.936** | 0.390 | 0.546 |
| EUR/USD | 5min | **0.574** | 0.462 | 0.112 | **0.588** | **0.699** | -0.111 |
| | 10min | **0.559** | 0.467 | 0.092 | **0.592** | **0.773** | -0.181 |
| | 30min | 0.641 | **0.437** | 0.204 | 0.636 | **0.624** | **0.012** |
| | 1h | **0.569** | 0.413 | 0.156 | **0.580** | **0.578** | 0.002 |
| | 3h | **0.508** | 0.316 | 0.192 | **0.580** | **0.598** | -0.019 |
| | 6h | **0.423** | 0.218 | 0.205 | **0.522** | 0.392 | 0.130 |
| EUR/JPY | 5min | **0.825** | **0.878** | -0.053 | **0.600** | **0.929** | -0.330 |
| | 10min | **0.869** | **0.798** | 0.072 | **0.598** | **0.754** | -0.157 |
| | 30min | 0.884 | **0.713** | **0.171** | 0.505 | **0.743** | **-0.238** |
| | 1h | **1.047** | **0.850** | 0.197 | **0.853** | 0.610 | 0.243 |
| | 3h | **0.922** | **0.792** | 0.129 | **0.965** | 0.495 | 0.473 |
| | 6h | **0.855** | 0.633 | 0.222 | **0.769** | 0.427 | 0.342 |
| EUR/GBP | 5min | **0.837** | 0.504 | 0.333 | **0.517** | **0.525** | -0.008 |
| | 10min | **0.672** | 0.465 | 0.206 | **0.674** | 0.330 | 0.344 |
| | 30min | 0.646 | **0.497** | 0.149 | 0.796 | **0.318** | 0.478 |
| | 1h | **0.671** | **0.581** | 0.090 | **0.752** | 0.520 | 0.232 |
| | 3h | **0.350** | **0.626** | -0.276 | **0.353** | **0.693** | -0.338 |
| | 6h | **0.258** | **0.533** | -0.274 | **0.260** | **0.647** | -0.387 |

Table 4.3.5: Results of Kantorovich metric obtained by comparing the simulated Gaussian ($\mathcal{N}(0, \sigma^2_{t_0^i - \Delta t})$) and pre-release ($t_0^i - \Delta t$) rates in calendar time. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i - \Delta t$ value used.

| | | Base | | | Quote | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $L$ | $L_D$ | $\Delta L$ | $L$ | $L_D$ | $\Delta L$ |
| USD/JPY | 5min | **31.614** | **79.410** | -47.796 | **13.301** | **122.337** | -109.037 |
| | 10min | **16.646** | **27.575** | -10.929 | **13.298** | 16.890 | -3.593 |
| | 30min | 17.192 | **11.126** | 6.066 | 9.578 | **9.469** | 0.110 |
| | 1h | **13.316** | 10.981 | 2.335 | **6.239** | 13.540 | -7.301 |
| | 3h | **9.596** | **8.897** | 0.639 | **5.222** | **11.408** | -6.233 |
| | 6h | **8.909** | 6.125 | 2.784 | **5.464** | 7.483 | -2.020 |
| GBP/USD | 5min | **17.550** | **44.688** | -27.138 | **25.171** | **56.508** | -31.337 |
| | 10min | **13.699** | 15.931 | -2.232 | **20.331** | 20.789 | -0.458 |
| | 30min | 13.142 | **9.300** | 3.842 | 12.488 | **14.160** | **-1.672** |
| | 1h | **9.395** | 13.512 | -4.117 | **10.672** | **13.140** | -2.467 |
| | 3h | **4.036** | **8.575** | -4.551 | **9.955** | 5.379 | 4.542 |
| | 6h | **3.619** | **7.687** | -4.068 | **7.781** | 5.247 | 2.534 |
| GBP/JPY | 5min | **29.662** | 37.459 | -7.797 | **22.868** | 28.220 | -5.352 |
| | 10min | **16.479** | 21.246 | -4.768 | **17.871** | 15.531 | 2.341 |
| | 30min | 13.517 | **13.015** | 0.502 | 12.319 | **12.286** | 0.033 |
| | 1h | **11.855** | 15.032 | -3.176 | **12.326** | 15.826 | -3.500 |
| | 3h | **5.666** | **9.551** | -3.890 | **6.094** | **12.964** | -6.897 |
| | 6h | **4.399** | **7.068** | -2.669 | **6.414** | 7.310 | -0.896 |
| EUR/USD | 5min | **18.186** | **45.463** | -27.277 | **24.768** | **57.990** | -33.222 |
| | 10min | **14.235** | 14.958 | -0.723 | **19.937** | 17.969 | 1.969 |
| | 30min | 10.167 | **9.768** | 0.400 | 13.250 | **9.534** | 3.716 |
| | 1h | **7.425** | 8.429 | -1.004 | **8.772** | 8.548 | 0.224 |
| | 3h | **4.338** | **6.526** | -2.193 | **7.959** | 7.760 | 0.204 |
| | 6h | **2.997** | **6.406** | -3.409 | **5.578** | **6.067** | -0.489 |
| EUR/JPY | 5min | **19.478** | **39.046** | -19.568 | **22.360** | **46.709** | -24.349 |
| | 10min | **19.114** | 20.587 | -1.473 | **15.133** | 13.140 | 1.993 |
| | 30min | 10.616 | **16.423** | **-5.807** | 13.396 | **10.977** | 2.419 |
| | 1h | **7.797** | **16.141** | -8.344 | **9.394** | 17.769 | -8.375 |
| | 3h | **4.600** | **10.406** | -5.825 | **3.944** | **12.286** | -8.406 |
| | 6h | **4.464** | **7.575** | -3.110 | **6.706** | 8.195 | -1.489 |
| EUR/GBP | 5min | **24.307** | **69.656** | -45.349 | **13.071** | **62.871** | -49.800 |
| | 10min | **10.673** | 17.758 | -7.084 | **13.127** | **16.637** | -3.509 |
| | 30min | 13.537 | **8.731** | 4.806 | 8.142 | **15.297** | **-7.155** |
| | 1h | **14.003** | 9.441 | 4.562 | **11.952** | 11.918 | 0.034 |
| | 3h | **11.107** | 3.297 | 7.818 | **8.538** | 3.800 | 4.702 |
| | 6h | **7.160** | 4.664 | 2.496 | **8.075** | 3.650 | 4.425 |

Table 4.3.6: Results of Lèvy metric obtained by comparing the simulated Gaussian ($\mathcal{N}(0, \sigma^2_{t_0^i - \Delta t})$) and pre-release ($t_0^i - \Delta t$) rates in calendar time. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i - \Delta t$ value used.

The last hypothesis to be tackled is Hypothesis 4.3 ("*News causes no effect on the post-release* ($t_0^i+\Delta t$ *or* $t_{0+j}^i$) *FX rates when compared to the pre-release* ($t_0^i-\Delta t$ *or* $t_{0-j}^i$) *when the effect of the news anticipation is accounted for.*'"). Results reveal a weak reaction to news when the pre-release exchange rate dynamics are taken into account. Results show a limited impact on average post-release returns because the metric difference is rarely significant, and without a clear pattern of significance across different $\Delta t$ or $j$ values or exchange rate pairs. Similar findings are observed on the volatility of the post-release returns, because the metric difference is rarely significant, but we observe only several cases where the metric and the dual are statistically significant (as presented in calendar time results in Tables 4.3.1, 4.3.2 and event time results in Tables A.2.5 and A.2.6). To summarise, we observe a reaction to the news content only in higher moments, after taking into account the pre-release returns dynamics but the reaction itself is not consistent.

We propose the following reasoning behind the rejection of the first two hypothesis and the failure to reject the third: the idea of comparing rates to the corresponding pre-release dynamics allows to account for the anticipation effect. As a result, the previously observed rejections of Hypthesis 4.1 and 4.2 are not leading to the rejection of Hypothesis 4.3. A more complex news release structure is revealed with lower news impact when compared to the existing literature. Taking the pre-release dynamics into account allows us to extract a clearer information shock structure and strengthen our findings. We conclude that findings in the existing literature (Evans and Speight, 2010a; Laakkonen and Lanne, 2013; Andersen et al., 2003) tend to report a confounded effect of the post-release reaction to the new information shock. Once accounted for the pre-release effect we are able to extract a more refined structure of news shock.

To conclude, news releases have two different effects that must be accounted for to accurately capture news shock effects. The pre-release dynamics have a strong influence on the post-release dynamics, and market agents react to the presence of new information by engaging in financial actions before news is released. Our results are in-line with the idea suggested by Kim (1998), that the presence of the news release alone (possibly irrespective of its content) cause an impact on the exchange rate dynamics.

### 4.3.3 Benchmark Results

In the following, we investigate the robustness of our findings by using alternative methods of analysis as outlined in Sections 4.2.3.1 and 4.2.3.2.

#### 4.3.3.1 Scaling Laws Effects

We first evaluate the scaling property of the exchange rate returns volatility. We focus our attention on the effect news releases cause on the scaling of volatility in the FX market (Glattfelder et al., 2011). The objective of the analysis is to determine whether (a) the proposed scaling law holds, (b) news releases cause an impact on the scaling behaviour, and (c) findings in the scaling law analysis support our findings in probability metric results. The existing literature suggests that the volatility is higher in the post-release ($t_0^i + \Delta t$ or $t_{0+j}^i$) period (Laakkonen and Lanne, 2013; Laakkonen, 2013; Fatum et al., 2012). We also differentiate between the news announcements released in the base, and quote countries of the FX pair to determine the origin of the most significant news releases.

We start by tackling our first objective (a). In Tables 4.3.7 and 4.3.8 we generally observe high $R^2$-values indicating the validity of the proposed scaling law of the volatility over time. The relation holds in event and calendar time grids. We progress to tackle the second objective (b) and to determine the impact of news releases, we focus on testing the hypothesis $H_0 : \alpha_{post} = \alpha_{pre}$ for each of the FX pairs and the country of the news release. The $p$-values of this test ($p$-val.($H_0$)) reveal three rejections (USD/JPY base country, GBP/USD base country and EUR/USD base country) in twelve tests at a 5% error level in calendar time results (see Table 4.3.7), and no rejections in event time results (see Table 4.3.8).

| FX pair | Country | $R^2_{post}$ | $R^2_{pre}$ | $\alpha_{post}$ | $\alpha_{pre}$ | $p$-val.$(H_0)$ |
|---|---|---|---|---|---|---|
| USD/JPY | Quote | 0.987 | 0.981 | 0.446 | 0.472 | 0.532 |
| | Base | 0.992 | 0.988 | 0.423 | 0.497 | 0.042 |
| GBP/USD | Quote | 0.994 | 0.989 | 0.523 | 0.541 | 0.627 |
| | Base | 0.982 | 0.996 | 0.386 | 0.509 | 0.001 |
| GBP/JPY | Quote | 0.989 | 0.993 | 0.530 | 0.534 | 0.904 |
| | Base | 0.992 | 0.976 | 0.472 | 0.446 | 0.518 |
| EUR/USD | Quote | 0.996 | 0.990 | 0.536 | 0.489 | 0.180 |
| | Base | 0.992 | 0.993 | 0.409 | 0.516 | 0.002 |
| EUR/JPY | Quote | 0.993 | 0.993 | 0.502 | 0.506 | 0.913 |
| | Base | 0.991 | 0.975 | 0.468 | 0.457 | 0.788 |
| EUR/GBP | Quote | 0.989 | 0.984 | 0.510 | 0.532 | 0.605 |
| | Base | 0.997 | 0.984 | 0.464 | 0.486 | 0.516 |

Table 4.3.7: Results of the scaling law regression ($\log(\sigma_\tau) = const + \alpha \log(\tau)$) for all FX pairs and with respect to the country of the news release in calendar time. The subindices *pre* and *post* refer to the pre-release ($t_0^i - \Delta t$) and post-release ($t_0^i + \Delta t$) periods, respectively. All estimated $\alpha$ parameters are significantly at the 0.001% level. The last column shows the $p$-value of the hypothesis $H_0 : \alpha_{post} = \alpha_{pre}$.

The three observed rejections in calendar time are in the opposite direction as expected. The $\alpha_{pre}$ parameter value is always higher than the $\alpha_{post}$ parameter, suggesting that volatility levels in the pre-release sample are higher than after the news release, contrary to findings in the literature which solely focuses on post release dynamics (Fatum et al., 2012), and reported higher volatility levels due to news releases. In addition, event time results in Table 4.3.8 show that the scaling law coefficient is not affected by the news information.

To tackle the final objective (c), we start by focusing on our findings in calendar time in Tables 4.3.1, 4.3.2. We do not observe the same features of an impact on the volatility level observed by the probability metrics as in the scaling law case, where we rejected the hypothesis of scaling coefficients being equal in Table 4.3.7. The same inconsistency is observed in event time results and selected probability metric results (Tables A.2.5 and A.2.6 focus on the cases where the metric and the dual is significant but the difference is between two is not versus 4.3.8). Our findings, based on the scaling law analysis, show contradicting results to the market microstructure reasoning (e.g. Lyons, 2006) that expects a higher

| FX pair | Country | $R^2_{post}$ | $R^2_{pre}$ | $\alpha_{post}$ | $\alpha_{pre}$ | $p$-val.($H_0$) |
|---|---|---|---|---|---|---|
| USD/JPY | Quote | 0.999 | 0.998 | 0.500 | 0.532 | 0.098 |
| | Base | 0.996 | 0.994 | 0.495 | 0.463 | 0.848 |
| GBP/USD | Quote | 0.999 | 0.993 | 0.494 | 0.491 | 0.532 |
| | Base | 0.997 | 0.997 | 0.500 | 0.473 | 0.837 |
| GBP/JPY | Quote | 0.998 | 0.998 | 0.498 | 0.513 | 0.281 |
| | Base | 0.997 | 0.996 | 0.479 | 0.510 | 0.144 |
| EUR/USD | Quote | 0.999 | 0.996 | 0.506 | 0.499 | 0.600 |
| | Base | 0.996 | 0.992 | 0.476 | 0.480 | 0.455 |
| EUR/JPY | Quote | 0.999 | 0.997 | 0.477 | 0.508 | 0.116 |
| | Base | 0.999 | 0.997 | 0.502 | 0.533 | 0.114 |
| EUR/GBP | Quote | 0.999 | 0.988 | 0.478 | 0.463 | 0.679 |
| | Base | 0.999 | 0.992 | 0.455 | 0.442 | 0.680 |

Table 4.3.8: Results of the scaling law regression ($\log(\sigma_\tau) = const + \alpha \log(\tau)$) for all FX pairs in event time and with respect to the country of the news release in event time. The subindices *pre* and *post* refer to the pre-release ($t_0^i - \Delta t$) and post-release ($t_0^i + \Delta t$) periods, respectively. All estimated $\alpha$ parameters are significantly at the 0.001% level. The last column shows the $p$-value of the hypothesis $H_0 : \alpha_{post} = \alpha_{pre}$.

level of volatility in the post-release period due the price discovery mechanism incorporating newly available information. Our results are robust with respect to the exchange rate pair or news originating country. The scaling law application suffers from the aggregation of information when compared to the probability metrics approach. To be specific, we are able to observe only an average influence over the whole period considered with scaling laws. On the other hand, probability metrics allow to identify influence at specific time points after the release and to extract a finer impact structure. To summarize, insights gained into the reaction to news are limited when compared to the probability metrics findings.

#### 4.3.3.2 Stochastic Dominance

We now discuss the results of the stochastic dominance tests. Objectives of the analysis in this section are to address the following questions: (a) how well do stochastic dominanc tests perform empirically when applied to FX rate returns; (b) what is the average impact on the post-release returns after accounting for the pre-release rate dynamics using the first order stochastic dominance tests and how it relates to the probability metrics findings; (c) what is the measured impact on the volatility levels after accounting for the pre-release rates by using the main and alternative second order stochastic dominance tests and how do results relate to the probability metric findings; (d) does the estimated scaling law in Section 4.3.3.1 translate to the second order stochastic dominance? Tables 4.3.9, A.2.2, 4.3.10 and A.2.3 show $p$-values of the stochastic dominance tests with the null hypothesis $H_0 : F_{t_0^i - \Delta t} \preceq_{FSD,SSD} F_{t_0^i + \Delta t}$ in top Panel A, and its reversed version $H_0 : F_{t_0^i + \Delta t} \preceq_{FSD,SSD} F_{t_0^i - \Delta t}$ in bottom Panel B, respectively. We establish the following relation between results of the stochastic dominance tests and probability metrics findings: a non-zero Kantorovich metric difference value would suggest a presence of the first order stochastic dominance under the null hypothesis (as tested in Tables 4.3.9 and A.2.2). To compare the second order dominance results, we focus on cases where the metric and/or the dual are significant, and the difference is insignificant.

We tackle the first objective (a) by focusing on the dominance tests results. The null hypothesis allows both returns distributions to be equal (Davidson and Duclosb, 2013), therefore we are looking at rejections in the main and reversed tests. For example, an undesired test outcome is observed in Table 4.3.9 for USD/JPY pair base economy news at $\Delta t = 1h$ time point, because the corresponding $p$-value of the main test in Panel A is 0.001, but the reversed test in Panel B indicates a $p$-value of 0.001. As a results we must reject the main and reversed test hypotheses leading to a paradox of both returns samples dominating each other. We first focus on the first order dominance test results in calendar time in Table 4.3.9. We observe 2 cases of rejections (GBP/USD $10min$ for the base economy and EUR/GBP $10min$ for the base economy) of the main, and reversed tests in time frames of up to $30min$, and it is along the lines of possible false positives at 5% error rate. The time period of 1 hour or more is filled with rejections of both the main and reversed tests indicating that tests performed poorly on the problem studied. Therefore we do not focus on the results from

| | | | $\Delta t$ | | | | | |
|---|---|---|---|---|---|---|---|---|
| Panel | FX pair | Country | 5min | 10min | 30min | 1h | 3h | 6h |
| **A** | USD/JPY | Quote | 0.566 | 0.016 | 0.001 | 0.001 | 0.001 | 0.001 |
| | | Base | 0.004 | 0.964 | 0.064 | 0.001 | 0.001 | 0.001 |
| | GBP/USD | Quote | 0.338 | 0.450 | 0.652 | 0.001 | 0.001 | 0.001 |
| | | Base | 0.200 | 0.034 | 0.902 | 0.046 | 0.001 | 0.001 |
| | GBP/JPY | Quote | 0.782 | 0.188 | 0.180 | 0.001 | 0.001 | 0.001 |
| | | Base | 0.044 | 0.180 | 0.886 | 0.092 | 0.001 | 0.018 |
| | EUR/USD | Quote | 0.092 | 0.882 | 0.082 | 0.001 | 0.001 | 0.001 |
| | | Base | 0.330 | 0.288 | 0.070 | 0.002 | 0.022 | 0.001 |
| | EUR/JPY | Quote | 0.812 | 0.722 | 0.298 | 0.001 | 0.010 | 0.001 |
| | | Base | 0.346 | 0.826 | 0.448 | 0.114 | 0.734 | 0.008 |
| | EUR/GBP | Quote | 0.332 | 0.016 | 0.001 | 0.022 | 0.001 | 0.498 |
| | | Base | 0.076 | 0.032 | 0.006 | 0.001 | 0.001 | 0.014 |
| **B** | USD/JPY | Quote | 0.944 | 0.092 | 0.126 | 0.188 | 0.174 | 0.334 |
| | | Base | 0.622 | 0.768 | 0.060 | 0.001 | 0.001 | 0.001 |
| | GBP/USD | Quote | 0.106 | 0.016 | 0.018 | 0.001 | 0.001 | 0.001 |
| | | Base | 0.014 | 0.028 | 0.048 | 0.006 | 0.012 | 0.152 |
| | GBP/JPY | Quote | 0.746 | 0.402 | 0.734 | 0.108 | 0.002 | 0.658 |
| | | Base | 0.268 | 0.372 | 0.306 | 0.936 | 0.034 | 0.038 |
| | EUR/USD | Quote | 0.008 | 0.056 | 0.528 | 0.001 | 0.001 | 0.001 |
| | | Base | 0.456 | 0.528 | 0.276 | 0.992 | 0.488 | 0.478 |
| | EUR/JPY | Quote | 0.768 | 0.648 | 0.198 | 0.872 | 0.536 | 0.060 |
| | | Base | 0.058 | 0.052 | 0.756 | 0.814 | 0.002 | 0.044 |
| | EUR/GBP | Quote | 0.810 | 0.084 | 0.364 | 0.432 | 0.001 | 0.008 |
| | | Base | 0.066 | 0.010 | 0.602 | 0.708 | 0.001 | 0.974 |

Table 4.3.9: The pre-release $(t_0^i - \Delta t)$ rate is compared to the post-release $(t_0^i + \Delta t)$ rate in calendar time, showing all FX pairs with respect to the country of the news release and time gap to the release point the $p$-values of the *first* order stochastic dominance tests $F_{t_0^i - \Delta t} \preceq_{FSD} F_{t_0^i + \Delta t}$ in top Panel A, and $F_{t_0^i + \Delta t} \preceq_{FSD} F_{t_0^i - \Delta t}$ (reversed test) in bottom Panel B, respectively.

those periods in later parts. On the other hand, event time results in Table A.2.2 do not have any double rejections suggesting for more reliable results.

We continue to investigate our first objective (a) on the reliability of findings but focus on the SSD test results. Theoretically, the FSD implies higher order dominance. Therefore, for the SSD results to be informative, we should observe failure to reject the null hypothesis in the main and reversed tests in the FSD tests. The theoretical relation does not hold for the calendar, nor for event-time results (see Tables 4.3.10 andA.2.1) in time frames of up to 30$min$ because we observe more than half of the FSD cases (Table 4.3.9) not leading to the SSD (corresponding event-time results in Tables A.2.3 and A.2.4 and compared to in Table A.2.2). For example, results for the base economy of the FX pair USD/JPY at $\Delta t = 5min$ indicates that the pre-release returns are dominating post-release returns with respect to the first order dominance test at 5% significance level (test statistic in Table 4.3.9 $p$-value is equal to 0.004 in Panel A and reversed test $p$-value is equal to 0.622 in Panel B). However, the second order dominance results in Table 4.3.10 for the same case indicates main test $p$-value equal to 0.276 in Panel A and reversed test $p$-value equal to 0.720 in Panel B or for both samples compared. We would expect to observe the same direction second order stochastic dominance, however we fail to do so. On the other hand, the inspection of double rejections from the main, and reversed tests in Tables 4.3.10 and A.2.1 for the calendar time and Tables A.2.3 and A.2.4 for the event time, identifies both tests procedures to be valid as the number of double rejections is at an acceptably low level.

To conclude, we observe that the theoretical relation between orders of dominance not to hold, while the second order results are found to be more reliable than the FSD tests results, in terms of the number of double rejections. We are unable to identify if the first or the second order main or alternative tests provide better robustness, as the number of double rejections appear to be within expected false positives bounds for all three tests (with exception of hours time frame for calendar time).

Regarding our second objective (b), results reveal a complex information absorption structure over time without a clear one-sided impact (Tables 4.3.9 and A.2.2 without a clear pattern of statistical significance over different $\Delta t$ or $j$ values). Results are interpreted as follows: higher USD/JPY average returns are observed at $\Delta t = 10min$ after quote economy news releases (Table 4.3.9) because the $p$-value of test comparing the $t_0^i - 10min$ returns to $t_0^i + 10min$ is equal to 1.60%

(Panel A). The corresponding reversed test results in Panel B show the probability value of 9.20%. Therefore, we observe the quote economy news releases to cause a positive reaction at a $10min$ window when compared to the corresponding rate from the pre-release period rate. We observe a variation in the direction of the dominance in multiple exchange rate pairs as we move to higher $\Delta t$ values after the news release. For example, for the quote country of the EUR/USD pair (Table 4.3.9), the $5min$ post-release returns dominate corresponding pre-release returns ($p$-value of 0.008) but at $30min$ mark we observe an opposite effect of the pre-release returns dominating post-release returns ($p$-value of 0.082). Irrespective of the news release or exchange rate pair, we do not observe a consistent impact of first or second order stochastic dominance and the direction of dominance varies substantially. A high similarity of the first order dominance test results is observed when compared to the probability metric results (the metric difference values in Tables 4.3.1 and A.2.5 compared versus statistically significant $p$-values in Tables 4.3.9 and A.2.2). However, probability metric results provide stronger evidence as dominance tests fail to identify direction correctly for higher $\Delta t$ or $j$ values.

We move to our third objective (c) and investigate whether news has an impact on the volatility, using the main and alternative SSD tests, once we account for the pre-release rate dynamic. A failure to reject the null hypothesis indicates that news releases cause higher levels of volatility on the post-release exchange rates after accounting for the pre-release rates. A high amount of ambiguous double rejections in the first order dominance results (as discussed earlier) prevents us from determining if we observe the second or the first order dominance, based on the second order dominance tests. In Tables 4.3.10 and A.2.1, we observe that the post-release period has a similar level of volatility when compared to the pre-release period returns, as we see only several cases of $p-$ values smaller than 0.05 (failure to reject main and reversed tests suggests for both return distributions to be equal). Event time results in Tables A.2.3 and A.2.4 show similar features, but with more robust results, as Panel B indicates a higher number of the null

| | | | $\Delta t$ | | | | | |
|---|---|---|---|---|---|---|---|---|
| Panel | FX pair | Country | 5min | 10min | 30min | 1h | 3h | 6h |
| **A** | USD/JPY | Quote | 0.196 | 0.001 | 0.050 | 0.002 | 0.001 | 0.040 |
| | | Base | 0.276 | 0.076 | 0.446 | 0.712 | 0.906 | 0.710 |
| | GBP/USD | Quote | 0.140 | 0.528 | 0.492 | 0.182 | 0.218 | 0.214 |
| | | Base | 0.736 | 0.824 | 0.614 | 0.596 | 0.012 | 0.200 |
| | GBP/JPY | Quote | 0.652 | 0.072 | 0.528 | 0.166 | 0.024 | 0.308 |
| | | Base | 0.106 | 0.530 | 0.304 | 0.284 | 0.122 | 0.438 |
| | EUR/USD | Quote | 0.130 | 0.186 | 0.342 | 0.148 | 0.164 | 0.758 |
| | | Base | 0.420 | 0.148 | 0.004 | 0.001 | 0.026 | 0.034 |
| | EUR/JPY | Quote | 0.456 | 0.544 | 0.508 | 0.856 | 0.138 | 0.748 |
| | | Base | 0.904 | 0.342 | 0.092 | 0.018 | 0.236 | 0.084 |
| | EUR/GBP | Quote | 0.502 | 0.042 | 0.001 | 0.002 | 0.120 | 0.094 |
| | | Base | 0.232 | 0.044 | 0.010 | 0.001 | 0.188 | 0.010 |
| **B** | USD/JPY | Quote | 0.440 | 0.302 | 0.518 | 0.780 | 0.364 | 0.734 |
| | | Base | 0.720 | 0.716 | 0.752 | 0.524 | 0.298 | 0.098 |
| | GBP/USD | Quote | 0.096 | 0.058 | 0.752 | 0.322 | 0.078 | 0.004 |
| | | Base | 0.820 | 0.538 | 0.804 | 0.368 | 0.394 | 0.624 |
| | GBP/JPY | Quote | 0.390 | 0.252 | 0.770 | 0.534 | 0.894 | 0.442 |
| | | Base | 0.252 | 0.574 | 0.540 | 0.228 | 0.248 | 0.826 |
| | EUR/USD | Quote | 0.090 | 0.056 | 0.738 | 0.398 | 0.230 | 0.734 |
| | | Base | 0.730 | 0.424 | 0.356 | 0.266 | 0.288 | 0.312 |
| | EUR/JPY | Quote | 0.528 | 0.300 | 0.514 | 0.420 | 0.890 | 0.530 |
| | | Base | 0.908 | 0.730 | 0.360 | 0.242 | 0.342 | 0.768 |
| | EUR/GBP | Quote | 0.772 | 0.966 | 0.972 | 0.768 | 0.434 | 0.320 |
| | | Base | 0.804 | 0.430 | 0.226 | 0.280 | 0.346 | 0.250 |

Table 4.3.10: The pre-release ($t_0^i-\Delta t$) rate is compared to the post-release ($t_0^i+\Delta t$) rate in calendar time, showing all FX pairs with respect to the country of the news release and time gap to the release point the $p$-values of the *second* order stochastic dominance tests $F_{t_0^i-\Delta t} \preceq_{SSD} F_{t_0^i+\Delta t}$ in top Panel A, and $F_{t_0^i+\Delta t} \preceq_{SSD} F_{t_0^i-\Delta t}$ (reversed test) in bottom Panel B, respectively.

hypothesis rejections, when compared to calendar time results. As with the first order dominance tests results, we observe a high similarity in cases identifying an impact of the release between second order tests results and probability metrics (the insignificant difference and significant metric and dual cases in Tables 4.3.1, 4.3.2 and A.2.5, A.2.6 compared versus statistically significant $p$-values in Tables 4.3.10 and A.2.3). As in the first order dominance case, probability metrics findings do not suffer from ambiguous test outcomes identified earlier in the section, making them the preferred method of our analysis.

The final objective (d) to be tackled is the described relations between the proposed scaling law in Section 4.2.3.1 and stochastic dominance results, as described in the end of Section 4.2.3.2. Calendar time results of the scaling law in Table 4.3.7 and second order tests results in Tables 4.3.10 and A.2.1 show that the relation does not hold. For example, scaling law results for the base economy news of the USD/JPY FX pair suggest higher volatility levels in the pre-release returns when compared to the post-release returns ($p$-value of the hypothesis is 0.042 and $\alpha_{post} = 0.423$ versus $\alpha_{pre} = 0.497$). The second order dominance results in Table 4.3.10 fail to reject the null hypothesis at higher $\Delta t$ values of $1h$, $2h$ and $3h$ in the main and reversed tests suggesting for the volatility levels to be equal. In general, scaling law results imply that the pre-release volatility levels are higher than the post-release volatility levels of the transformed returns of the base economy news for pairs USD/JPY, GBP/USD and EUR/USD. However, when focusing on the reversed test results of the second order tests ($F_{t_0^i+\Delta t} \preceq_{SSD} F_{t_0^i-\Delta t}$ (see Tables 4.3.10 and A.2.1), we do not observe the expected relation to hold, even at the time frame longer than 1 hour. Event time results for the scaling law in Table 4.3.8 did not identify any cases of different scaling effects and as expected, we do not observe any patterns over different events since the release (see Tables A.2.3 and A.2.4).

To summarise, the accounting for the pre-release transformed rates allows us to reveal a complex structure of new release impacts in the mean and variance-based on the stochastic dominance tests. We do not observe a consistent effect across all FX pairs being considered, but contrary to the existing literature, we observe that the pre-release FX dynamics generally have a higher level of volatility than after the release (Laakkonen, 2013; Laakkonen and Lanne, 2013; Fatum et al., 2012; Evans and Speight, 2010a). Event time data gives more robust findings when compared to the calendar results of the stochastic dominance tests. In general, we observe poor empirical performance of the stochastic dominance tests, and probability metrics show superior features for our problem.

## 4.4 Conclusions

We analyse the impact of public macroeconomic news announcements on five major exchange rate dynamics (EUR/USD, EUR/JPY, EUR/GBP, GBP/USD and USD/JPY), and propose a probability metrics based framework to study the news shocks in calendar and event time settings. The framework allows to compare affected and unaffected financial instrument distributions and to account for possibly confounding factors. The possibility of the pre-release news effect in the macroeconomic news studies was suggested by Kim (1998), and studied by Evans and Speight (2010a), with a simple lead-lag parametric framework on the 5 minutes data. We approached the problem by first investigating the effect of the news release in the post-release rates, and then incorporated the pre-release FX dynamics.

Our first contribution is that to quantify news effects we use the probability metrics where we disentangle the problem by focusing on individual effects. We first focus on the post-release rates, where we observe a strong effect on the variance and higher moments of the post-release exchange rates, as reported in the existing literature (Laakkonen, 2013; Laakkonen and Lanne, 2013; Fatum et al., 2012; Evans and Speight, 2010a). To investigate the claim that the pre-release exchange rate has an influence on the post-release dynamics, we focus on the overall effect of the pre-release in the same structure. The pre-release effect investigation reveals a strong impact on the FX rates distribution just due to the anticipation effect. To remove the anticipation effect, we proposed to account for the pre-release exchange rate dynamics when studying the news release effect on the post-release returns in order to measure the true information content impact, instead of focusing on the confounded effects as done in the existing literature (Laakkonen and Lanne, 2013; Fatum et al., 2012; Evans and Speight, 2010a) and others. We observed a complex impact structure, after accounting for the pre-release returns, that differs from the results focusing only on the post-release returns solely. The applied literature argues that news shock impact lasts up to 2 hours (Laakkonen, 2013; Laakkonen and Lanne, 2013) and others, but we do not observe a clearly defined impact consistent across news releases and exchange rate pairs.

Our second contribution is that we present similarities and differences of our findings when compared to alternative available methods, and start with the scaling law approach. Our results reveal that we rarely observe an impact on the estimated scaling parameter, which is in contrast to the previously highlighted literature, in particular as well as the market microstructure approach (Lyons, 2006), that suggest a higher level of volatility, when new information content is expected to be absorbed into the price. To extract a more detailed structure of the impact, we validate our results with stochastic dominance tests of the pre- versus post-release exchange rate samples. Results reveal similar findings as in the probability metric approach, where we observe only weak evidence of the higher level of volatility in the post-release exchange rates after accounting for the pre-release rates.

Our third contribution is that the overall analysis reveals that the impact of news release is not consistent across FX pairs, when we account for the pre-release dynamics. Substantially different results were observed in the existing literature (using calendar time analysis only) that focuses on comparing post-release returns to the theoretical no-information state. Event time grid results show the shock effect to be more consistent as opposed to calendar time results and therefore it suggests event time approach to be more appropriate when studying new information absorption. Our conclusions are insensitive to parametric model assumptions, exchange rate pair used, and the time measurement grid imposed leading to stronger results compared to empirical studies by Laakkonen (2013), (Laakkonen and Lanne, 2013), Fatum et al. (2012) and others.

In the previous chapter, we proposed a new way of restructuring FX data to investigate information absorption dynamics. We were able to identify the superior method to be used for the study. The anticipation effect was found to cause a substantial influence on results of the analysis. In the next chapter (Chapter 5), we move to investigate the influence of factors used in models studied in Chapter 3, but focusing only on the information impact effects in a framework proposed in Chapter 4.

# Chapter 5

# Decomposing News: Any News is Good News

In the previous chapter (Chapter 4), we introduced an appropriate methodology to investigate pure information shock effects. In this chapter, our methodology from Chapter 4 is applied to study information shocks by conditioning on the weekday, the time of the day or the sign of the news release. As this chapter extends our methodology application further, there is no additional literature review provided.

Our contributions in this chapter are: (a) an investigation of the influence that specific weekdays, or releases appearing on those days, cause on the reaction to news; (b) an investigation of the effect of the specific time period of the day, or the level of market liquidity that has on news reaction dynamics; (c) a study of effects that the direction of individual news release variables (previous, forecast or released values) have on FX dynamics around the release point.

The remainder is structured as follows: Section 5.2 presents the methodology of analysis highlighting important deviations from previous methods when relevant; In Section 5.3 we present our findings of the conditional shock investigation; Section 5.4 concludes.

## 5.1 Introduction

The existing literature focused on the post-release reactions to news in FX markets (Andersen et al., 2003; Laakkonen and Lanne, 2013; Ehrmann and Fratzscher, 2005), without accounting for the pre-release dynamics. The anticipation effect was observed to cause a substantial impact on the observed shock dynamics in Chapter 4, and was based on the rationale that: *If a trader believes for news to cause an impact on FX rates, he is more likely to engage in speculative or hedging activities before the release.*

Ehrmann and Fratzscher (2005) proposed to include dummy variables for Monday and Friday when modeling conditional volatility to account for more volatile trading due to the beginning or ending of the week. We propose to condition news reactions on weekdays to investigate if such a claim is valid after accounting for the pre-release dynamics. In addition, equity market studies (Högholma et al. (2011); Kiyma and Berumen (2001)), have documented a day of the week to cause a substantial effect on returns and volatility. We extend ideas by Ehrmann and Fratzscher (2005) and evaluate the effect each weekday has on observed reactions. We investigate whether we are able to observe an impact of each individual weekday, either due to the clustering of certain impact indicators or selective timing of the body releasing news. In some cases, it could be more preferential for the institution releasing news to announce important information right before the weekend to create a longer window of time to process the information released. In other cases, it could be preferable to release information as early in the week as possible to allow for liquid markets to price the information released. To investigate the above claim, we propose a hypothesis of individual weekdays having no effect on FX returns and evaluate the evidence against it.

FX markets trade 24 hours a day from Monday to Friday, as financial markets are closed during weekends around the world. We postulate that the liquidity levels during certain hours have an effect on reactions to news. We focus on two liquid trading periods of London and New York markets, and outline three periods of interest: London time, London and New York and only New York time period (see Figure 5.1 for further clarification). Several exchange rate pairs investigated have limited amount of releases during the selected hours of interest and are removed when irrelevant. We postulate the following hypothesis and evaluate the evidence against it: "*news releases during different time periods of the day have similar magnitude reactions.*" Evans and Speight (2010a) and Andersen et al. (2003), among others highlighted that U.S. releases have the strongest impact on all major exchange rate pairs, but the number of macroeconomic indicators in datasets studied was skewed to U.S indicators.

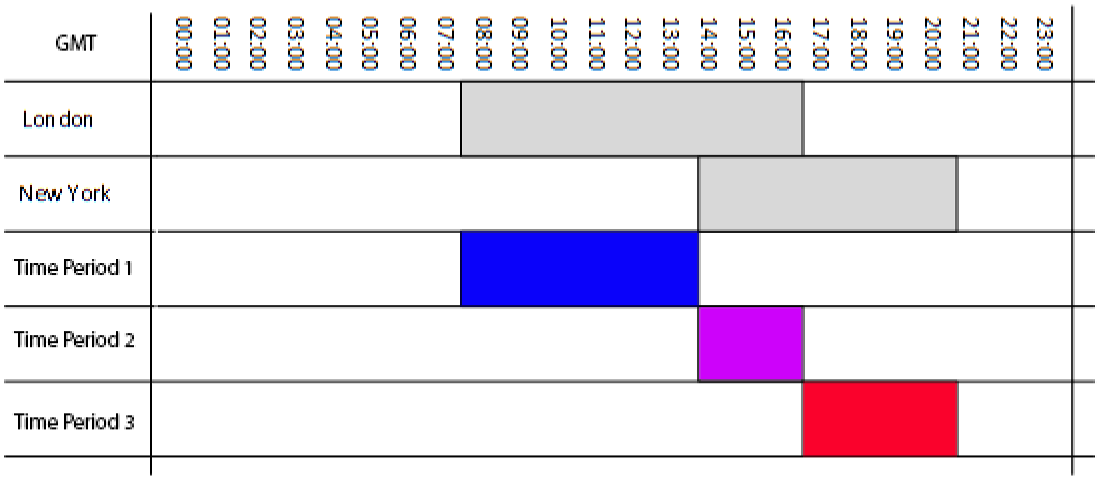


Figure 5.1: A mapping of time periods of interest when London and New York markets are open based on GMT timezone. Shaded areas identify market hours of interest from corresponding markets. Blue area identifies London time period; red area - New York period; purple area - overlapping period.

The evaluation of different news transformations in Chapter 3 did not reveal a superior transformation. As a result, instead of investigating conditional impact based on different news transformations, we focus on the raw data. Three data points are available around each quantitative news release: previous, expected and released indicator values. We postulated in Chapter 4 that the direction of each data point has no effect on the news reactions observed. It is expected for the sign of previous and expected indicator values to have no effect on the dynamics, as this information is known before the release.

Our results allow to extend the previous literature, that investigated news releases, by studying the influece that each weekday has on major FX pairs. We focus on specific time of the day periods to further our understanding of the physical time influence on the news reaction dynamics. In addition, the previous literature and our investigation in Chapter 3 jumped to the analysis of news influence by using transformed news release data. In this chapter, we focus on a more general question of if the direction of each of news release component has any influence on the release dynamics around the news announcement point.

## 5.2 Methodology

The same dataset as in Chapter 4 is used for the analysis with the same features as outlined in Section 4.2 in Chapter 4.

### 5.2.1 Probability Metrics

We modify the methodology of Chapter 4, to be able to capture the direction of the impact. We use probability distances in this thesis as they allow us to quantify the magnitude of the difference between two data samples compared. Two samples correspond to two states of interest. I.e. A state with no new information versus a case where new information is being absorbed. In this application, we use same metrics as in Chapter 4, namely Kantorovich and Lévy quasi-semi distances and their corresponding dual values (the value obtained by swapping the arguments $X$ and $Y$ when computing the distance) to compare the pre- and post-release returns. Let $X$ and $Y$ denote the normalised FX rate at $t_0^i - \Delta t$ and $t_0^i + \Delta t$, respectively. $F_X$ and $F_Y$ represents their corresponding cumulative distribution functions (CDF). In addition, we define the following augmentations to allow to account for the directional effect of the observed impact. In Chapter 4, we were able to quantify only the magnitude of the shock as explained in detail in Section 4.2.1, but with the following alteration we are able to capture the direction of the impact as well. Let $\mathcal{B}(X, Y)$ be defined as follows:

$$\mathcal{B}(X, Y) = \begin{cases} 1, & Var(Y) \geq Var(X) \\ -1, & Var(Y) < Var(X) \end{cases} \tag{5.1}$$

giving an indicator function that will allow to account for the directional effect.

Kantorovich quasi-semi distance allows to measure the overall area of by how much one distribution function overlaps with another one. The distance $\breve{\kappa}$ and its dual $\breve{\kappa}_{\mathcal{D}}$ are defined as (e.g. Rachev et al., 2011, p. 329):

$$\breve{\kappa}\left(\mathcal{X}, \mathcal{Y}\right) = \mathcal{B}(X, Y) \times \kappa\left(X, Y\right) \tag{5.2}$$

$$\breve{\kappa}_{\mathcal{D}}\left(\mathcal{X}, \mathcal{Y}\right) = \breve{\kappa}\left(\mathcal{Y}, \mathcal{X}\right) \tag{5.3}$$

describing the positive area between the CDFs of $X$ and $Y$ (see Figure 4.2, bottom panels). To obtain the estimates of the distances, we follow the same implementation as in Chapter 4.

The Lévy metric of the $n$-th order order is defined as:

$$\breve{L}_{\lambda,n}\left(X, Y\right) = \mathcal{B}(X, Y) \times L_{\lambda,n}\left(X, Y\right) \tag{5.4}$$

$$\breve{L}_{D,\lambda,n}\left(X, Y\right) = \breve{L}_{\lambda,n}\left(Y, X\right) \tag{5.5}$$

extending the methodology from Chapter 4 and in a similar spirit $\lambda$ (identifying the order of the metric) is fixed to be equal to 1 to preserve the maximum distance interpretation as argued by Rachev et al. (2011).

To maintain coherence, we present our augmented metric insights under situations considered in Chapter 4, Section 4.3 in Figure 4.6. Under Case A, the augmented Kantorovich metric difference indicates the direction of the difference of the locations of two probability densities considered. The augmented Lévy difference supports Kantorovich results with similar conclusion of a location difference. Under Case B, augmented Kantorovich metric and dual results identify a volatility difference and augmented Lévy results support the claim. Under Case C, we can only identify a location difference direction based on both augmented metrics. Under Case D, augmented Kantorovich results provide similar insights as under Case B, but augmented Lévy results allows to identify the direction of the skewness.

### 5.2.2 Hypothesis Testing

The objective of this chapter is to establish the magnitude and direction of the effect on news releases caused by different weekdays, market liquidity or time periods of the day. The following research hypotheses are tackled:

**5.1** "*The weekday of the news release causes no effect on the post-release ($t_0^i+\Delta t$) returns when compared to the pre-release ($t_0^i-\Delta t$) returns.*" This hypothesis extends the suggested idea by Ehrmann and Fratzscher (2005) and investigates effects of each individual day instead of focusing only on two weekdays. We expect that Mondays and Fridays will have higher volatility as observed by Ehrmann and Fratzscher (2005).

**5.2** "*The time of the day of the release causes no effect on the post-release ($t_0^i+\Delta t$) returns when compared to the pre-release ($t_0^i-\Delta t$) returns.*" We aim to measure the impact that market liquidity has on the news release reactions. The market micro structure literature (Lyons, 2006) suggests volatility levels to vary during different time periods, as the information processing speed is affected by the number of market agents. The volatility is assumed to be reflective of the price discovery mechanism speed. We expect to observe a strong impact on the volatility level during the most liquid market periods. The focus is on the two most significant markets in terms of the liquidity (London and New York). We postulate that when both markets are opened (Figure 5.1 *Time Period 2*) the effect of reaction on the volatility will be substantially higher when compared to the cases when only one market is opened (Figure 5.1 *Time Period 1 or 3*).

**5.3** "*The news content released causes no effect on the post-release* $(t_0^i + \Delta t)$ *returns when compared to the pre-release* $(t_0^i - \Delta t)$ *returns.*" Hypothesis extends the existing literature (Evans and Speight, 2010a; Laakkonen, 2013; Laakkonen and Lanne, 2013; Andersen et al., 2003, and others) of macroeconomic news releases in the FX market, by investigating empirical reactions to news sign as opposed to including them as an additional factor to conditional models. Our approach differs from the existing literature by focusing on using the empirical macroeconomic data, instead of following a traditional approach of using transformed macroeconomic data.

Our results allow to fill existing gaps in the literature that focused on the transformed macroeconomic data only, two of five possible days of the week, ignored the effect of liquidity or looked at reactions observed only in post-release returns (Laakkonen and Lanne, 2013; Evans and Speight, 2010a; Andersen et al., 2003, and others).

## 5.3 Results

The following section has the same interpretation of metric, dual and difference values as used in Chapter 4. We will start our analysis by tackling Hypothesis 5.1 in objective (a) that will provide evidence of the weekday effect on news reaction in Section 5.3.1. The second objective (b) will be the evaluation of hypothesis 5.2 that will investigate liquidity effect on news reaction in Section 5.3.2. The final objective (c) will tackle hypothesis 5.3 that focuses on the sign effect of each indicator available at the news release in Section 5.3.3. The objective (c) will be divided into smaller objectives investigating the sign impact of the previous value (c,i), the sign impact of the expected value (c,ii) and the sign impact of the newly released value (c,iii). In each objective, we provide part of results with an interpretation of the relation to the corresponding research hypothesis, followed by an overview of remaining results presented in the appropriate appendix chapter.

### 5.3.1 Weekday Effect on News Reactions

We start by tackling the first objective (a) and the corresponding research hypothesis: "*The day of the news release cause no effect on the post-release ($t_0^i + \Delta t$) returns when compared to the pre-release ($t_0^i - \Delta t$) returns.*" We first focus on the calendar time results in Table 5.3.1 (additional results for remaining weekdays are presented in Appendix A.3.1 in Tables A.3.1 to A.3.3). Our result show a strong impact on the variance at the 6 hours point of the USD/JPY pair as the Kantorovich metric and its dual are statistically significant, but the difference between two is not (corresponding bold entries in Table 5.3.1). In addition, Lèvy metric results confirm the claim as the metric and its dual are statistically significant. The insignificant difference of Lèvy metric identifies no effect on the asymmetry. In general, the calendar time results display scattered evidence of an inconsistent impact on the average return, only at 1 hours or longer time frames after the release. The effect is the strongest on Friday (results in Table 5.3.2) followed by Monday (Table 5.3.1) and Thursday (see Table A.3.3). Only for the USD/JPY pair only at the 6 hours mark, we observe a consistent effect of higher volatility on Mondays and Fridays.

| | | Kantorovich | | | Lèvy | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 5min | 0.300 | 0.008 | 0.293 | 1.060 | 3.561 | -2.501 |
| | 10min | -0.212 | -0.008 | -0.204 | -0.520 | -4.777 | 4.257 |
| | 30min | -0.161 | -0.012 | -0.149 | -2.822 | -3.213 | 0.391 |
| | 1h | -0.263 | -0.017 | -0.245 | -1.009 | -3.786 | 2.777 |
| | 3h | -0.126 | -0.140 | 0.014 | -2.368 | -2.771 | 0.402 |
| | 6h | **0.181** | **0.198** | -0.017 | **3.536** | **3.484** | 0.052 |
| GBP/USD | 5min | -0.300 | -0.021 | -0.279 | -4.543 | -5.731 | 1.188 |
| | 10min | -0.107 | -0.089 | -0.019 | -6.025 | -2.237 | -3.788 |
| | 30min | -0.338 | -0.035 | -0.303 | -3.077 | -11.263 | **8.187** |
| | 1h | -0.302 | -0.003 | -0.299 | -0.306 | -5.784 | **5.478** |
| | 3h | **-0.323** | -0.008 | **-0.316** | -0.265 | -5.671 | 5.406 |
| | 6h | **0.404** | 0.001 | **0.403** | 0.198 | **7.856** | -7.658 |
| GBP/JPY | 5min | 0.165 | 0.093 | 0.072 | 0.719 | 9.040 | -8.321 |
| | 10min | 0.079 | 0.088 | -0.009 | 3.308 | 3.143 | 0.165 |
| | 30min | -0.303 | -0.033 | -0.270 | -3.908 | -10.253 | 6.345 |
| | 1h | -0.203 | -0.017 | -0.186 | -0.875 | -5.580 | 4.705 |
| | 3h | 0.250 | 0.026 | 0.225 | 4.163 | 3.728 | 0.435 |
| | 6h | **0.252** | 0.046 | 0.206 | 1.232 | 3.967 | -2.735 |
| EUR/USD | 5min | 0.141 | 0.077 | 0.064 | 9.069 | 0.693 | 8.375 |
| | 10min | -0.069 | -0.065 | -0.003 | -1.153 | -3.300 | 2.147 |
| | 30min | -0.131 | -0.026 | -0.105 | -2.866 | -3.270 | 0.404 |
| | 1h | -0.090 | -0.075 | -0.015 | -2.248 | -2.444 | 0.195 |
| | 3h | -0.048 | -0.094 | 0.046 | -1.847 | -2.084 | 0.237 |
| | 6h | 0.135 | **0.146** | -0.011 | 1.848 | 1.952 | -0.104 |
| EUR/JPY | 5min | 0.078 | 0.109 | -0.032 | 4.758 | 2.752 | 2.006 |
| | 10min | 0.062 | 0.079 | -0.017 | 1.864 | 1.818 | 0.047 |
| | 30min | -0.118 | -0.084 | -0.034 | -4.492 | -0.747 | -3.745 |
| | 1h | -0.029 | -0.131 | 0.103 | -4.145 | -3.550 | -0.594 |
| | 3h | 0.034 | 0.127 | -0.092 | 3.862 | 0.867 | 2.996 |
| | 6h | 0.041 | **0.177** | **-0.136** | 1.808 | 1.380 | 0.428 |
| EURGBP | 5min | 0.084 | 0.062 | 0.022 | 5.548 | 2.327 | 3.220 |
| | 10min | -0.006 | -0.194 | 0.188 | -3.416 | -1.511 | -1.905 |
| | 30min | -0.069 | -0.074 | 0.005 | -2.774 | -9.317 | 6.543 |
| | 1h | -0.068 | -0.053 | -0.016 | -0.772 | -1.853 | 1.082 |
| | 3h | -0.035 | -0.032 | -0.002 | -2.148 | -1.028 | -1.121 |
| | 6h | 0.059 | 0.045 | 0.014 | 1.304 | 0.935 | 0.369 |

Table 5.3.1: Results of both metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data only on Monday. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

| | | Kantorovich | | | Lèvy | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 5min | 0.024 | 0.131 | -0.107 | 3.985 | 4.120 | -0.135 |
| | 10min | -0.066 | -0.062 | -0.004 | -4.870 | -3.456 | -1.414 |
| | 30min | -0.018 | -0.201 | **0.183** | -4.768 | -3.038 | -1.730 |
| | 1h | -0.037 | -0.211 | 0.173 | -1.721 | -3.993 | 2.272 |
| | 3h | -0.063 | **-0.234** | 0.171 | -2.554 | -1.591 | -0.964 |
| | 6h | **0.193** | **0.287** | -0.093 | **3.772** | **3.606** | 0.166 |
| GBP/USD | 5min | -0.102 | -0.032 | -0.070 | -3.260 | -2.487 | -0.773 |
| | 10min | -0.042 | -0.062 | 0.020 | -6.113 | -2.315 | -3.798 |
| | 30min | -0.017 | -0.117 | 0.100 | -5.004 | -1.113 | -3.891 |
| | 1h | -0.016 | -0.114 | 0.098 | -3.552 | -0.456 | -3.097 |
| | 3h | -0.030 | -0.101 | 0.071 | **-4.865** | -1.121 | -3.745 |
| | 6h | **0.186** | 0.079 | 0.107 | 1.781 | 1.903 | -0.122 |
| GBP/JPY | 5min | 0.067 | 0.092 | -0.025 | 9.558 | 3.868 | 5.690 |
| | 10min | 0.075 | 0.101 | -0.025 | 8.199 | 0.690 | 7.508 |
| | 30min | -0.007 | -0.394 | 0.387 | -6.096 | -1.209 | -4.887 |
| | 1h | -0.001 | **-0.386** | 0.385 | -5.531 | -0.165 | -5.366 |
| | 3h | 0.011 | **0.324** | -0.313 | 4.189 | 2.304 | 1.884 |
| | 6h | 0.008 | **0.418** | -0.409 | 5.057 | 0.908 | 4.149 |
| EUR/USD | 5min | 0.084 | 0.038 | 0.045 | 5.574 | 3.231 | 2.343 |
| | 10min | -0.157 | -0.083 | -0.074 | -2.733 | -2.980 | 0.247 |
| | 30min | -0.059 | -0.088 | 0.030 | -2.488 | -3.120 | 0.632 |
| | 1h | -0.076 | -0.035 | -0.041 | -2.937 | -3.249 | 0.312 |
| | 3h | -0.035 | -0.108 | **0.073** | -1.720 | -1.721 | 0.001 |
| | 6h | **0.152** | 0.093 | 0.059 | 1.133 | 1.799 | -0.666 |
| EUR/JPY | 5min | 0.183 | 0.017 | 0.166 | 3.626 | 6.599 | -2.973 |
| | 10min | 0.236 | 0.015 | 0.221 | 1.272 | 15.003 | -13.731 |
| | 30min | -0.143 | -0.023 | -0.121 | -0.591 | -12.316 | **11.725** |
| | 1h | -0.153 | -0.047 | -0.106 | -0.945 | -11.405 | 10.461 |
| | 3h | 0.222 | 0.023 | 0.199 | 0.904 | 6.835 | -5.931 |
| | 6h | **0.206** | 0.022 | **0.184** | 3.520 | 6.545 | -3.026 |
| EURGBP | 5min | 0.117 | 0.120 | -0.003 | 11.324 | 0.478 | 10.846 |
| | 10min | -0.108 | -0.031 | -0.076 | -4.420 | -2.299 | -2.121 |
| | 30min | -0.061 | -0.103 | 0.042 | -6.008 | -4.126 | -1.882 |
| | 1h | -0.067 | -0.056 | -0.011 | -2.815 | -2.178 | -0.638 |
| | 3h | -0.025 | -0.118 | **0.093** | **-7.553** | -0.521 | **-7.033** |
| | 6h | 0.066 | 0.060 | 0.006 | **7.248** | 0.700 | **6.549** |

Table 5.3.2: Results of both metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data only on Friday. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

The event time results display weaker reactions across different weekdays (see Tables A.3.4 to A.3.8 in Appendix A.3.2 display fewer significant values across all cases considered). The consistent pattern of influence on USD/JPY pair is not visible anymore, despite the fact that the longest window covers 9000 ticks, on average, a wider window if translated into the calendar time (see Tables A.3.4 and A.3.8 in Appendix A.3.2 and compare them with Tables 5.3.1 and 5.3.2).

To conclude, we observe enough evidence to reject the null hypothesis of no reaction to conditioning on the weekday effect of Hypothesis 5.1. An effect on the exchange rate dynamics, due to different weekdays exists but without a clear pattern of influence across different FX pairs and time grids. We do not observe a consistent effect on the volatility at all, contrary to suggestions of (Ehrmann and Fratzscher, 2005), and other newer studies that followed-up, suggesting no effect on the volatility, due to the actual news content released on various weekdays. As we have observed earlier in Chapter 4, most of the post-release effect is due to the presence of the releases. The effect can be attributed to the importance of both days, as markets are about to close and open or due to clustering of indicators.

### 5.3.2 Time Period Effect on News Reactions

We move to investigate the second objective (b) and evaluate the evidence against the corresponding research hypothesis: "*The time period during the release causes no effect on the post-release* $(t_0^i + \Delta t)$ *returns when compared to the pre-release* $(t_0^i - \Delta t)$ *returns.*" We start with the calendar time results in Tables 5.3.3, 5.3.4 (results for USD/JPY and GBP/JPY pairs are omitted due to a small number of observations) and 5.3.5. We first compare London and New York time periods individually in Tables 5.3.3 and 5.3.5. Table 5.3.3 shows London time period results, and an effect on average return of USD/JPY pair releases at 6 hours time windows, because Kantorovich metric and the difference are significant. There is no influence on the asymmetry as only Lèvy dual is statistically significant. The comparison to New York time period results in Table 5.3.5 shows stronger reaction in New York time period, indicating a strong effect on the FX dynamics. However, this is not evidence against the hypothesis, as results from the period with the highest liquidity in Table 5.3.4 show almost no reaction due to conditioning.

| | | Kantorovich | | | Lèvy | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 5min | -0.236 | -0.376 | 0.141 | -16.218 | -9.083 | -7.135 |
| | 10min | -0.365 | -0.450 | 0.085 | -19.519 | -13.731 | -5.788 |
| | 30min | -0.742 | -0.310 | -0.432 | -10.282 | -9.766 | -0.516 |
| | 1h | -0.784 | -0.745 | -0.040 | -12.347 | -9.184 | -3.163 |
| | 3h | -0.554 | -0.484 | -0.070 | **-9.413** | -5.064 | -4.350 |
| | 6h | **-2.999** | -0.423 | **-2.576** | -2.223 | **-9.107** | 6.885 |
| GBP/USD | 5min | 0.043 | 0.131 | -0.088 | 7.550 | 5.289 | 2.261 |
| | 10min | -0.209 | -0.084 | -0.126 | -6.846 | -6.302 | -0.544 |
| | 30min | -0.393 | -0.113 | -0.280 | -2.348 | -8.892 | 6.544 |
| | 1h | -0.766 | -0.129 | -0.636 | -2.441 | -4.507 | 2.066 |
| | 3h | -0.725 | -0.023 | -0.702 | -0.688 | **-7.092** | 6.405 |
| | 6h | **-1.532** | -0.054 | **-1.478** | -0.878 | **-5.013** | 4.135 |
| GBP/JPY | 5min | -0.227 | -0.226 | -0.001 | -8.247 | -12.818 | 4.571 |
| | 10min | -0.151 | -0.232 | 0.081 | -7.386 | -10.533 | 3.146 |
| | 30min | -0.349 | -0.237 | -0.113 | -2.332 | -6.741 | 4.409 |
| | 1h | **-0.691** | -0.182 | -0.508 | -2.460 | -5.674 | 3.214 |
| | 3h | **-0.794** | -0.027 | **-0.767** | -4.134 | **-10.034** | 5.900 |
| | 6h | **-0.554** | -0.027 | **-0.527** | -2.742 | **-10.673** | 7.931 |
| EUR/USD | 5min | -0.272 | -0.038 | -0.234 | -7.135 | -7.395 | 0.260 |
| | 10min | -0.133 | -0.113 | -0.020 | -2.645 | -5.752 | 3.107 |
| | 30min | -0.342 | -0.095 | -0.247 | -2.070 | -3.629 | 1.560 |
| | 1h | -0.271 | -0.010 | -0.261 | -1.985 | -2.496 | 0.511 |
| | 3h | -0.273 | -0.077 | -0.196 | -2.808 | **-4.400** | 1.592 |
| | 6h | **-1.014** | -0.143 | **-0.871** | **-3.119** | **-4.215** | 1.096 |
| EUR/JPY | 5min | 0.054 | 0.036 | 0.019 | 2.022 | 4.900 | -2.878 |
| | 10min | -0.323 | -0.076 | -0.246 | -2.324 | -13.971 | 11.647 |
| | 30min | -0.430 | -0.065 | -0.364 | -0.898 | **-11.287** | 10.389 |
| | 1h | -0.443 | -0.148 | -0.295 | -0.947 | **-7.854** | 6.907 |
| | 3h | **-0.522** | -0.198 | -0.324 | -1.543 | **-8.600** | 7.057 |
| | 6h | **-0.591** | **-0.339** | -0.252 | -1.977 | **-7.990** | 6.013 |
| EURGBP | 5min | 0.067 | 0.051 | 0.016 | 0.067 | 0.051 | 0.016 |
| | 10min | -0.104 | -0.144 | 0.040 | -0.104 | -0.144 | 0.040 |
| | 30min | -0.352 | -0.287 | -0.065 | -0.352 | -0.287 | -0.065 |
| | 1h | **-0.432** | **-0.393** | -0.039 | **-0.432** | **-0.393** | -0.039 |
| | 3h | **-0.229** | -0.066 | -0.163 | **-0.229** | -0.066 | -0.163 |
| | 6h | **-0.167** | -0.022 | -0.146 | **-0.167** | -0.022 | **-0.146** |

Table 5.3.3: Results of both metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data only in time period 1. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

| | | Kantorovich | | | Lèvy | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 5min | - | - | - | - | - | - |
| | 10min | - | - | - | - | - | - |
| | 30min | - | - | - | - | - | - |
| | 1h | - | - | - | - | - | - |
| | 3h | - | - | - | - | - | - |
| | 6h | - | - | - | - | - | - |
| GBP/USD | 5min | 0.276 | 0.259 | 0.017 | 8.508 | 5.317 | 3.191 |
| | 10min | -0.013 | -1.137 | 1.124 | -11.684 | -2.132 | -9.552 |
| | 30min | -0.417 | -1.259 | 0.842 | -17.810 | -5.548 | -12.262 |
| | 1h | -0.754 | -0.962 | 0.208 | -6.075 | -6.215 | 0.140 |
| | 3h | -0.756 | -0.474 | -0.281 | -3.524 | -6.066 | 2.543 |
| | 6h | **-3.919** | -0.746 | **-3.173** | -4.663 | **-6.438** | 1.775 |
| GBP/JPY | 5min | - | - | - | - | - | - |
| | 10min | - | - | - | - | - | - |
| | 30min | - | - | - | - | - | - |
| | 1h | - | - | - | - | - | - |
| | 3h | - | - | - | - | - | - |
| | 6h | - | - | - | - | - | - |
| EUR/USD | 5min | -0.059 | -1.518 | 1.459 | -33.090 | -8.093 | -24.997 |
| | 10min | 0.000 | -1.898 | 1.898 | -12.488 | -1.141 | -11.347 |
| | 30min | -0.090 | -1.492 | 1.402 | -17.122 | -3.903 | -13.220 |
| | 1h | -0.648 | -1.225 | 0.578 | -8.511 | -6.991 | -1.519 |
| | 3h | -0.448 | -0.790 | 0.342 | -4.338 | -6.083 | 1.745 |
| | 6h | **-3.521** | -0.667 | **-2.854** | -4.493 | -5.395 | 0.902 |
| EUR/JPY | 5min | 0.054 | 0.459 | -0.406 | 8.639 | 1.059 | 7.579 |
| | 10min | -0.495 | -1.336 | 0.841 | -5.904 | -14.936 | 9.032 |
| | 30min | -0.901 | -1.401 | 0.500 | -15.139 | -8.429 | -6.710 |
| | 1h | -1.400 | -1.137 | -0.263 | -7.867 | -7.675 | -0.193 |
| | 3h | -0.622 | -0.498 | -0.124 | -2.931 | -5.487 | 2.556 |
| | 6h | -0.180 | -1.362 | 1.182 | -6.014 | -2.402 | -3.612 |
| EURGBP | 5min | 0.423 | 0.057 | 0.366 | 2.659 | 1.937 | 0.721 |
| | 10min | -0.618 | -0.219 | -0.399 | -29.900 | -26.487 | -3.413 |
| | 30min | -0.858 | -0.481 | -0.376 | -14.466 | -26.890 | 12.425 |
| | 1h | -0.804 | -0.701 | -0.103 | -6.099 | -12.131 | 6.032 |
| | 3h | -0.669 | -0.527 | -0.142 | -5.329 | -8.914 | 3.585 |
| | 6h | -0.896 | **-1.346** | 0.451 | -9.169 | -9.628 | 0.459 |

Table 5.3.4: Results of both metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data only in time period 2. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used. Results for USD/JPY and GBP/JPY pairs are omitted due to a small number of observations

| | | Kantorovich | | | Lèvy | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 5min | -0.180 | -0.106 | -0.074 | -18.394 | -4.498 | -13.896 |
| | 10min | -0.200 | -0.325 | 0.125 | -7.070 | -5.641 | -1.429 |
| | 30min | -0.419 | -0.621 | 0.202 | -9.837 | -5.034 | -4.803 |
| | 1h | **-0.805** | **-1.114** | **0.308** | **-10.495** | -6.821 | -3.674 |
| | 3h | **-0.796** | **-0.993** | **0.197** | **-7.953** | **-7.982** | 0.029 |
| | 6h | **-0.670** | **-0.965** | 0.296 | **-6.372** | **-7.410** | 1.038 |
| GBP/USD | 5min | 0.189 | 0.060 | 0.129 | 5.096 | 5.834 | -0.738 |
| | 10min | -0.632 | -0.052 | -0.580 | -8.438 | -4.180 | -4.259 |
| | 30min | **-0.878** | -0.510 | -0.368 | -10.576 | -9.497 | -1.079 |
| | 1h | **-1.440** | **-0.828** | **-0.612** | -6.691 | **-15.245** | 8.554 |
| | 3h | **-1.288** | **-0.778** | **-0.510** | **-6.828** | **-10.280** | **3.452** |
| | 6h | **-1.114** | **-0.843** | **-0.271** | **-7.504** | **-8.889** | 1.385 |
| GBP/JPY | 5min | -1.323 | -0.596 | -0.726 | -2.923 | -26.290 | 23.367 |
| | 10min | -1.692 | -0.229 | -1.463 | -3.640 | -20.195 | 16.556 |
| | 30min | -1.831 | -0.736 | -1.096 | -20.535 | -24.980 | 4.446 |
| | 1h | -0.926 | -0.525 | -0.401 | -7.090 | -16.086 | 8.996 |
| | 3h | -1.625 | -0.549 | -1.076 | -5.483 | -20.474 | 14.990 |
| | 6h | -0.727 | -0.765 | 0.038 | -4.052 | -4.436 | 0.384 |
| EUR/USD | 5min | -0.581 | -0.019 | -0.561 | -7.971 | -11.577 | 3.606 |
| | 10min | -0.834 | -0.044 | -0.791 | -8.483 | -9.143 | 0.660 |
| | 30min | **-1.006** | -0.443 | -0.563 | -6.280 | -7.400 | 1.120 |
| | 1h | **-1.331** | **-0.906** | -0.425 | -7.545 | **-11.568** | 4.023 |
| | 3h | **-1.202** | **-0.806** | **-0.395** | **-6.615** | **-10.075** | **3.460** |
| | 6h | **-0.997** | **-0.834** | -0.163 | **-6.489** | **-7.902** | 1.413 |
| EUR/JPY | 5min | 0.122 | 0.112 | 0.010 | 2.265 | 0.683 | 1.582 |
| | 10min | -0.052 | -2.288 | 2.235 | -22.697 | -1.227 | -21.470 |
| | 30min | -0.970 | -1.934 | 0.964 | -30.974 | -13.586 | -17.389 |
| | 1h | -0.228 | -2.830 | **2.602** | -15.743 | -2.360 | -13.384 |
| | 3h | -0.470 | -1.766 | 1.295 | **-18.600** | -3.876 | -14.724 |
| | 6h | -0.983 | -1.836 | 0.853 | -12.919 | -7.626 | -5.293 |
| EURGBP | 5min | 0.465 | 0.144 | 0.321 | 6.013 | 9.583 | -3.571 |
| | 10min | -1.165 | -0.112 | -1.053 | -3.336 | -19.310 | **15.975** |
| | 30min | -1.076 | -0.619 | -0.457 | -3.698 | -12.157 | 8.458 |
| | 1h | **-1.502** | -0.721 | -0.782 | -8.027 | -11.570 | 3.543 |
| | 3h | **-1.171** | -0.886 | -0.285 | -5.691 | -9.837 | 4.146 |
| | 6h | **-0.941** | **-0.995** | 0.054 | -6.863 | **-7.329** | 0.467 |

Table 5.3.5: Results of both metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data only in time period 3. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

The event time results show similar features with weaker responses (see Tables A.3.9 to A.3.11 in Appendix A.3.3). Table A.3.11 shows a substantially weaker response to news releases during New York time period without clear patterns of influence, contrary to calendar time results (see Table 5.3.5).

To conclude, we do not observe enough evidence to reject the null hypothesis of no effect, as most of the influence is attributed to the important indicators clustering during specific hours rather than the liquidity effect and time period 2 produced the weakest response of all three cases considered. Results suggest that market liquidity has no effect on the magnitude of reaction to news content after taking into account the pre-release dynamics.

### 5.3.3 News Content Direction Effect on News Reactions

We now move to tackling the third objective (c) and the corresponding research hypothesis : "*The news content released cause no effect on the post-release* $(t_0^i + \Delta t)$ *returns when compared to the pre-release* $(t_0^i - \Delta t)$ *returns.*" We start by focusing on the objective (c,i) and the calendar time Kantorovich metric results in Table 5.3.6, with Levy results in Table 5.3.7.

The first objective (c,i) of the previous value sign impact, is tackled in results presented in Tables 5.3.6 and 5.3.7 for the calendar time. We interpret results as follows: we observe a positive reaction to GBP/USD pair releases at 6 hours window, as Kantorovich metric difference (Table 5.3.6) is statistically significant for positive and negative outcomes. Lèvy results (Table 5.3.7) indicate an effect on the asymmetry for positive releases as the difference is statistically significant. A consistent positive impact that is stronger on positive news at 6 hours windows on Kantorovich difference, is observed on several pairs studied. Only limited signs of an impact on the volatility levels is observed in Kantorovich results (Table 5.3.6, cases where the metric and the dual are significant but not the difference). Lèvy results in Table 5.3.7 show no clear pattern of influence with evidence of an effect on news due to previous value sign.

| | | Positive Outcome | | | Negative Outcome | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ |
| USD/JPY | 5min | 0.110 | 0.134 | -0.024 | 0.043 | 0.372 | -0.329 |
| | 10min | 0.128 | 0.420 | -0.292 | 0.039 | 0.656 | -0.617 |
| | 30min | 0.321 | 0.635 | -0.313 | 0.205 | **0.963** | -0.758 |
| | 1h | 0.516 | 0.925 | **-0.409** | 0.443 | **1.305** | -0.863 |
| | 3h | 0.378 | 0.636 | -0.259 | 0.270 | **1.032** | -0.761 |
| | 6h | 0.509 | **1.265** | **1.775** | **0.785** | -0.536 | 0.249 |
| GBP/USD | 5min | 0.077 | 0.189 | -0.113 | 0.307 | 0.052 | 0.255 |
| | 10min | 0.296 | 0.087 | 0.209 | 0.047 | 0.327 | -0.280 |
| | 30min | 0.620 | 0.307 | 0.313 | 0.207 | 0.489 | -0.282 |
| | 1h | 0.998 | 0.415 | 0.583 | **0.725** | 0.409 | 0.315 |
| | 3h | 0.826 | 0.285 | 0.541 | **0.811** | 0.146 | **0.665** |
| | 6h | 0.363 | **1.586** | **1.956** | 0.200 | **0.528** | **0.732** |
| GBP/JPY | 5min | 0.071 | 0.353 | -0.282 | 0.428 | 0.047 | 0.382 |
| | 10min | 0.123 | 0.277 | -0.154 | 0.203 | 0.250 | -0.047 |
| | 30min | 0.362 | 0.232 | 0.131 | 0.163 | 0.795 | -0.632 |
| | 1h | 0.237 | 0.199 | 0.038 | 0.354 | 0.378 | -0.023 |
| | 3h | **0.366** | 0.191 | 0.175 | 0.284 | 0.120 | 0.165 |
| | 6h | **0.275** | 0.007 | **0.288** | 0.198 | 0.088 | 0.291 |
| EUR/USD | 5min | 0.185 | 0.114 | 0.071 | 0.281 | 0.238 | 0.043 |
| | 10min | 0.178 | 0.164 | 0.014 | 0.108 | 0.159 | -0.051 |
| | 30min | 0.467 | 0.397 | 0.070 | 0.498 | 0.155 | 0.343 |
| | 1h | 0.654 | 0.446 | 0.208 | 0.359 | 0.228 | 0.131 |
| | 3h | 0.396 | 0.249 | 0.148 | **0.371** | 0.141 | 0.230 |
| | 6h | 0.236 | **1.208** | **1.447** | 0.096 | 0.205 | **0.300** |
| EUR/JPY | 5min | 0.235 | 0.107 | 0.128 | 0.127 | 0.427 | -0.300 |
| | 10min | 0.330 | 0.045 | 0.285 | 0.114 | 0.318 | -0.204 |
| | 30min | 0.412 | 0.139 | 0.273 | 0.190 | 0.621 | -0.431 |
| | 1h | 0.278 | 0.294 | -0.017 | 0.166 | 0.368 | -0.202 |
| | 3h | **0.373** | 0.308 | 0.065 | 0.175 | 0.314 | -0.139 |
| | 6h | **0.438** | -0.053 | **0.394** | **0.407** | -0.096 | 0.319 |
| EURGBP | 5min | 0.149 | 0.175 | -0.026 | 0.262 | 0.031 | 0.232 |
| | 10min | 0.161 | 0.097 | 0.064 | 0.108 | 0.259 | -0.151 |
| | 30min | **0.503** | 0.275 | 0.229 | 0.100 | 0.362 | -0.262 |
| | 1h | **0.566** | **0.426** | 0.140 | 0.188 | 0.322 | -0.134 |
| | 3h | **0.360** | 0.086 | **0.275** | 0.081 | 0.210 | -0.130 |
| | 6h | 0.014 | **0.185** | **0.198** | 0.115 | -0.001 | 0.112 |

Table 5.3.6: Results of Kantorovich metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data by focusing on previous value outcomes only. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

| | | Positive Outcome | | | Negative Outcome | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 5min | 9.032 | 11.713 | -2.680 | 17.393 | 12.974 | 4.418 |
| | 10min | 7.560 | 3.308 | 4.252 | 13.266 | 3.567 | 9.699 |
| | 30min | 6.161 | 3.815 | 2.346 | 13.220 | 5.025 | 8.195 |
| | 1h | **7.868** | 5.504 | 2.364 | **13.515** | 6.738 | 6.777 |
| | 3h | **4.215** | 3.878 | 0.336 | **9.069** | 4.558 | 4.511 |
| | 6h | **3.881** | -1.647 | 2.286 | 3.318 | 1.913 | **5.219** |
| GBP/USD | 5min | 9.914 | 10.123 | -0.209 | 13.405 | 8.379 | 5.027 |
| | 10min | 4.877 | 2.850 | 2.027 | 9.689 | 5.160 | 4.528 |
| | 30min | 3.398 | 6.707 | -3.309 | 10.913 | 6.223 | 4.689 |
| | 1h | 3.809 | **7.348** | -3.538 | 4.025 | 8.292 | -4.267 |
| | 3h | 2.456 | **5.293** | -2.836 | 3.529 | **6.724** | -3.195 |
| | 6h | **4.505** | -1.875 | **2.660** | **4.856** | -3.390 | 1.460 |
| GBP/JPY | 5min | 11.643 | 10.314 | 1.329 | 6.339 | 13.689 | -7.350 |
| | 10min | 6.621 | 7.899 | -1.278 | 13.770 | 4.900 | 8.870 |
| | 30min | 2.871 | 5.495 | -2.624 | 9.860 | 4.316 | 5.543 |
| | 1h | 3.135 | 3.960 | -0.825 | 4.837 | 4.257 | 0.581 |
| | 3h | 3.221 | **8.348** | -5.127 | 2.645 | 3.428 | -0.783 |
| | 6h | **7.246** | -4.364 | 2.934 | 4.178 | -0.271 | 4.016 |
| EUR/USD | 5min | 5.660 | 4.817 | 0.843 | 17.504 | 12.117 | 5.387 |
| | 10min | 3.696 | 1.542 | 2.154 | 5.033 | 7.860 | -2.827 |
| | 30min | 4.947 | 3.403 | 1.545 | 4.734 | 5.198 | -0.464 |
| | 1h | **4.422** | **4.610** | -0.188 | 4.947 | 4.798 | 0.149 |
| | 3h | 1.704 | 2.813 | -1.109 | 1.361 | 4.260 | **-2.899** |
| | 6h | **2.977** | -1.503 | 1.528 | 4.071 | -3.285 | 0.794 |
| EUR/JPY | 5min | 7.269 | 24.430 | **-17.161** | 10.471 | 14.909 | -4.438 |
| | 10min | 1.652 | 11.754 | -10.102 | 7.295 | 6.277 | 1.018 |
| | 30min | 4.191 | 9.977 | **-5.786** | 3.997 | 8.637 | -4.640 |
| | 1h | 1.027 | 5.551 | **-4.524** | 3.858 | 6.670 | -2.811 |
| | 3h | 1.638 | **6.335** | -4.696 | 5.285 | **7.048** | -1.763 |
| | 6h | **5.451** | -3.027 | 2.451 | **7.958** | -3.091 | 4.982 |
| EURGBP | 5min | 16.933 | 10.238 | 6.695 | 15.573 | 16.579 | -1.006 |
| | 10min | 6.233 | 2.878 | 3.355 | 6.072 | 3.226 | 2.846 |
| | 30min | **10.660** | **8.102** | 2.558 | 7.478 | 6.734 | 0.745 |
| | 1h | **5.871** | **6.637** | -0.766 | 3.237 | 4.096 | -0.859 |
| | 3h | 2.387 | **4.226** | -1.838 | 2.293 | 4.156 | -1.862 |
| | 6h | **3.315** | **-1.945** | 1.390 | 2.611 | -1.078 | 1.497 |

Table 5.3.7: Results of Lèvy metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data by focusing on previous value outcomes only. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

The event time results in Appendix A.3.4, Tables A.3.12 and A.3.13 show similar features as in previous cases but of weaker signs of effect across all cases considered. In most cases, only after 1000 ticks or further, a response is observable suggesting a delayed influence of the previous value sign.

Regarding our second objective (c,ii) of the expected value sign impact, we start by investigating results in Tables 5.3.8 and 5.3.9 for the calendar time findings. In general, influence of the conditioning is only visible at 1 hour or longer time frame, in both metric results, similar to the previous value findings. Similarly, a positive response is visible for several pairs at 6 hours since the release, and is stronger for positive news but is positive for the negative releases too. The event time results in Tables A.3.16 and A.3.17 in Appendix A.3.4, display a weaker and in some cases negative response to conditioning on positive news, while there is no directional response to negative sign cases.

| | | Positive Outcome | | | Negative Outcome | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ |
| USD/JPY | 5min | 0.128 | 0.085 | 0.043 | 0.073 | 0.587 | -0.515 |
| | 10min | 0.153 | 0.389 | -0.236 | 0.021 | 1.048 | -1.027 |
| | 30min | 0.319 | 0.586 | -0.267 | 0.140 | **1.246** | -1.107 |
| | 1h | 0.491 | 0.952 | -0.461 | 0.431 | **1.410** | -0.980 |
| | 3h | 0.339 | 0.686 | -0.348 | 0.333 | **1.058** | -0.725 |
| | 6h | 0.543 | **1.052** | **1.596** | **0.814** | -0.531 | 0.284 |
| GBP/USD | 5min | 0.109 | 0.126 | -0.017 | 0.292 | 0.209 | 0.083 |
| | 10min | 0.277 | 0.164 | 0.113 | 0.180 | 0.264 | -0.084 |
| | 30min | 0.560 | 0.342 | 0.218 | 0.319 | 0.508 | -0.189 |
| | 1h | 0.963 | 0.431 | 0.533 | **0.783** | 0.516 | 0.267 |
| | 3h | 0.799 | 0.279 | 0.520 | **0.857** | 0.185 | **0.672** |
| | 6h | 0.372 | **1.465** | **1.843** | 0.228 | **0.550** | **0.782** |
| GBP/JPY | 5min | 0.115 | 0.320 | -0.206 | 0.213 | 0.244 | -0.031 |
| | 10min | 0.051 | 0.420 | -0.369 | 0.171 | 0.331 | -0.160 |
| | 30min | 0.308 | 0.246 | 0.062 | 0.150 | 1.064 | **-0.913** |
| | 1h | 0.246 | 0.331 | -0.085 | 0.248 | 0.396 | -0.148 |
| | 3h | 0.362 | 0.256 | 0.106 | 0.329 | 0.223 | 0.106 |
| | 6h | **0.334** | -0.089 | 0.251 | 0.260 | 0.057 | 0.320 |
| EUR/USD | 5min | 0.180 | 0.136 | 0.044 | 0.449 | 0.111 | 0.339 |
| | 10min | 0.129 | 0.183 | -0.053 | 0.155 | 0.163 | -0.009 |
| | 30min | 0.362 | 0.425 | -0.063 | 0.650 | 0.223 | 0.427 |
| | 1h | 0.570 | 0.407 | 0.162 | **0.585** | 0.440 | 0.145 |
| | 3h | 0.309 | 0.244 | 0.065 | **0.612** | 0.200 | **0.412** |
| | 6h | 0.214 | **1.019** | **1.234** | 0.126 | **0.338** | **0.463** |
| EUR/JPY | 5min | 0.353 | 0.075 | 0.278 | 0.128 | 0.448 | -0.320 |
| | 10min | 0.320 | 0.055 | 0.265 | 0.138 | 0.647 | -0.509 |
| | 30min | 0.301 | 0.202 | 0.099 | 0.217 | 0.669 | -0.452 |
| | 1h | 0.235 | 0.423 | -0.188 | 0.242 | 0.345 | -0.103 |
| | 3h | 0.315 | **0.364** | -0.050 | 0.208 | 0.236 | -0.029 |
| | 6h | **0.538** | -0.153 | **0.397** | 0.200 | 0.055 | 0.256 |
| EURGBP | 5min | 0.138 | 0.167 | -0.029 | 0.194 | 0.067 | 0.127 |
| | 10min | 0.052 | 0.208 | -0.156 | 0.235 | 0.214 | 0.021 |
| | 30min | 0.407 | 0.372 | 0.034 | 0.208 | 0.317 | -0.109 |
| | 1h | **0.523** | **0.468** | 0.054 | 0.198 | 0.424 | -0.225 |
| | 3h | **0.297** | 0.088 | 0.209 | 0.142 | 0.203 | -0.061 |
| | 6h | 0.026 | 0.124 | 0.149 | 0.070 | 0.064 | 0.129 |

Table 5.3.8: Results of Kantorovich metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data by focusing on forecast value outcomes only. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

| | | Positive Outcome | | | Negative Outcome | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 5min | 9.409 | 8.189 | 1.219 | 14.621 | 25.742 | -11.121 |
| | 10min | 8.707 | 4.767 | 3.940 | 17.936 | 4.134 | 13.803 |
| | 30min | 6.225 | 3.824 | 2.401 | 14.430 | 3.896 | 10.534 |
| | 1h | **8.051** | 5.655 | 2.396 | **15.303** | 6.639 | 8.664 |
| | 3h | **4.344** | **4.023** | 0.322 | **9.774** | 4.282 | 5.492 |
| | 6h | **3.557** | -1.246 | 2.339 | 3.866 | 1.915 | **5.794** |
| GBP/USD | 5min | 9.661 | 7.623 | 2.038 | 13.087 | 12.618 | 0.469 |
| | 10min | 6.891 | 2.632 | 4.259 | 14.108 | 8.091 | 6.017 |
| | 30min | 3.057 | 5.874 | -2.817 | 10.892 | 11.256 | -0.364 |
| | 1h | 3.737 | **6.786** | **-3.049** | 4.497 | **9.561** | -5.063 |
| | 3h | 2.195 | **5.052** | -2.857 | 3.849 | **7.818** | -3.969 |
| | 6h | **4.286** | -1.691 | 2.608 | **5.754** | -3.641 | 2.085 |
| GBP/JPY | 5min | 10.576 | 13.340 | -2.764 | 11.497 | 13.491 | -1.994 |
| | 10min | 11.733 | 7.421 | 4.312 | 10.196 | 5.721 | 4.476 |
| | 30min | 2.924 | 6.463 | -3.539 | 12.039 | 4.656 | 7.383 |
| | 1h | 2.839 | 4.337 | -1.498 | 5.612 | 5.027 | 0.585 |
| | 3h | 2.317 | **7.680** | -5.362 | 6.022 | 3.647 | 2.375 |
| | 6h | **7.690** | -4.733 | 3.071 | 3.363 | 0.960 | 4.354 |
| EUR/USD | 5min | 8.884 | 4.327 | 4.556 | 12.330 | 16.450 | -4.120 |
| | 10min | 4.144 | 2.043 | 2.101 | 3.920 | 15.086 | **-11.165** |
| | 30min | 6.067 | 2.688 | 3.379 | 6.357 | 8.609 | -2.251 |
| | 1h | 4.194 | **4.666** | -0.471 | 5.515 | 5.530 | -0.015 |
| | 3h | 1.494 | 2.712 | -1.218 | 1.689 | **6.382** | -4.693 |
| | 6h | **3.084** | -1.868 | 1.261 | **5.436** | -4.481 | 1.000 |
| EUR/JPY | 5min | 11.219 | 27.471 | -16.253 | 10.365 | 19.407 | -9.041 |
| | 10min | 1.927 | 11.070 | **-9.143** | 12.086 | 7.013 | 5.073 |
| | 30min | 3.814 | 9.274 | **-5.461** | 4.153 | 6.996 | -2.842 |
| | 1h | 3.506 | 5.898 | -2.392 | 2.913 | 6.019 | -3.106 |
| | 3h | 1.813 | **5.233** | -3.419 | 4.072 | 7.353 | -3.281 |
| | 6h | **5.371** | -2.486 | 2.963 | **7.693** | **-3.719** | 4.069 |
| EURGBP | 5min | 16.298 | 10.627 | 5.671 | 11.225 | 10.573 | 0.652 |
| | 10min | 8.793 | 1.151 | 7.642 | 4.484 | 4.349 | 0.135 |
| | 30min | **12.441** | 6.793 | 5.647 | 7.040 | 6.864 | 0.176 |
| | 1h | **7.543** | **7.338** | 0.205 | 5.090 | 4.422 | 0.668 |
| | 3h | 2.503 | **4.799** | **-2.296** | 2.080 | 4.248 | -2.168 |
| | 6h | **3.496** | -2.094 | 1.410 | 2.088 | -0.893 | 1.136 |

Table 5.3.9: Results of Lèvy metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data by focusing on forecast value outcomes only. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

Finally, the last objective (c,iii) investigates on the sign effect of the newly released figure. Its it the only case of three smaller objectives considered where the newly released information is unknown before the release. The calendar time results in Tables 5.3.10 and 5.3.11, show a stronger positive response pattern observed than in all of the previous cases considered when conditioning on the content. Table 5.3.10 displays a similar positive reaction to positive news as in previous cases, but the negative news response is substantially stronger than positive news. The influence is observable mainly at 3 and 6 hours windows. However, Lèvy metric results in Table A.3.14 show a stronger effect on the positive news when compared to the negative news results. The event time results in Tables A.3.14 and A.3.15 in Appendix A.3.4, show a substantially weaker response to conditioning with similar strength of effects observed as in the first (c,i) or second (c,ii) targets.

| | | Positive Outcome | | | Negative Outcome | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ |
| USD/JPY | 5min | 0.122 | 0.132 | -0.010 | 0.103 | 0.533 | -0.429 |
| | 10min | 0.193 | 0.416 | -0.223 | 0.012 | 1.013 | -1.001 |
| | 30min | 0.345 | 0.657 | -0.311 | 0.064 | **1.070** | -1.007 |
| | 1h | 0.452 | 1.060 | -0.608 | 0.510 | **1.050** | -0.541 |
| | 3h | 0.322 | 0.775 | **-0.453** | 0.357 | **0.772** | -0.415 |
| | 6h | 0.617 | **1.106** | **1.725** | **0.585** | -0.250 | **0.335** |
| GBP/USD | 5min | 0.069 | 0.148 | -0.079 | 0.305 | 0.274 | 0.031 |
| | 10min | 0.249 | 0.167 | 0.082 | 0.191 | 0.244 | -0.053 |
| | 30min | 0.579 | 0.328 | 0.251 | 0.303 | 0.467 | -0.164 |
| | 1h | 0.888 | 0.478 | 0.409 | **0.972** | 0.322 | **0.649** |
| | 3h | 0.757 | 0.337 | 0.420 | **1.001** | 0.105 | **0.896** |
| | 6h | 0.412 | **1.494** | **1.913** | 0.150 | **0.694** | **0.847** |
| GBP/JPY | 5min | 0.073 | 0.308 | -0.235 | 0.253 | 0.136 | 0.117 |
| | 10min | 0.085 | 0.393 | -0.309 | 0.344 | 0.168 | 0.176 |
| | 30min | 0.268 | 0.231 | 0.037 | 0.371 | 0.817 | -0.447 |
| | 1h | 0.175 | 0.386 | -0.211 | 0.663 | 0.183 | 0.481 |
| | 3h | 0.282 | 0.341 | -0.059 | **0.725** | 0.030 | **0.695** |
| | 6h | **0.381** | **-0.169** | 0.217 | 0.106 | **0.491** | **0.602** |
| EUR/USD | 5min | 0.148 | 0.080 | 0.068 | 0.407 | 0.288 | 0.119 |
| | 10min | 0.163 | 0.174 | -0.011 | 0.104 | 0.154 | -0.049 |
| | 30min | 0.447 | 0.390 | 0.057 | 0.460 | 0.175 | 0.285 |
| | 1h | 0.586 | 0.481 | 0.105 | **0.519** | 0.126 | 0.394 |
| | 3h | 0.356 | 0.300 | 0.056 | **0.484** | 0.019 | **0.465** |
| | 6h | 0.282 | **1.133** | **1.418** | 0.006 | **0.398** | **0.403** |
| EUR/JPY | 5min | 0.248 | 0.095 | 0.153 | 0.154 | 0.356 | -0.201 |
| | 10min | 0.356 | 0.039 | 0.316 | 0.130 | 0.363 | -0.233 |
| | 30min | 0.392 | 0.150 | 0.242 | 0.216 | 0.564 | -0.349 |
| | 1h | 0.238 | 0.370 | -0.132 | 0.246 | 0.159 | 0.087 |
| | 3h | 0.313 | **0.366** | -0.053 | 0.351 | 0.218 | 0.133 |
| | 6h | **0.494** | -0.138 | **0.366** | 0.288 | 0.108 | **0.401** |
| EURGBP | 5min | 0.127 | 0.201 | -0.075 | 0.331 | 0.015 | 0.316 |
| | 10min | 0.078 | 0.182 | -0.104 | 0.304 | 0.094 | 0.210 |
| | 30min | 0.403 | 0.318 | 0.085 | 0.312 | 0.228 | 0.084 |
| | 1h | **0.435** | **0.525** | -0.090 | **0.477** | 0.132 | 0.345 |
| | 3h | **0.240** | 0.145 | 0.095 | 0.322 | 0.033 | 0.289 |
| | 6h | 0.048 | 0.058 | 0.104 | 0.033 | **0.291** | **0.324** |

Table 5.3.10: Results of Kantorovich metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data by focusing on released value outcomes only. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

| | | Positive Outcome | | | Negative Outcome | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 5min | 9.363 | 8.397 | 0.966 | 15.382 | 16.919 | -1.537 |
| | 10min | 8.430 | 3.847 | 4.583 | 12.176 | 3.674 | 8.501 |
| | 30min | 6.054 | 3.869 | 2.184 | **13.417** | 3.266 | 10.151 |
| | 1h | **8.668** | 5.520 | 3.148 | **12.690** | 5.631 | 7.059 |
| | 3h | **4.462** | 4.104 | 0.358 | **7.540** | 3.830 | 3.710 |
| | 6h | **3.878** | -1.316 | 2.599 | 3.308 | 1.028 | **4.351** |
| GBP/USD | 5min | 9.329 | 7.756 | 1.574 | 13.436 | 11.394 | 2.042 |
| | 10min | 4.959 | 2.536 | 2.423 | 12.572 | 5.961 | 6.611 |
| | 30min | 3.498 | 6.739 | -3.241 | 10.127 | 7.996 | 2.130 |
| | 1h | 3.815 | **6.782** | **-2.967** | 4.878 | **9.028** | -4.150 |
| | 3h | 2.538 | **4.846** | -2.308 | 3.981 | **7.216** | **-3.235** |
| | 6h | **4.273** | -1.478 | **2.831** | **5.557** | -3.775 | 1.795 |
| GBP/JPY | 5min | 8.993 | 11.463 | -2.470 | 10.499 | 10.680 | -0.181 |
| | 10min | 7.710 | 6.894 | 0.816 | 11.588 | 5.367 | 6.221 |
| | 30min | 2.619 | 5.582 | -2.963 | 11.213 | 7.342 | 3.871 |
| | 1h | 2.429 | 3.361 | -0.932 | 4.484 | 4.169 | 0.315 |
| | 3h | 2.995 | **7.517** | -4.522 | 3.475 | 4.242 | -0.767 |
| | 6h | **7.472** | -3.882 | 3.699 | 3.771 | -1.107 | 2.733 |
| EUR/USD | 5min | 6.878 | 5.689 | 1.189 | 12.522 | 11.721 | 0.801 |
| | 10min | 3.380 | 1.968 | 1.412 | 5.300 | 10.314 | -5.014 |
| | 30min | 3.587 | 3.146 | 0.441 | 4.866 | 6.073 | -1.207 |
| | 1h | **4.411** | **4.666** | -0.255 | 4.993 | 5.065 | -0.072 |
| | 3h | 1.790 | 2.961 | -1.172 | 1.255 | 3.932 | -2.677 |
| | 6h | **2.992** | **-1.370** | 1.674 | 4.038 | -3.815 | 0.263 |
| EUR/JPY | 5min | 10.252 | 21.233 | -10.981 | 10.689 | 18.855 | -8.166 |
| | 10min | 1.390 | 12.454 | -11.064 | 7.819 | 4.771 | 3.048 |
| | 30min | 1.882 | 10.110 | -8.227 | 3.247 | 6.859 | -3.612 |
| | 1h | 1.588 | 5.636 | **-4.049** | 2.858 | 6.919 | -4.061 |
| | 3h | 1.704 | **5.556** | -3.853 | 4.074 | **8.239** | **-4.165** |
| | 6h | **5.721** | -3.072 | 2.729 | **7.843** | -4.385 | 3.549 |
| EURGBP | 5min | 19.829 | 10.184 | 9.646 | 13.441 | 15.208 | -1.767 |
| | 10min | 7.693 | 1.511 | 6.182 | 3.507 | 3.642 | -0.135 |
| | 30min | **10.659** | 6.390 | 4.268 | 6.503 | 6.056 | 0.447 |
| | 1h | **6.348** | **5.555** | 0.793 | 3.135 | 5.245 | -2.110 |
| | 3h | 2.662 | **3.961** | -1.299 | 2.297 | 4.675 | -2.378 |
| | 6h | **3.226** | -1.959 | 1.290 | 2.404 | -0.905 | 1.448 |

Table 5.3.11: Results of Lèvy metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data by focusing on released value outcomes only. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

Reactions to new information are stronger than when compared to reaction observed when tackling the previous value impact (c,i) or the expected value (c,ii) targets. Contrary to what is expected, the negative actual value direction has the strongest positive influence on average FX returns, after accounting for the pre-release dynamics. Results suggest that news content does not cause any consistent effect on the high-frequency returns around the release point at all.

To conclude, we observe that releases have a complex news absorption structure in average returns and higher moments. Mondays and Fridays along with Thursdays were found to have the strongest effect on FX dynamics, irrespective of the news content or time grid, but with limited signs of consistent effect, contrary to suggestions by Ehrmann and Fratzscher (2005). The time period effect was found to be the strongest for the New York market, but the combined period of two had a limited effect, suggesting for observed impacts to be due to the important indicators clustering. The event time findings showed substantially weaker reactions irrespective of the conditioning case considered. We observed contradicting findings to the FX market micro-structure theory (Lyons, 2006), where the information absorption was postulated to be reflected by a higher level of volatility in the post-release returns. The conditioning on indicator signs revealed intriguing evidence. The influence was the strongest for the actual figure released as expected. However, irrespective of the direction of the actual value, a positive strong effect was observed. Irrespective of the content, news releases showed a positive response to the economy in question, and people were more optimistic about the future and the content released did not matter after accounting for the pre-release dynamics.

## 5.4 Conclusions

In this chapter, we provide an empirical analysis of conditional FX rate dynamics around public macroeconomic news shocks on EUR/USD, EUR/JPY, EUR/GBP, GBP/USD and USD/JPY pairs. We study the influence of the day, time period, and news content direction, on the after-release reaction and took into account pre-release dynamics to remove the anticipation effect.

We discover that reaction to news depends on the following factors: the day of the week when it is released and the expected direction of the news indicator. Friday and Monday releases seem to cause the strongest impact, and it could be attributed to the nature of the data being released during those week days. As expected from the existing literature (Andersen et al., 2003), U.S. news releases were found to have the strongest impact, due to clustering of the most important indicators during certain hours. Initially, we expected that the overlapping of London and New York markets would have the strongest impact, however findings indicated that the New York market release to react the strongest.

The news content impact analysis showed that the direction of the actual newly released value had the strongest response. In general, the response to positive and negative signs was positive, resulting in a higher on average FX return after accounting for the pre-release exchange rate dynamics. In general, we observed a general feature, for, irrespective of the news content, a positive reaction to news was observed, leading to the conclusion of an optimistic attitude by markets towards any news released. These findings are new to the literature and have not been reported before to the best of our knowledge.

# Chapter 6

# Summary

In this thesis, we have investigated the impact that quantitative news have on exchange rates. There exist many theories explaining exchange rate dynamics in the long-run, based on one or several macroeconomic indicators (for more detailed information, Chapter 2). All theoretical models are silent about the short-term exchange rate dynamics, and there is an ample amount of volatility on intra-day or daily frequency. The speculation is often argued to be the driving force behind this volatility. One begs to ask how a market with so many institutional trades can be mainly driven by speculation? In this thesis, we propose the hypothesis that there is no relation between exchange rate dynamics, and macroeconomic indicators, and challenge the evidence against it.

We started our investigation following the path of the existing literature. The most common approach when studying public macroeconomic releases is based on using a time-series model with 5 minutes frequency data. The macroeconomic data is transformed to combine three available data points around each release (previous, forecasted and newly released values) into a single value, and used in an ARMAX-GARCHX class time-series model. Depending on the authors' preferences, the main focus of the study is either on the news release impact (for example Evans and Speight, 2010a), or the in-between release dynamics (for example Fatum et al., 2012). In general, such models yield statistically significant macroeconomic estimates, and, as a result it is often concluded that macroeconomic data is related to exchange rate dynamics.

In Chapter 3, we followed the same path, but attempted to combine long-run and short-run components together, and varied the news transformation used. Results indicated a superior ability to explain exchange rate dynamics when compared to previous studies. Our approach relied on using fewer variables, and results were robust with respect to the exchange rate pair, news transformation, data subset, residuals distribution, or the formulation of the hypothesis of macroeconomic news significance. Our results further indicated that the existing literature has overlooked the importance of combining both components. We highlighted that a transformed version of macroeconomic data must not by confused with the actual macroeconomic data, as just by using a different transformation, we were able to observe a limited relation between exchange rate dynamics and transformed macroeconomic data. By comparing results of the out-of-sample performance from different years, we were able to observe that only for the years when the market sentiment was similar, residuals showed similar distributions, suggesting the importance of market sentiment on FX dynamics. The observation of such poor performance of the popular methodology from the literature, leads to a more detailed investigation of the actual impact that news releases have on exchange rates. We only scratched the surface of potential future areas of exploration. The future research should explore appropriate information transformations for the long- and short-term components separately. Its is reasonable to expect that previous macroeconomic indicator value should be relevant to the short-term component, due to cognitive biases of market participants, but it is unlikely to be relevant for the long-run component, as it does not convey any new information about the future. In addition, future research must incorporate market sentiment indicators as reactions to news were observed to be dependent on market conditions in our results. Our research took a path of instead of using a time-series model, we asked a more general question: what methodology can we use that requires the least amount of assumptions?

In Chapter 4, we transformed the data to a different framework. We stacked all news releases around the point of release and focused on the dynamics around the release point. The evaluation of the most appropriate methodology was the primary objective of the chapter, and therefore each release was assumed to be independent from the previous one. Our framework allowed us to make a deeper insight, as by comparing the post- and pre-release dynamics, we were able to remove the anticipation of the release effect that has been previously ignored. As our methodology of analysis relied on using bootstrapped statistics to determine the significance and was data intensive, we decided to use 5 second and 5 data ticks time frequencies. Only studies by Kim (1998) and Evans and Speight (2010a) noted a pre-release reaction to news, but further investigation was not carried out. Our results too showed a strong pre-release effect and a substantial reaction in the volatility dynamics. The post-release dynamics showed a significant reaction as well. This was in-line with the results in the existing literature and the approach used in Chapter 3. However, after accounting for the pre-release dynamics, we were unable to observe any consistent effects. Our results were contradicting the market microstructure reasoning (Lyons, 2006) that implies volatility to reflect new information processing. As a result, we should observe higher volatility levels after news releases but we were unable to see evidence in favor of the claim after taking into account the dynamics of before releases. In addition, the event time results indicated more consistent evidence, suggesting for the measurement grid to be more appropriate when studying news shock dynamics. The evaluation of methodologies revealed that the use of selected probability distances was the most appropriate method to measure observed effects.

In Chapter 5, we looked into the effect of a weekday, liquidity levels or the sign of each individual macroeconomic data point have on the observed reaction after accounting for the pre-release dynamics. Monday and Friday releases showed the strongest effect on the observed dynamics, either due to the importance of individual weekdays or due to indicator clustering, but event-time results showed substantially weaker reactions. On the other hand, the period of the day seemed to have no influence on the news reactions. Therefore, we concluded that indicator clustering was the main driving force behind the certain day or the hour of the day. The conditioning on the sign of the macroeconomic indicator showed that the actual figure released caused the strongest reaction as expected. However, the direction of the reaction was mainly positive, irrespective of the indicator direction studied. Therefore, we concluded that people were more optimistic about the future or over-reacted to negative news before the release and under-reacted to positive direction news. Just by incorporating several factors we gained multiple interesting insights, but the future research should look into possibly exploring order-flows and order placement data in our proposed framework. Orders data would allow to have more accurate measurements on information flows, and would allow to develop potential tools for the insider trading detection. Alternative market data should be explored in the future. For example, equity market data would allow to model news shocks from all news releases around a certain yearly quarter, to measure the influence of market mood on observed reaction.

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# Appendix A

# Appendix

## A.1 Additional Material: Importance of Macroeconomic News Definition in FX Market

| Components | | In-Sample | | | Out-of-Sample | | |
|---|---|---|---|---|---|---|---|
| $(SR, LR)$ | | *Sub 1* | *Sub 2* | *Sub 3* | *Sub 2* | *Sub 3* | *Sub 4* |
| $(D_t, D_t)$ | Mean | 0.2484 | -0.2299 | -0.0892 | 0.8924 | -0.2882 | -0.0901 |
| | St.D. | 1.0711 | 1.0242 | 1.1407 | 1.5596 | 0.8449 | 1.2202 |
| | Skew. | -0.2384 | 0.3668 | 0.2173 | -0.1452 | 0.2974 | 0.1935 |
| | Kurt. | 3.0497 | 12.5923 | 2.7693 | 3.0189 | 8.2102 | 5.3089 |
| | MSE | 0.1174 | 0.0932 | 0.1970 | 0.4658 | 0.0650 | 0.2485 |
| | Bias | 0.1174 | 0.0932 | 0.1970 | 0.4658 | 0.0650 | 0.2485 |
| $(S_t, D_t)$ | Mean | 0.0857 | 0.1869 | -0.2449 | 0.1118 | -0.1505 | -0.0722 |
| | St.D. | 1.1503 | 1.0881 | 1.0231 | 1.9547 | 0.8815 | 0.9274 |
| | Skew. | 0.2533 | 0.7986 | -0.1699 | 0.5446 | -0.1911 | 0.7361 |
| | Kurt. | 13.8742 | 28.5455 | 13.4838 | 23.9271 | 14.8904 | 51.4149 |
| | MSE | 0.0177 | 0.0680 | 0.0397 | 0.0611 | 0.0429 | 0.0301 |
| | Bias | 0.0177 | 0.0680 | 0.0397 | 0.0611 | 0.0429 | 0.0301 |
| $(M_t, D_t)$ | Mean | 0.0856 | 0.1868 | -0.2447 | 0.1117 | -0.1504 | -0.0721 |
| | St.D. | 1.1495 | 1.0877 | 1.0222 | 1.9538 | 0.8813 | 0.9268 |
| | Skew. | 0.2532 | 0.7991 | -0.1701 | 0.5454 | -0.1913 | 0.7375 |
| | Kurt. | 13.8897 | 28.5721 | 13.4996 | 23.9581 | 14.9013 | 51.5260 |
| | MSE | 0.0256 | 0.0713 | 0.0432 | 0.0628 | 0.0464 | 0.0313 |
| | Bias | 0.0256 | 0.0713 | 0.0432 | 0.0628 | 0.0464 | 0.0313 |
| $(D_t, S_t)$ | Mean | -0.0795 | 0.0594 | -0.0180 | -0.0542 | 0.0464 | 0.0189 |
| | St.D. | 1.0782 | 1.0866 | 1.0143 | 1.8842 | 0.8983 | 0.8681 |
| | Skew. | 0.1687 | 0.3807 | -0.4892 | 0.2216 | -0.5181 | 0.7805 |
| | Kurt. | 15.4003 | 29.5121 | 16.3758 | 25.2576 | 14.1311 | 85.4486 |
| | MSE | 0.0160 | 0.0613 | 0.0346 | 0.0567 | 0.0413 | 0.0246 |
| | Bias | 0.0160 | 0.0613 | 0.0346 | 0.0567 | 0.0413 | 0.0246 |
| $(S_t, S_t)$ | Mean | -0.0967 | 0.0649 | -0.0150 | -0.0535 | 0.0521 | 0.0188 |
| | St.D. | 1.0957 | 1.0632 | 0.9880 | 1.8852 | 0.9008 | 0.8425 |
| | Skew. | 0.1518 | 0.4353 | -0.5070 | 0.2515 | -0.4908 | 0.8228 |
| | Kurt. | 16.4244 | 29.6838 | 15.3772 | 27.3216 | 13.5791 | 77.4144 |
| | MSE | 0.0160 | 0.0626 | 0.0349 | 0.0559 | 0.0441 | 0.0246 |
| | Bias | 0.0160 | 0.0626 | 0.0349 | 0.0559 | 0.0441 | 0.0246 |
| $(M_t, S_t)$ | Mean | -0.0056 | 0.0012 | -0.0262 | -0.0072 | 0.0014 | -0.0235 |
| | St.D. | 0.3022 | 0.9819 | 0.9374 | 0.5903 | 0.6857 | 0.8346 |
| | Skew. | -0.0361 | 0.1286 | -0.3857 | 0.0708 | -0.4778 | 1.1775 |
| | Kurt. | 24.2452 | 43.4484 | 25.9946 | 39.6057 | 33.1395 | 148.3169 |
| | MSE | 0.0131 | 0.0515 | 0.0243 | 0.0515 | 0.0242 | 0.0185 |
| | Bias | 0.0131 | 0.0515 | 0.0243 | 0.0515 | 0.0242 | 0.0185 |

Table A.1.1: Descriptive statistics of the innovations of the augmented model $R_{AUG,t}(N_t^{SR}, N_t^{LR})$ for the EUR/JPY FX pair.

| Components $(SR, LR)$ | | In-Sample *Sub 1* | *Sub 2* | *Sub 3* | Out-of-Sample *Sub 2* | *Sub 3* | *Sub 4* |
|---|---|---|---|---|---|---|---|
| $(D_t, D_t)$ | Mean | -0.0159 | -0.0478 | -0.4811 | 0.1896 | -0.0307 | -0.0045 |
| | St.D. | 0.6673 | 0.3433 | 0.8449 | 0.8621 | 0.3323 | 1.3164 |
| | Skew. | 0.0900 | 0.4301 | 0.0662 | -0.1366 | 0.2850 | 0.4527 |
| | Kurt. | 2.5318 | 13.0618 | 3.8924 | 2.6220 | 6.2291 | 2.9642 |
| | MSE | 0.0652 | 0.0486 | 0.0622 | 0.1571 | 0.0353 | 0.1201 |
| | Bias | 0.0652 | 0.0485 | 0.0622 | 0.1571 | 0.0353 | 0.1201 |
| $(S_t, D_t)$ | Mean | -0.0564 | 0.3036 | -0.3185 | 0.3829 | -0.2057 | -0.1012 |
| | St.D. | 1.2052 | 1.1331 | 1.0659 | 1.6555 | 1.1405 | 0.9499 |
| | Skew. | 0.3154 | 0.5228 | 0.3199 | 0.1326 | 0.5516 | 0.2497 |
| | Kurt. | 18.3909 | 6.7180 | 6.2031 | 10.0755 | 4.5670 | 6.4981 |
| | MSE | 0.0083 | 0.0472 | 0.0270 | 0.0307 | 0.0467 | 0.0189 |
| | Bias | 0.0083 | 0.0472 | 0.0270 | 0.0307 | 0.0467 | 0.0189 |
| $(M_t, D_t)$ | Mean | -0.0563 | 0.3034 | -0.3183 | 0.3825 | -0.2057 | -0.1011 |
| | St.D. | 1.2037 | 1.1326 | 1.0646 | 1.6538 | 1.1401 | 0.9490 |
| | Skew. | 0.3173 | 0.5229 | 0.3192 | 0.1329 | 0.5512 | 0.2509 |
| | Kurt. | 18.4501 | 6.7177 | 6.2023 | 10.1008 | 4.5653 | 6.5034 |
| | MSE | 0.0108 | 0.0507 | 0.0302 | 0.0308 | 0.0500 | 0.0201 |
| | Bias | 0.0107 | 0.0507 | 0.0302 | 0.0308 | 0.0500 | 0.0201 |
| $(D_t, S_t)$ | Mean | -0.0748 | 0.1084 | 0.0118 | 0.0256 | 0.0971 | 0.0382 |
| | St.D. | 0.4837 | 1.0370 | 1.0507 | 0.8489 | 1.0948 | 0.7922 |
| | Skew. | 0.2670 | 0.4694 | 0.0496 | 0.3600 | 0.0490 | 0.1463 |
| | Kurt. | 50.0519 | 8.6216 | 5.3626 | 13.7104 | 4.1725 | 10.4606 |
| | MSE | 0.0060 | 0.0354 | 0.0261 | 0.0224 | 0.0399 | 0.0139 |
| | Bias | 0.0060 | 0.0354 | 0.0261 | 0.0224 | 0.0399 | 0.0139 |
| $(S_t, S_t)$ | Mean | -0.2215 | 0.1132 | -0.0253 | -0.0398 | 0.1026 | 0.0258 |
| | St.D. | 1.1085 | 1.0367 | 1.0123 | 1.5906 | 1.1134 | 0.8380 |
| | Skew. | 0.1736 | 0.4475 | 0.0648 | 0.2378 | 0.0561 | 0.2106 |
| | Kurt. | 31.1321 | 7.8691 | 7.0908 | 12.9279 | 3.9293 | 11.9098 |
| | MSE | 0.0063 | 0.0368 | 0.0200 | 0.0228 | 0.0431 | 0.0130 |
| | Bias | 0.0063 | 0.0368 | 0.0200 | 0.0228 | 0.0431 | 0.0130 |
| $(M_t, S_t)$ | Mean | -0.0783 | 0.0051 | -0.0221 | -0.0780 | 0.0041 | -0.0220 |
| | St.D. | 0.9380 | 0.7964 | 0.6385 | 1.4669 | 0.5620 | 0.6011 |
| | Skew. | 0.2366 | 0.3971 | 0.2939 | 0.3248 | 0.3628 | 0.2936 |
| | Kurt. | 37.3832 | 20.7225 | 20.6098 | 13.9299 | 23.7427 | 24.6003 |
| | MSE | 0.0050 | 0.0198 | 0.0095 | 0.0203 | 0.0095 | 0.0082 |
| | Bias | 0.0050 | 0.0198 | 0.0095 | 0.0203 | 0.0095 | 0.0082 |

Table A.1.2: Descriptive statistics of the innovations of the augmented model $R_{AUG,t}(N_t^{SR}, N_t^{LR})$ for the EUR/GBP FX pair.

| Components | | In-Sample | | | Out-of-Sample | | |
|---|---|---|---|---|---|---|---|
| $(SR, LR)$ | | *Sub 1* | *Sub 2* | *Sub 3* | *Sub 2* | *Sub 3* | *Sub 4* |
| $(D_t, D_t)$ | Mean | 0.0848 | -0.2290 | -0.4493 | -0.1405 | 0.2156 | -0.0726 |
| | St.D. | 1.2688 | 0.9081 | 0.8835 | 1.8169 | 0.7986 | 1.1594 |
| | Skew. | -0.1518 | 0.2622 | 0.3343 | 0.4458 | -0.3036 | 0.3172 |
| | Kurt. | 2.2117 | 10.9832 | 2.9490 | 2.2934 | 8.8977 | 2.1732 |
| | MSE | 0.1702 | 0.0401 | 0.1045 | 0.5352 | 0.0241 | 0.1557 |
| | Bias | 0.1701 | 0.0401 | 0.1045 | 0.5352 | 0.0241 | 0.1557 |
| $(S_t, D_t)$ | Mean | 0.3321 | 0.2658 | -0.2756 | 0.3117 | -0.1757 | -0.0896 |
| | St.D. | 1.0697 | 1.1066 | 1.0842 | 1.4758 | 1.0430 | 0.8948 |
| | Skew. | 0.0445 | 0.4461 | 0.1771 | 0.2714 | 0.4204 | 0.0342 |
| | Kurt. | 3.7287 | 9.8956 | 6.1694 | 9.7582 | 5.0862 | 6.3483 |
| | MSE | 0.0259 | 0.0574 | 0.0340 | 0.0499 | 0.0496 | 0.0211 |
| | Bias | 0.0259 | 0.0574 | 0.0340 | 0.0499 | 0.0496 | 0.0211 |
| $(M_t, D_t)$ | Mean | 0.3319 | 0.2657 | -0.2754 | 0.3116 | -0.1756 | -0.0895 |
| | St.D. | 1.0692 | 1.1064 | 1.0832 | 1.4749 | 1.0428 | 0.8940 |
| | Skew. | 0.0443 | 0.4464 | 0.1755 | 0.2726 | 0.4201 | 0.0358 |
| | Kurt. | 3.7272 | 9.8951 | 6.1632 | 9.7615 | 5.0854 | 6.3530 |
| | MSE | 0.0311 | 0.0619 | 0.0376 | 0.0508 | 0.0533 | 0.0223 |
| | Bias | 0.0311 | 0.0619 | 0.0376 | 0.0508 | 0.0533 | 0.0223 |
| $(D_t, S_t)$ | Mean | 0.2182 | 0.0482 | 0.0312 | 0.0397 | 0.0208 | 0.0393 |
| | St.D. | 1.0267 | 1.0549 | 1.0435 | 1.5868 | 0.7964 | 0.7206 |
| | Skew. | -0.0903 | 0.2174 | -0.1232 | 0.1556 | -0.2403 | -0.0973 |
| | Kurt. | 5.2189 | 15.9391 | 5.8704 | 11.8411 | 10.5104 | 9.2798 |
| | MSE | 0.0159 | 0.0374 | 0.0335 | 0.0403 | 0.0210 | 0.0151 |
| | Bias | 0.0159 | 0.0374 | 0.0335 | 0.0403 | 0.0210 | 0.0151 |
| $(S_t, S_t)$ | Mean | 0.2895 | 0.0978 | 0.0120 | 0.0856 | 0.0908 | 0.0331 |
| | St.D. | 0.9955 | 1.0320 | 1.0074 | 1.4300 | 1.0152 | 0.7303 |
| | Skew. | -0.1510 | 0.2237 | -0.1478 | 0.1142 | -0.0531 | -0.1136 |
| | Kurt. | 4.1870 | 11.4578 | 6.9263 | 11.1220 | 4.6864 | 10.3646 |
| | MSE | 0.0208 | 0.0475 | 0.0293 | 0.0427 | 0.0459 | 0.0148 |
| | Bias | 0.0208 | 0.0475 | 0.0293 | 0.0427 | 0.0459 | 0.0148 |
| $(M_t, S_t)$ | Mean | -0.0300 | 0.0026 | -0.0221 | -0.0324 | 0.0043 | -0.0213 |
| | St.D. | 0.6186 | 0.8909 | 0.8024 | 1.3092 | 0.5838 | 0.6546 |
| | Skew. | 0.0568 | -0.1872 | -0.1003 | -0.1421 | -0.1261 | -0.2066 |
| | Kurt. | 17.8520 | 22.7953 | 18.5046 | 17.6670 | 20.4687 | 26.1585 |
| | MSE | 0.0058 | 0.0311 | 0.0132 | 0.0311 | 0.0132 | 0.0085 |
| | Bias | 0.0058 | 0.0311 | 0.0132 | 0.0311 | 0.0132 | 0.0085 |

Table A.1.3: Descriptive statistics of the innovations of the augmented model $R_{AUG,t}(N_t^{SR}, N_t^{LR})$ for the GBP/USD FX pair.

| Components |  | In-Sample |  |  | Out-of-Sample |  |  |
|---|---|---|---|---|---|---|---|
| $(SR, LR)$ |  | *Sub 1* | *Sub 2* | *Sub 3* | *Sub 2* | *Sub 3* | *Sub 4* |
| $(D_t, D_t)$ | Mean | 0.1903 | -0.3186 | -0.4977 | -0.3432 | -0.1101 | -0.0161 |
|  | St.D. | 1.3602 | 1.0957 | 0.9645 | 1.7308 | 1.0603 | 1.3856 |
|  | Skew. | -0.2613 | -0.2286 | 0.1757 | 0.7762 | 0.1541 | 0.3270 |
|  | Kurt. | 1.8485 | 5.0863 | 3.5127 | 2.6266 | 2.6322 | 2.9052 |
|  | MSE | 0.4294 | 0.1481 | 0.1343 | 1.6121 | 0.1148 | 0.2405 |
|  | Bias | 0.4294 | 0.1481 | 0.1343 | 1.6120 | 0.1148 | 0.2405 |
| $(S_t, D_t)$ | Mean | 0.0385 | 0.2659 | -0.3013 | -0.0060 | -0.1871 | -0.0933 |
|  | St.D. | 1.2747 | 1.1176 | 1.0389 | 1.6547 | 1.0397 | 0.9325 |
|  | Skew. | 0.0281 | 0.3149 | -0.1217 | -0.3394 | 0.2572 | 1.9242 |
|  | Kurt. | 18.1620 | 20.2808 | 13.7034 | 28.0052 | 8.4732 | 163.8989 |
|  | MSE | 0.0151 | 0.0529 | 0.0272 | 0.0333 | 0.0446 | 0.0196 |
|  | Bias | 0.0151 | 0.0529 | 0.0272 | 0.0333 | 0.0446 | 0.0196 |
| $(M_t, D_t)$ | Mean | 0.0384 | 0.2657 | -0.3011 | -0.0061 | -0.1870 | -0.0932 |
|  | St.D. | 1.2713 | 1.1174 | 1.0379 | 1.6515 | 1.0395 | 0.9319 |
|  | Skew. | 0.0312 | 0.3150 | -0.1223 | -0.3414 | 0.2571 | 1.9278 |
|  | Kurt. | 18.2321 | 20.2930 | 13.7302 | 28.1557 | 8.4774 | 164.3087 |
|  | MSE | 0.0324 | 0.0566 | 0.0296 | 0.0357 | 0.0481 | 0.0205 |
|  | Bias | 0.0321 | 0.0566 | 0.0296 | 0.0357 | 0.0481 | 0.0205 |
| $(D_t, S_t)$ | Mean | 0.0347 | 0.0845 | -0.1097 | -0.0561 | 0.0693 | -0.0283 |
|  | St.D. | 1.0567 | 1.0118 | 1.0581 | 1.4712 | 0.9530 | 0.8962 |
|  | Skew. | 0.0168 | 0.0256 | -0.1758 | -0.4223 | -0.1799 | 2.5052 |
|  | Kurt. | 24.6836 | 27.5806 | 17.5410 | 31.5365 | 10.3396 | 265.4925 |
|  | MSE | 0.0134 | 0.0420 | 0.0209 | 0.0320 | 0.0368 | 0.0145 |
|  | Bias | 0.0134 | 0.0420 | 0.0209 | 0.0320 | 0.0368 | 0.0145 |
| $(S_t, S_t)$ | Mean | -0.0534 | 0.1105 | -0.0499 | -0.1144 | 0.1053 | 0.0064 |
|  | St.D. | 1.2312 | 1.0508 | 0.9988 | 1.6245 | 1.1057 | 0.8177 |
|  | Skew. | 0.0386 | 0.0113 | -0.2645 | -0.4529 | -0.0839 | 2.7762 |
|  | Kurt. | 21.6378 | 21.7566 | 16.1191 | 29.2904 | 6.3883 | 300.8116 |
|  | MSE | 0.0138 | 0.0485 | 0.0226 | 0.0317 | 0.0540 | 0.0146 |
|  | Bias | 0.0138 | 0.0485 | 0.0226 | 0.0317 | 0.0540 | 0.0146 |
| $(M_t, S_t)$ | Mean | -0.0378 | 0.0028 | -0.0172 | -0.0328 | 0.0024 | -0.0155 |
|  | St.D. | 1.3333 | 0.8110 | 0.7859 | 1.6810 | 0.5600 | 0.6864 |
|  | Skew. | -0.8985 | -0.5459 | -0.2634 | -1.8152 | -0.5182 | 5.2307 |
|  | Kurt. | 71.6654 | 55.5960 | 38.8537 | 99.1329 | 47.8449 | 695.5635 |
|  | MSE | 0.0127 | 0.0289 | 0.0134 | 0.0290 | 0.0134 | 0.0101 |
|  | Bias | 0.0127 | 0.0289 | 0.0134 | 0.0290 | 0.0134 | 0.0101 |

Table A.1.4: Descriptive statistics of the innovations of the augmented model $R_{AUG,t}(N_t^{SR}, N_t^{LR})$ for the USD/JPY FX pair.

## A.2 Additional Material: Observers Effect in FX Market Financial News

### A.2.1 Stochastic Dominance Testing

| Panel | FX pair | Country | $\Delta t$ | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | 5min | 10min | 30min | 1h | 3h | 6h |
| A | USD/JPY | Quote | 0.986 | 0.024 | 0.001 | 0.001 | 0.001 | 0.001 |
| | | Base | 0.010 | 0.764 | 0.530 | 0.424 | 0.546 | 0.762 |
| | GBP/USD | Quote | 0.666 | 0.626 | 0.936 | 0.974 | 0.288 | 0.270 |
| | | Base | 0.044 | 0.840 | 0.310 | 0.762 | 0.006 | 0.001 |
| | GBP/JPY | Quote | 0.856 | 0.058 | 0.410 | 0.001 | 0.001 | 0.001 |
| | | Base | 0.020 | 0.380 | 0.538 | 0.236 | 0.182 | 0.001 |
| | EUR/USD | Quote | 0.078 | 0.936 | 0.186 | 0.620 | 0.332 | 0.736 |
| | | Base | 0.066 | 0.404 | 0.184 | 0.012 | 0.036 | 0.001 |
| | EUR/JPY | Quote | 0.932 | 0.928 | 0.614 | 0.018 | 0.001 | 0.002 |
| | | Base | 0.090 | 0.426 | 0.228 | 0.008 | 0.584 | 0.008 |
| | EUR/GBP | Quote | 0.162 | 0.012 | 0.001 | 0.326 | 0.386 | 0.352 |
| | | Base | 0.014 | 0.001 | 0.030 | 0.001 | 0.306 | 0.752 |
| B | USD/JPY | Quote | 0.974 | 0.594 | 0.330 | 0.506 | 0.528 | 0.872 |
| | | Base | 0.840 | 0.390 | 0.046 | 0.008 | 0.001 | 0.001 |
| | GBP/USD | Quote | 0.168 | 0.064 | 0.254 | 0.004 | 0.001 | 0.001 |
| | | Base | 0.998 | 0.002 | 0.174 | 0.270 | 0.260 | 0.348 |
| | GBP/JPY | Quote | 0.494 | 0.374 | 0.314 | 0.452 | 0.356 | 0.254 |
| | | Base | 0.374 | 0.372 | 0.426 | 0.660 | 0.556 | 0.292 |
| | EUR/USD | Quote | 0.492 | 0.400 | 0.738 | 0.030 | 0.001 | 0.001 |
| | | Base | 0.292 | 0.324 | 0.938 | 0.524 | 0.388 | 0.260 |
| | EUR/JPY | Quote | 0.812 | 0.716 | 0.316 | 0.986 | 0.274 | 0.430 |
| | | Base | 0.612 | 0.406 | 0.310 | 0.370 | 0.742 | 0.322 |
| | EUR/GBP | Quote | 0.358 | 0.702 | 0.918 | 0.452 | 0.001 | 0.004 |
| | | Base | 0.332 | 0.400 | 0.322 | 0.594 | 0.002 | 0.918 |

Table A.2.1: The pre-release ($t_0^i - \Delta t$) rates are compared to the post-release ($t_0^i + \Delta t$) rates in calendar time, showing for all FX pairs with respect to the country of the news release and time gap to the release point the $p$-values of the alternative *second* order stochastic dominance tests $F_{t_0^i - \Delta t} \preceq_{SSD} F_{t_0^i + \Delta t}$ in top Panel A, and $F_{t_0^i + \Delta t} \preceq_{SSD} F_{t_0^i - \Delta t}$ (reversed test) in bottom Panel B, respectively.

| | | | *j* (Number of events) | | | | | |
|---|---|---|---|---|---|---|---|---|
| Panel | FX pair | Country | 500 | 2500 | 5000 | 10000 | 15000 | 20000 |
| A | USD/JPY | Quote | 0.948 | 0.200 | 0.936 | 0.176 | 0.240 | 0.872 |
| | | Base | 0.572 | 0.024 | 0.002 | 0.002 | 0.002 | 0.002 |
| | GBP/USD | Quote | 0.012 | 0.002 | 0.002 | 0.084 | 0.760 | 0.048 |
| | | Base | 0.800 | 0.012 | 0.002 | 0.004 | 0.304 | 0.284 |
| | GBP/JPY | Quote | 0.472 | 0.320 | 0.348 | 0.188 | 0.372 | 0.020 |
| | | Base | 0.004 | 0.002 | 0.002 | 0.004 | 0.002 | 0.008 |
| | EUR/USD | Quote | 0.372 | 0.332 | 0.528 | 0.088 | 0.452 | 0.660 |
| | | Base | 0.088 | 0.900 | 0.164 | 0.040 | 0.002 | 0.002 |
| | EUR/JPY | Quote | 0.916 | 0.692 | 0.416 | 0.108 | 0.004 | 0.002 |
| | | Base | 0.112 | 0.656 | 0.204 | 0.012 | 0.002 | 0.016 |
| | EUR/GBP | Quote | 0.164 | 0.136 | 0.032 | 0.004 | 0.024 | 0.002 |
| | | Base | 0.028 | 0.004 | 0.016 | 0.652 | 0.568 | 0.104 |
| B | USD/JPY | Quote | 0.002 | 0.002 | 0.004 | 0.032 | 0.556 | 0.288 |
| | | Base | 0.356 | 0.002 | 0.002 | 0.264 | 0.808 | 0.492 |
| | GBP/USD | Quote | 0.176 | 0.736 | 0.100 | 0.536 | 0.828 | 0.600 |
| | | Base | 0.092 | 0.872 | 0.100 | 0.328 | 0.592 | 0.944 |
| | GBP/JPY | Quote | 0.124 | 0.002 | 0.002 | 0.002 | 0.032 | 0.100 |
| | | Base | 0.720 | 0.060 | 0.002 | 0.004 | 0.816 | 0.684 |
| | EUR/USD | Quote | 0.724 | 0.840 | 0.280 | 0.608 | 0.556 | 0.660 |
| | | Base | 0.892 | 0.732 | 0.248 | 0.008 | 0.002 | 0.004 |
| | EUR/JPY | Quote | 0.188 | 0.324 | 0.002 | 0.160 | 0.040 | 0.312 |
| | | Base | 0.324 | 0.012 | 0.048 | 0.056 | 0.036 | 0.148 |
| | EUR/GBP | Quote | 0.002 | 0.002 | 0.748 | 0.064 | 0.592 | 0.284 |
| | | Base | 0.120 | 0.560 | 0.336 | 0.316 | 0.312 | 0.884 |

Table A.2.2: The pre-release $(t_0^i - \Delta t)$ rates are compared to the post-release $(t_0^i + \Delta t)$ rates in event time, showing for all FX pairs with respect to the country of the news release and time gap to the release point the $p$-values of the *first* order stochastic dominance tests $F_{t_0^i - \Delta t} \preceq_{FSD} F_{t_0^i + \Delta t}$ in top Panel A, and $F_{t_0^i + \Delta t} \preceq_{FSD} F_{t_0^i - \Delta t}$ (reversed test) in bottom Panel B, respectively.

| | | | $j$ (Number of events) | | | | | |
|---|---|---|---|---|---|---|---|---|
| Panel | FX pair | Country | 500 | 2500 | 5000 | 10000 | 15000 | 20000 |
| A | USD/JPY | Quote | 0.828 | 0.100 | 0.252 | 0.428 | 0.312 | 0.252 |
| | | Base | 0.140 | 0.776 | 0.636 | 0.292 | 0.002 | 0.002 |
| | GBP/USD | Quote | 0.040 | 0.060 | 0.128 | 0.724 | 0.124 | 0.264 |
| | | Base | 0.268 | 0.100 | 0.060 | 0.002 | 0.308 | 0.708 |
| | GBP/JPY | Quote | 0.404 | 0.816 | 0.672 | 0.668 | 0.408 | 0.544 |
| | | Base | 0.002 | 0.412 | 0.496 | 0.584 | 0.056 | 0.016 |
| | EUR/USD | Quote | 0.864 | 0.828 | 0.896 | 0.832 | 0.700 | 0.752 |
| | | Base | 0.108 | 0.260 | 0.152 | 0.028 | 0.016 | 0.096 |
| | EUR/JPY | Quote | 0.252 | 0.988 | 0.648 | 0.092 | 0.744 | 0.976 |
| | | Base | 0.280 | 0.628 | 0.164 | 0.002 | 0.060 | 0.036 |
| | EUR/GBP | Quote | 0.200 | 0.608 | 0.196 | 0.004 | 0.020 | 0.024 |
| | | Base | 0.002 | 0.556 | 0.548 | 0.480 | 0.632 | 0.692 |
| B | USD/JPY | Quote | 0.002 | 0.002 | 0.028 | 0.084 | 0.312 | 0.184 |
| | | Base | 0.608 | 0.002 | 0.020 | 0.820 | 0.572 | 0.796 |
| | GBP/USD | Quote | 0.060 | 0.704 | 0.204 | 0.832 | 0.016 | 0.940 |
| | | Base | 0.248 | 0.524 | 0.428 | 0.556 | 0.632 | 0.572 |
| | GBP/JPY | Quote | 0.388 | 0.004 | 0.002 | 0.276 | 0.476 | 0.624 |
| | | Base | 0.488 | 0.460 | 0.008 | 0.052 | 0.620 | 0.668 |
| | EUR/USD | Quote | 0.656 | 0.456 | 0.288 | 0.392 | 0.196 | 0.268 |
| | | Base | 0.592 | 0.616 | 0.540 | 0.192 | 0.476 | 0.384 |
| | EUR/JPY | Quote | 0.992 | 0.200 | 0.016 | 0.544 | 0.316 | 0.272 |
| | | Base | 0.740 | 0.640 | 0.524 | 0.692 | 0.528 | 0.888 |
| | EUR/GBP | Quote | 0.002 | 0.004 | 0.844 | 0.828 | 0.936 | 0.548 |
| | | Base | 0.520 | 0.184 | 0.660 | 0.844 | 0.136 | 0.716 |

Table A.2.3: The pre-release ($t_0^i - \Delta t$) rates are compared to the post-release ($t_0^i + \Delta t$) rates in event time, showing for all FX pairs with respect to the country of the news release and time gap to the release point the $p$-values of the *second* order stochastic dominance tests $F_{t_0^i - \Delta t} \preceq_{SSD} F_{t_0^i + \Delta t}$ in top Panel A, and $F_{t_0^i + \Delta t} \preceq_{SSD} F_{t_0^i - \Delta t}$ (reversed test) in bottom Panel B, respectively.

| | | | $j$ (Number of events) | | | | | |
|---|---|---|---|---|---|---|---|---|
| Panel | FX pair | Country | 500 | 2500 | 5000 | 10000 | 15000 | 20000 |
| A | USD/JPY | Quote | 0.332 | 0.472 | 0.120 | 0.024 | 0.032 | 0.032 |
| | | Base | 0.292 | 0.212 | 0.768 | 0.172 | 0.028 | 0.676 |
| | GBP/USD | Quote | 0.968 | 0.016 | 0.112 | 0.172 | 0.448 | 0.216 |
| | | Base | 0.712 | 0.048 | 0.700 | 0.060 | 0.668 | 0.516 |
| | GBP/JPY | Quote | 0.360 | 0.668 | 0.460 | 0.764 | 0.500 | 0.300 |
| | | Base | 0.124 | 0.076 | 0.580 | 0.420 | 0.124 | 0.748 |
| | EUR/USD | Quote | 0.636 | 0.640 | 0.548 | 0.292 | 0.860 | 0.492 |
| | | Base | 0.002 | 0.036 | 0.088 | 0.724 | 0.236 | 0.052 |
| | EUR/JPY | Quote | 0.436 | 0.708 | 0.912 | 0.484 | 0.992 | 0.924 |
| | | Base | 0.980 | 0.936 | 0.344 | 0.112 | 0.008 | 0.300 |
| | EUR/GBP | Quote | 0.664 | 0.660 | 0.400 | 0.284 | 0.908 | 0.856 |
| | | Base | 0.002 | 0.084 | 0.216 | 0.224 | 0.016 | 0.028 |
| B | USD/JPY | Quote | 0.002 | 0.068 | 0.636 | 0.992 | 0.440 | 0.876 |
| | | Base | 0.296 | 0.002 | 0.136 | 0.108 | 0.176 | 0.104 |
| | GBP/USD | Quote | 0.804 | 0.904 | 0.788 | 0.924 | 0.548 | 0.452 |
| | | Base | 0.328 | 0.340 | 0.304 | 0.332 | 0.672 | 0.888 |
| | GBP/JPY | Quote | 0.640 | 0.512 | 0.672 | 0.800 | 0.940 | 0.896 |
| | | Base | 0.840 | 0.972 | 0.972 | 0.232 | 0.732 | 0.680 |
| | EUR/USD | Quote | 0.908 | 0.476 | 0.784 | 0.568 | 0.972 | 0.712 |
| | | Base | 0.556 | 0.464 | 0.988 | 0.288 | 0.392 | 0.500 |
| | EUR/JPY | Quote | 0.204 | 0.832 | 0.384 | 0.568 | 0.976 | 0.860 |
| | | Base | 0.836 | 0.304 | 0.848 | 0.772 | 0.472 | 0.176 |
| | EUR/GBP | Quote | 0.002 | 0.002 | 0.512 | 0.852 | 0.140 | 0.352 |
| | | Base | 0.628 | 0.760 | 0.352 | 0.592 | 0.824 | 0.340 |

Table A.2.4: The pre-release ($t_0^i - \Delta t$) rates are compared to the post-release ($t_0^i + \Delta t$) rates in event time, showing for all FX pairs with respect to the country of the news release and time gap to the release point the $p$-values of the alternative *second* order stochastic dominance tests $F_{t_0^i - \Delta t} \preceq_{SSD} F_{t_0^i + \Delta t}$ in top Panel A, and $F_{t_0^i + \Delta t} \preceq_{SSD} F_{t_0^i - \Delta t}$ (reversed test) in bottom Panel B, respectively.

### A.2.2 Probability Metric Boostrap

| | | Base | | | Quote | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $j$ | $\kappa$ | $\kappa_D$ | $\Delta\kappa$ | $\kappa$ | $\kappa_D$ | $\Delta\kappa$ |
| USD/JPY | 100 | **0.525** | 0.168 | 0.357 | **0.329** | **2.014** | -1.686 |
| | 500 | **0.460** | **1.369** | -0.909 | **0.189** | **1.831** | -1.642 |
| | 1000 | **0.707** | **0.724** | -0.017 | 0.161 | **1.143** | -0.981 |
| | 2000 | **0.639** | 0.424 | 0.214 | **0.236** | **0.986** | -0.750 |
| | 3000 | **0.847** | 0.187 | **0.660** | 0.093 | 0.704 | -0.611 |
| | 4000 | **1.133** | 0.073 | **1.060** | 0.143 | 0.850 | -0.708 |
| GBP/USD | 100 | **0.147** | 0.569 | -0.422 | **0.629** | 0.178 | 0.451 |
| | 500 | **0.813** | 0.197 | 0.616 | **0.776** | 0.232 | **0.544** |
| | 1000 | **0.817** | 0.101 | **0.716** | **0.816** | 0.353 | **0.463** |
| | 2000 | **1.184** | 0.004 | **1.180** | **0.320** | 0.146 | 0.174 |
| | 3000 | **0.416** | 0.087 | 0.329 | **0.171** | 0.189 | -0.019 |
| | 4000 | **0.402** | 0.140 | 0.262 | **0.177** | 0.366 | -0.190 |
| GBP/JPY | 100 | **0.669** | 0.291 | 0.378 | **0.507** | 0.601 | -0.094 |
| | 500 | **0.326** | 0.334 | -0.008 | 0.076 | **1.291** | -1.215 |
| | 1000 | **0.504** | 0.235 | 0.269 | 0.160 | **1.723** | -1.563 |
| | 2000 | **1.092** | 0.012 | **1.080** | **0.431** | **1.185** | -0.755 |
| | 3000 | **1.053** | 0.038 | **1.015** | **0.308** | 0.736 | -0.428 |
| | 4000 | **1.037** | 0.081 | **0.956** | **0.243** | 0.689 | -0.446 |
| EUR/USD | 100 | **0.454** | 0.196 | 0.259 | **0.637** | 0.168 | **0.468** |
| | 500 | **0.418** | 0.069 | 0.349 | **0.592** | 0.299 | 0.293 |
| | 1000 | **0.459** | 0.204 | 0.255 | **0.780** | **0.507** | 0.273 |
| | 2000 | **0.586** | **0.645** | -0.059 | **0.635** | 0.475 | 0.161 |
| | 3000 | **0.721** | **0.621** | 0.099 | **0.625** | 0.122 | **0.503** |
| | 4000 | **0.545** | 0.495 | 0.050 | **0.564** | 0.043 | **0.521** |
| EUR/JPY | 100 | **0.452** | 0.381 | 0.071 | **0.648** | 0.138 | 0.509 |
| | 500 | **0.430** | 0.569 | -0.139 | 0.042 | 0.722 | -0.679 |
| | 1000 | **0.734** | 0.413 | 0.321 | 0.129 | **1.271** | -1.143 |
| | 2000 | **1.002** | 0.347 | **0.656** | **0.354** | 0.836 | -0.483 |
| | 3000 | **0.853** | 0.429 | 0.424 | **0.506** | **1.044** | -0.537 |
| | 4000 | **1.093** | 0.222 | **0.871** | **0.567** | **1.216** | -0.649 |
| EUR/GBP | 100 | **0.795** | 0.039 | **0.756** | 0.058 | **1.029** | -0.971 |
| | 500 | **0.586** | 0.420 | 0.166 | **0.697** | **0.825** | -0.128 |
| | 1000 | **0.360** | 0.287 | 0.073 | **0.745** | 0.214 | 0.532 |
| | 2000 | **0.127** | 0.211 | -0.085 | **0.735** | 0.022 | **0.714** |
| | 3000 | 0.081 | 0.142 | -0.061 | **0.665** | 0.019 | **0.646** |
| | 4000 | **0.128** | 0.083 | 0.045 | **0.685** | 0.034 | **0.651** |

Table A.2.5: Results of Kantorovich metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) rates in event time. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

| | | Base | | | Quote | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $j$ | $L$ | $L_D$ | $\Delta L$ | $L$ | $L_D$ | $\Delta L$ |
| USD/JPY | 100 | 5.996 | 13.021 | -7.024 | **9.580** | 27.242 | -17.662 |
| | 500 | **13.899** | 5.125 | **8.774** | **5.839** | 12.256 | -6.417 |
| | 1000 | **9.288** | 6.145 | 3.143 | **7.165** | 6.950 | 0.215 |
| | 2000 | **13.209** | 6.337 | **6.872** | **3.798** | 8.642 | -4.844 |
| | 3000 | **10.506** | 4.274 | **6.232** | **6.332** | 8.818 | -2.486 |
| | 4000 | **7.025** | 4.405 | 2.620 | **4.625** | 7.231 | -2.607 |
| GBP/USD | 100 | **10.111** | 17.182 | -7.070 | **12.175** | 9.880 | 2.295 |
| | 500 | **4.684** | 11.461 | -6.777 | **4.512** | 6.880 | -2.368 |
| | 1000 | 3.353 | 4.671 | -1.318 | **3.702** | **8.491** | -4.789 |
| | 2000 | 0.418 | 7.804 | -7.387 | **2.536** | 3.622 | -1.086 |
| | 3000 | **3.820** | 6.276 | -2.456 | **4.651** | 2.362 | 2.290 |
| | 4000 | 1.890 | 4.962 | -3.072 | **3.657** | 3.012 | 0.645 |
| GBP/JPY | 100 | 4.808 | **32.682** | -27.874 | 9.594 | 27.532 | -17.938 |
| | 500 | **12.536** | 8.964 | 3.573 | **10.497** | 6.675 | 3.822 |
| | 1000 | 3.772 | 8.195 | -4.423 | **9.333** | 4.918 | 4.414 |
| | 2000 | 2.681 | **12.629** | -9.948 | **7.896** | 2.854 | 5.042 |
| | 3000 | 2.164 | **9.206** | -7.042 | **8.993** | 3.232 | 5.761 |
| | 4000 | 1.236 | 7.082 | -5.846 | **5.909** | 3.690 | 2.219 |
| EUR/USD | 100 | **9.403** | 15.764 | -6.361 | **8.189** | 12.952 | -4.763 |
| | 500 | **6.219** | 9.015 | -2.795 | **4.736** | 3.948 | 0.788 |
| | 1000 | **6.330** | 6.479 | -0.149 | **7.753** | 7.866 | -0.114 |
| | 2000 | **5.236** | **7.738** | -2.502 | **5.073** | **6.947** | -1.874 |
| | 3000 | **5.793** | **7.346** | -1.553 | **2.701** | 4.444 | -1.743 |
| | 4000 | **4.905** | 5.596 | -0.691 | **1.614** | 2.609 | -0.995 |
| EUR/JPY | 100 | 7.131 | 13.699 | -6.568 | 4.820 | 22.005 | -17.185 |
| | 500 | 2.968 | 11.476 | -8.508 | **8.586** | 2.680 | 5.907 |
| | 1000 | 2.756 | **12.249** | -9.493 | **10.175** | 5.754 | 4.421 |
| | 2000 | 2.627 | **13.637** | -11.009 | **6.325** | 3.302 | 3.022 |
| | 3000 | 2.721 | 6.116 | -3.394 | **7.821** | 6.492 | 1.329 |
| | 4000 | **2.679** | **7.302** | -4.623 | **10.689** | 3.208 | **7.481** |
| EUR/GBP | 100 | 7.466 | 13.168 | -5.702 | **9.487** | 16.547 | -7.060 |
| | 500 | **18.198** | 4.045 | **14.153** | **9.834** | 11.017 | -1.183 |
| | 1000 | **7.439** | 3.954 | 3.485 | **4.662** | 9.647 | -4.985 |
| | 2000 | **5.228** | 4.280 | 0.948 | 0.787 | **7.967** | -7.181 |
| | 3000 | **2.108** | 2.535 | -0.427 | 1.889 | **7.103** | -5.214 |
| | 4000 | 1.865 | 2.951 | -1.086 | **4.290** | 3.551 | 0.739 |

Table A.2.6: Results of Lèvy metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) rates in event time. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

### A.2.3 Hypothesis Tests of Post-release Effects

| | | Base | | | Quote | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $j$ | $\kappa$ | $\kappa_D$ | $\Delta\kappa$ | $\kappa$ | $\kappa_D$ | $\Delta\kappa$ |
| USD/JPY | 500 | **0.497** | **0.855** | -0.357 | **0.359** | **1.167** | -0.808 |
| | 1000 | **0.979** | 0.557 | 0.422 | **0.260** | 0.852 | -0.592 |
| | 2000 | **1.208** | 0.785 | 0.423 | **0.408** | 0.885 | -0.477 |
| | 3000 | **1.081** | 0.308 | **0.773** | **0.286** | **1.052** | -0.766 |
| | 4000 | **0.983** | 0.125 | **0.858** | **0.162** | 0.920 | -0.758 |
| GBP/USD | 100 | **0.879** | 0.672 | 0.208 | **0.910** | 0.776 | 0.134 |
| | 500 | **0.650** | 0.258 | 0.392 | **0.844** | 0.581 | 0.263 |
| | 1000 | **0.792** | 0.377 | 0.415 | **0.523** | 0.448 | 0.075 |
| | 2000 | **0.649** | 0.215 | 0.435 | **0.226** | 0.490 | -0.264 |
| | 3000 | **0.511** | 0.301 | 0.210 | **0.159** | 0.436 | -0.277 |
| | 4000 | **0.438** | 0.172 | 0.266 | **0.114** | **0.598** | -0.484 |
| GBP/JPY | 100 | **1.479** | 0.842 | 0.637 | **1.697** | 1.508 | 0.189 |
| | 500 | **0.965** | 0.637 | 0.327 | **0.711** | **1.408** | -0.697 |
| | 1000 | **1.002** | 0.594 | 0.408 | **0.435** | **1.167** | -0.732 |
| | 2000 | **1.195** | 0.744 | 0.451 | **0.485** | 0.937 | -0.452 |
| | 3000 | **1.162** | 0.683 | 0.478 | **0.227** | 0.842 | -0.616 |
| | 4000 | **1.083** | 0.677 | 0.406 | **0.292** | 0.874 | -0.582 |
| EUR/USD | 100 | **0.654** | 0.579 | 0.075 | **0.765** | **0.853** | -0.088 |
| | 500 | **0.630** | 0.442 | 0.188 | **0.633** | **0.584** | 0.050 |
| | 1000 | **0.540** | 0.316 | 0.224 | **0.540** | 0.407 | 0.133 |
| | 2000 | **0.285** | 0.351 | -0.066 | **0.365** | 0.259 | 0.106 |
| | 3000 | **0.332** | 0.372 | -0.040 | **0.243** | 0.190 | 0.053 |
| | 4000 | **0.295** | 0.395 | -0.100 | **0.188** | 0.189 | -0.002 |
| EUR/JPY | 100 | **1.122** | **1.196** | -0.073 | **1.510** | **1.456** | 0.053 |
| | 500 | **0.948** | 0.869 | 0.079 | **0.395** | **1.037** | -0.643 |
| | 1000 | **1.061** | 0.587 | 0.474 | **0.302** | 0.906 | -0.604 |
| | 2000 | **1.109** | 0.804 | 0.305 | **0.346** | 0.767 | -0.421 |
| | 3000 | **0.727** | 0.654 | 0.073 | **0.350** | 1.012 | -0.662 |
| | 4000 | **0.869** | 0.466 | 0.403 | **0.254** | **1.169** | -0.915 |
| EUR/GBP | 100 | **1.185** | 0.575 | 0.610 | **0.476** | **0.786** | -0.311 |
| | 500 | **0.683** | 0.351 | 0.332 | **0.388** | 0.587 | -0.200 |
| | 1000 | **0.731** | 0.139 | 0.592 | **0.460** | 0.256 | 0.204 |
| | 2000 | **0.593** | 0.202 | 0.391 | **0.386** | 0.246 | 0.140 |
| | 3000 | **0.327** | 0.218 | 0.109 | **0.376** | 0.169 | 0.207 |
| | 4000 | **0.323** | 0.260 | 0.062 | **0.363** | 0.097 | 0.266 |

Table A.2.7: Results of Kantorovich metric obtained by comparing the post-release ($t_0^i+\Delta t$) and simulated Gaussian ($\mathcal{N}(0, \sigma^2_{t_0^i+\Delta t})$) rates in event time. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i + \Delta t$ value used.

| | | Base | | | Quote | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $j$ | $L$ | $L_D$ | $\Delta L$ | $L$ | $L_D$ | $\Delta L$ |
| USD/JPY | 100 | **14.160** | **24.002** | -9.842 | **10.120** | 26.163 | -16.043 |
| | 500 | **14.351** | 9.422 | 4.930 | **5.593** | 14.824 | -9.232 |
| | 1000 | **13.672** | 9.107 | 4.565 | **5.339** | 11.211 | -5.872 |
| | 2000 | **14.880** | 7.788 | 7.092 | **4.967** | 9.741 | -4.774 |
| | 3000 | **11.147** | 4.779 | 6.368 | **8.607** | 10.231 | -1.624 |
| | 4000 | **8.050** | 3.819 | 4.231 | **4.382** | 7.533 | -3.150 |
| GBP/USD | 100 | **18.860** | 24.003 | -5.142 | **20.267** | 16.018 | 4.249 |
| | 500 | **5.136** | **15.702** | -10.567 | **13.899** | 13.998 | -0.100 |
| | 1000 | **7.302** | 6.902 | 0.400 | **7.760** | 8.042 | -0.282 |
| | 2000 | **5.442** | 7.761 | -2.319 | **6.171** | 5.988 | 0.183 |
| | 3000 | **8.415** | 6.794 | 1.621 | **5.974** | 3.995 | 1.979 |
| | 4000 | **4.496** | 6.102 | -1.606 | **4.198** | 3.852 | 0.346 |
| GBP/JPY | 100 | **13.352** | **45.086** | -31.734 | **18.442** | 34.976 | -16.534 |
| | 500 | **9.081** | **19.017** | -9.936 | **11.404** | 16.924 | -5.520 |
| | 1000 | **8.493** | **13.750** | -5.257 | **10.809** | 7.048 | 3.762 |
| | 2000 | **8.935** | **15.038** | -6.103 | **10.937** | 8.853 | 2.084 |
| | 3000 | **6.654** | **11.320** | -4.667 | **9.072** | 2.321 | 6.751 |
| | 4000 | **5.524** | **10.178** | -4.653 | **5.775** | 5.956 | -0.181 |
| EUR/USD | 100 | **15.160** | 21.372 | -6.212 | **16.569** | **25.248** | -8.679 |
| | 500 | **9.282** | 10.720 | -1.438 | **10.308** | **12.822** | -2.514 |
| | 1000 | **8.085** | 6.973 | 1.113 | **7.473** | 7.914 | -0.441 |
| | 2000 | **4.032** | 5.984 | -1.952 | **4.182** | **7.933** | -3.751 |
| | 3000 | **6.407** | 2.755 | 3.652 | **3.145** | **6.425** | -3.280 |
| | 4000 | **6.378** | 2.812 | 3.565 | **2.237** | 3.968 | -1.731 |
| EUR/JPY | 100 | **19.938** | 20.264 | -0.326 | **8.571** | 21.316 | -12.745 |
| | 500 | **9.995** | 14.571 | -4.576 | **12.048** | 13.235 | -1.187 |
| | 1000 | **5.685** | **12.127** | -6.443 | **9.423** | 6.557 | 2.867 |
| | 2000 | **6.691** | **11.084** | -4.394 | **8.906** | 4.840 | 4.067 |
| | 3000 | **7.316** | **8.859** | -1.544 | **8.550** | 2.351 | 6.199 |
| | 4000 | **6.414** | 7.314 | -0.900 | **8.296** | 2.944 | 5.352 |
| EURGBP | 100 | **16.790** | 29.224 | -12.434 | **9.822** | 23.350 | -13.528 |
| | 500 | **8.502** | 10.093 | -1.591 | **6.984** | 10.708 | -3.724 |
| | 1000 | **2.861** | **9.167** | -6.307 | **5.530** | 9.424 | -3.894 |
| | 2000 | **3.991** | 6.181 | -2.189 | **3.150** | **6.747** | -3.598 |
| | 3000 | **2.719** | 4.897 | -2.179 | **2.555** | 3.970 | -1.415 |
| | 4000 | **3.258** | 5.021 | -1.763 | **4.075** | 2.440 | 1.635 |

Table A.2.8: Results of Lèvy metric obtained by comparing the post-release ($t_0^i + \Delta t$) and simulated Gaussian ($\mathcal{N}(0, \sigma^2_{t_0^i+\Delta t})$) rates in event time. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i + \Delta t$ value used.

### A.2.4 Hypothesis Tests of Pre-release Effects

| FX Pair | $j$ | Base $\kappa$ | Base $\kappa_D$ | Base $\Delta\kappa$ | Quote $\kappa$ | Quote $\kappa_D$ | Quote $\Delta\kappa$ |
|---|---|---|---|---|---|---|---|
| USD/JPY | 100 | **0.655** | 0.688 | -0.033 | **0.217** | 0.867 | -0.651 |
| | 500 | **0.344** | **0.971** | -0.627 | **0.394** | **1.094** | -0.700 |
| | 1000 | **0.365** | **0.840** | -0.475 | **0.165** | 0.735 | -0.570 |
| | 2000 | **0.294** | 0.511 | -0.216 | **0.408** | 0.570 | -0.163 |
| | 3000 | **0.298** | 0.332 | -0.034 | **0.471** | 0.371 | 0.099 |
| | 4000 | **0.478** | 0.222 | 0.257 | **0.498** | 0.372 | 0.126 |
| GBP/USD | 100 | **0.304** | **1.072** | -0.768 | **1.168** | 0.681 | 0.487 |
| | 500 | **0.700** | 0.431 | 0.269 | **0.839** | 0.555 | 0.284 |
| | 1000 | **0.505** | 0.253 | 0.253 | **0.756** | 0.332 | 0.424 |
| | 2000 | **0.835** | 0.150 | 0.685 | **0.635** | 0.240 | 0.395 |
| | 3000 | **0.332** | 0.274 | 0.059 | **0.471** | 0.217 | 0.254 |
| | 4000 | **0.391** | 0.376 | 0.014 | **0.442** | 0.171 | 0.272 |
| GBP/JPY | 100 | **0.794** | **1.104** | -0.310 | **0.972** | **0.975** | -0.003 |
| | 500 | **0.772** | **1.150** | -0.378 | **0.929** | **1.489** | -0.560 |
| | 1000 | **0.724** | 0.765 | -0.040 | **0.591** | **1.414** | -0.823 |
| | 2000 | **0.990** | 0.368 | 0.622 | **0.764** | **1.130** | -0.366 |
| | 3000 | **0.916** | 0.414 | 0.502 | **0.829** | 0.688 | 0.142 |
| | 4000 | **1.010** | 0.522 | 0.488 | **0.725** | 0.630 | 0.095 |
| EUR/USD | 100 | **0.507** | 0.325 | 0.183 | **0.978** | 0.399 | 0.579 |
| | 500 | **0.505** | 0.311 | 0.194 | **0.526** | 0.306 | 0.219 |
| | 1000 | **0.405** | 0.349 | 0.056 | **0.588** | 0.503 | 0.085 |
| | 2000 | **0.306** | 0.365 | -0.059 | **0.346** | 0.348 | -0.002 |
| | 3000 | **0.379** | 0.205 | 0.174 | **0.530** | 0.073 | 0.457 |
| | 4000 | **0.294** | 0.246 | 0.048 | **0.522** | 0.042 | 0.481 |
| EUR/JPY | 100 | **0.860** | **0.987** | -0.128 | **0.773** | 0.518 | 0.255 |
| | 500 | **0.678** | **0.938** | -0.260 | **0.681** | 0.729 | -0.049 |
| | 1000 | **0.814** | **0.993** | -0.179 | **0.561** | **0.934** | -0.372 |
| | 2000 | **1.005** | 0.565 | 0.440 | **0.570** | 0.735 | -0.166 |
| | 3000 | **1.024** | 0.749 | 0.276 | **0.699** | 0.450 | 0.249 |
| | 4000 | **1.018** | 0.595 | 0.423 | **0.897** | 0.510 | 0.387 |
| EUR/GBP | 100 | **0.759** | 0.545 | 0.214 | **0.125** | **0.939** | -0.814 |
| | 500 | **0.533** | **0.734** | -0.200 | **0.675** | 0.588 | 0.087 |
| | 1000 | **0.191** | **0.630** | -0.440 | **0.615** | 0.304 | 0.311 |
| | 2000 | **0.138** | **0.652** | -0.514 | **0.684** | 0.122 | 0.563 |
| | 3000 | **0.167** | 0.394 | -0.228 | **0.569** | 0.097 | 0.473 |
| | 4000 | **0.231** | 0.317 | -0.086 | **0.527** | 0.128 | 0.399 |

Table A.2.9: Results of Kantorovich metric obtained by comparing the simulated Gaussian ($\mathcal{N}(0, \sigma^2_{t_0^i-\Delta t})$) and pre-release ($t_0^i - \Delta t$) rates in event time. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i - \Delta t$ value used.

| | | Base | | | Quote | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $j$ | $L$ | $L_D$ | $\Delta L$ | $L$ | $L_D$ | $\Delta L$ |
| USD/JPY | 100 | **17.018** | **21.269** | -4.252 | **13.463** | 14.690 | -1.226 |
| | 500 | **13.372** | 8.704 | 4.669 | **12.015** | 12.064 | -0.049 |
| | 1000 | **15.001** | 10.253 | 4.748 | **10.255** | 5.987 | 4.269 |
| | 2000 | **8.388** | 5.947 | 2.441 | **4.740** | 8.399 | -3.659 |
| | 3000 | **4.571** | 3.919 | 0.652 | **5.493** | 5.671 | -0.178 |
| | 4000 | **4.098** | 4.625 | -0.528 | **4.551** | 5.631 | -1.080 |
| GBP/USD | 100 | **18.538** | 27.949 | -9.411 | **25.436** | **26.338** | -0.902 |
| | 500 | **5.360** | 11.953 | -6.593 | **12.142** | 11.937 | 0.206 |
| | 1000 | **4.535** | 7.550 | -3.014 | **5.045** | **11.090** | -6.045 |
| | 2000 | **5.207** | **10.365** | -5.159 | **5.960** | **7.177** | -1.218 |
| | 3000 | **3.554** | **7.735** | -4.181 | **7.123** | 5.641 | 1.483 |
| | 4000 | **4.379** | 6.429 | -2.050 | **4.790** | 5.084 | -0.294 |
| GBP/JPY | 100 | **19.243** | 27.868 | -8.625 | **22.446** | 20.902 | 1.544 |
| | 500 | **22.681** | 13.787 | 8.894 | **18.362** | 16.040 | 2.322 |
| | 1000 | **9.779** | 12.953 | -3.175 | **16.205** | 8.204 | 8.001 |
| | 2000 | **5.486** | 9.355 | -3.869 | **15.438** | 10.122 | 5.316 |
| | 3000 | **5.154** | 8.089 | -2.935 | **10.551** | 10.899 | -0.348 |
| | 4000 | **5.122** | **8.892** | -3.770 | **10.530** | 7.579 | 2.952 |
| EUR/USD | 100 | **13.449** | 16.323 | -2.875 | **19.931** | 19.366 | 0.565 |
| | 500 | **5.358** | 9.380 | -4.023 | **10.892** | 8.904 | 1.989 |
| | 1000 | **3.709** | 7.788 | -4.078 | **7.896** | **9.388** | -1.492 |
| | 2000 | **3.736** | **8.485** | -4.748 | **5.842** | 5.450 | 0.392 |
| | 3000 | **1.634** | **6.634** | -4.999 | **4.296** | 4.649 | -0.354 |
| | 4000 | **1.880** | 3.792 | -1.913 | **2.967** | 3.477 | -0.510 |
| EUR/JPY | 100 | **16.964** | 24.990 | -8.026 | **11.996** | 16.915 | -4.919 |
| | 500 | **6.412** | **19.621** | -13.209 | **16.717** | 6.189 | 10.528 |
| | 1000 | **4.621** | 10.487 | -5.866 | **15.496** | 4.721 | 10.774 |
| | 2000 | **5.798** | 7.487 | -1.689 | **9.732** | 9.062 | 0.670 |
| | 3000 | **6.001** | 6.345 | -0.344 | **5.498** | 7.517 | -2.019 |
| | 4000 | **3.928** | 5.889 | -1.961 | **7.383** | 5.280 | 2.104 |
| EUR/GBP | 100 | **23.933** | 17.122 | 6.811 | **17.130** | 11.751 | 5.379 |
| | 500 | **21.103** | 6.222 | 14.881 | **11.057** | 9.995 | 1.062 |
| | 1000 | **13.113** | 3.149 | 9.964 | **5.685** | 10.207 | -4.522 |
| | 2000 | **7.651** | 6.005 | 1.646 | **2.938** | **8.335** | -5.398 |
| | 3000 | **4.088** | 3.623 | 0.465 | **2.127** | **7.578** | -5.451 |
| | 4000 | **3.538** | 3.061 | 0.477 | **3.969** | 4.936 | -0.967 |

Table A.2.10: Results of Lèvy metric obtained by comparing the simulated Gaussian ($\mathcal{N}(0, \sigma^2_{t_0^i - \Delta t})$) and pre-release ($t_0^i - \Delta t$) rates in event time. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i - \Delta t$ value used.

## A.3 Additional Material: Decomposing News: Any News is Good News

### A.3.1 Day Effect on Calendar time

| | | Kantorovich | | | Lèvy | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 5min | 0.244 | 0.019 | 0.225 | 2.695 | 6.216 | -3.520 |
| | 10min | -0.093 | -0.018 | -0.075 | -3.911 | -5.480 | 1.569 |
| | 30min | -0.052 | -0.073 | 0.021 | -3.070 | -3.692 | 0.622 |
| | 1h | -0.021 | -0.096 | 0.075 | -1.033 | -1.378 | 0.346 |
| | 3h | -0.010 | **-0.216** | 0.206 | -2.898 | -0.750 | -2.148 |
| | 6h | 0.069 | **0.308** | -0.238 | **3.971** | 1.478 | 2.493 |
| GBP/USD | 5min | -0.098 | -0.084 | -0.014 | -2.270 | -4.448 | 2.178 |
| | 10min | -0.054 | -0.032 | -0.022 | -2.114 | -1.125 | -0.988 |
| | 30min | -0.045 | -0.063 | 0.018 | -2.480 | -1.591 | -0.889 |
| | 1h | -0.035 | -0.091 | 0.056 | -3.286 | -2.405 | -0.882 |
| | 3h | -0.129 | -0.076 | -0.053 | -2.091 | -1.786 | -0.305 |
| | 6h | **0.158** | **0.133** | 0.025 | 2.400 | **2.793** | -0.393 |
| GBP/JPY | 5min | 0.107 | 0.102 | 0.005 | 5.491 | 2.473 | 3.018 |
| | 10min | 0.052 | 0.105 | -0.053 | 5.027 | 4.361 | 0.666 |
| | 30min | -0.074 | -0.143 | 0.069 | -5.269 | -4.476 | -0.793 |
| | 1h | -0.038 | -0.157 | 0.118 | -4.378 | -2.027 | -2.351 |
| | 3h | 0.062 | 0.080 | -0.018 | 2.322 | 1.431 | 0.891 |
| | 6h | 0.063 | 0.098 | -0.035 | 2.232 | 1.137 | 1.095 |
| EUR/USD | 5min | 0.213 | 0.021 | 0.192 | 11.487 | 5.942 | 5.545 |
| | 10min | -0.135 | -0.072 | -0.063 | -2.855 | -1.933 | -0.921 |
| | 30min | -0.262 | -0.046 | -0.216 | -2.337 | -2.766 | 0.430 |
| | 1h | -0.146 | -0.065 | -0.082 | -1.493 | -1.954 | 0.461 |
| | 3h | -0.069 | -0.030 | -0.039 | -1.381 | -1.566 | 0.185 |
| | 6h | 0.057 | 0.098 | -0.042 | 1.977 | 1.447 | 0.529 |
| EUR/JPY | 5min | 0.155 | 0.038 | 0.117 | 10.868 | 7.910 | 2.958 |
| | 10min | 0.055 | 0.270 | -0.215 | 4.254 | 3.948 | 0.307 |
| | 30min | -0.082 | -0.132 | 0.050 | -3.689 | -4.202 | 0.513 |
| | 1h | -0.058 | -0.125 | 0.067 | -1.936 | -4.766 | 2.830 |
| | 3h | 0.057 | 0.097 | -0.039 | 1.272 | 1.774 | -0.502 |
| | 6h | 0.080 | 0.142 | -0.062 | 1.408 | 1.947 | -0.539 |
| EURGBP | 5min | 0.069 | 0.034 | 0.035 | 2.335 | 5.828 | -3.494 |
| | 10min | -0.026 | -0.073 | 0.046 | -1.091 | -3.813 | 2.722 |
| | 30min | -0.049 | -0.124 | 0.075 | -0.794 | -2.950 | 2.156 |
| | 1h | -0.038 | -0.112 | 0.074 | -3.174 | -2.216 | -0.958 |
| | 3h | -0.046 | -0.096 | 0.050 | -2.526 | -1.021 | -1.505 |
| | 6h | 0.065 | 0.048 | 0.017 | 1.017 | **2.136** | -1.120 |

Table A.3.1: Results of both metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data only on Tuesday. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

| | | Kantorovich | | | Lèvy | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 5min | 0.030 | 0.119 | -0.089 | 6.780 | 1.766 | 5.014 |
| | 10min | -0.052 | -0.094 | 0.042 | -4.101 | -5.231 | 1.130 |
| | 30min | -0.035 | -0.058 | 0.022 | -3.184 | -1.340 | -1.845 |
| | 1h | -0.025 | -0.144 | **0.119** | -2.859 | -2.544 | -0.316 |
| | 3h | -0.042 | -0.101 | 0.059 | -2.467 | -2.114 | -0.353 |
| | 6h | 0.055 | **0.215** | -0.160 | **2.815** | 2.203 | 0.612 |
| GBP/USD | 5min | -0.061 | -0.040 | -0.021 | -1.929 | -4.913 | 2.984 |
| | 10min | -0.116 | -0.119 | 0.003 | -4.409 | -2.938 | -1.471 |
| | 30min | -0.089 | -0.054 | -0.035 | -2.324 | -2.180 | -0.144 |
| | 1h | -0.035 | -0.067 | 0.033 | -1.889 | -3.992 | 2.103 |
| | 3h | -0.079 | -0.049 | -0.030 | -2.110 | -1.598 | -0.513 |
| | 6h | **0.176** | 0.079 | 0.097 | 1.616 | 2.843 | -1.226 |
| GBP/JPY | 5min | 0.117 | 0.038 | 0.079 | 4.403 | 3.975 | 0.429 |
| | 10min | 0.060 | 0.211 | -0.151 | 4.485 | 2.943 | 1.543 |
| | 30min | -0.016 | -0.216 | 0.200 | -3.867 | -2.245 | -1.621 |
| | 1h | -0.011 | -0.231 | 0.220 | -3.934 | -2.168 | -1.766 |
| | 3h | 0.037 | 0.150 | **-0.113** | 3.185 | 4.343 | -1.159 |
| | 6h | 0.130 | 0.156 | -0.026 | 1.672 | **5.241** | -3.569 |
| EUR/USD | 5min | 0.102 | 0.084 | 0.017 | 2.127 | 11.933 | -9.806 |
| | 10min | -0.082 | -0.168 | 0.085 | -1.572 | -9.197 | **7.625** |
| | 30min | -0.043 | -0.069 | 0.026 | -3.786 | -1.466 | -2.320 |
| | 1h | -0.017 | -0.124 | 0.107 | -4.639 | -1.291 | -3.348 |
| | 3h | -0.017 | -0.081 | 0.065 | -3.091 | -0.529 | -2.562 |
| | 6h | 0.071 | **0.123** | -0.052 | **4.793** | 1.965 | 2.828 |
| EUR/JPY | 5min | 0.017 | 0.219 | -0.202 | 5.337 | 0.377 | 4.960 |
| | 10min | 0.003 | 0.293 | -0.289 | 6.077 | 1.810 | 4.267 |
| | 30min | -0.002 | -0.317 | 0.315 | -3.528 | -0.979 | -2.549 |
| | 1h | -0.003 | -0.210 | 0.207 | -3.031 | -0.530 | -2.501 |
| | 3h | 0.012 | 0.164 | -0.152 | 1.875 | 2.161 | -0.286 |
| | 6h | 0.013 | **0.229** | -0.217 | 1.798 | 2.034 | -0.236 |
| EURGBP | 5min | 0.065 | 0.031 | 0.034 | 5.776 | 1.763 | 4.013 |
| | 10min | -0.039 | -0.047 | 0.008 | -5.619 | -0.954 | -4.665 |
| | 30min | -0.018 | -0.143 | 0.125 | -3.886 | -1.105 | -2.781 |
| | 1h | -0.018 | -0.173 | 0.155 | -1.444 | -1.581 | 0.137 |
| | 3h | -0.050 | -0.078 | 0.028 | -1.196 | -2.246 | 1.051 |
| | 6h | **0.132** | 0.076 | 0.056 | 1.178 | **2.267** | -1.089 |

Table A.3.2: Results of both metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data only on Wednesday. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

| | | Kantorovich | | | Lèvy | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 5min | 0.090 | 0.039 | 0.051 | 0.446 | 5.256 | -4.810 |
| | 10min | -0.094 | -0.049 | -0.045 | -3.505 | -2.527 | -0.978 |
| | 30min | -0.052 | -0.078 | 0.027 | -1.211 | -8.979 | 7.768 |
| | 1h | -0.085 | -0.017 | -0.069 | -1.801 | -2.651 | 0.850 |
| | 3h | -0.013 | -0.109 | 0.096 | **-7.146** | -0.827 | **-6.319** |
| | 6h | 0.018 | **0.200** | -0.182 | 2.660 | 1.044 | 1.616 |
| GBP/USD | 5min | -0.122 | -0.018 | -0.104 | -3.400 | -4.781 | 1.381 |
| | 10min | -0.113 | -0.010 | -0.103 | -2.068 | -2.804 | 0.736 |
| | 30min | -0.035 | -0.084 | 0.050 | -1.158 | -2.818 | 1.660 |
| | 1h | -0.119 | -0.037 | -0.082 | -1.843 | -2.297 | 0.455 |
| | 3h | -0.018 | -0.072 | 0.054 | -3.014 | -0.654 | -2.360 |
| | 6h | 0.082 | **0.139** | -0.058 | **3.547** | 0.695 | 2.852 |
| GBP/JPY | 5min | 0.409 | 0.023 | 0.386 | 6.127 | 7.764 | -1.637 |
| | 10min | 0.226 | 0.017 | 0.209 | 5.357 | 7.687 | -2.331 |
| | 30min | -0.237 | -0.003 | -0.233 | -0.964 | -7.565 | 6.601 |
| | 1h | -0.279 | -0.001 | -0.278 | -0.283 | -5.342 | 5.059 |
| | 3h | 0.119 | 0.064 | 0.056 | 1.644 | 2.570 | -0.926 |
| | 6h | 0.148 | 0.060 | 0.089 | 1.501 | **3.417** | -1.917 |
| EUR/USD | 5min | 0.074 | 0.104 | -0.030 | 3.054 | 2.267 | 0.787 |
| | 10min | -0.051 | -0.077 | 0.026 | -2.897 | -1.768 | -1.129 |
| | 30min | -0.037 | -0.082 | 0.045 | -2.547 | -2.184 | -0.362 |
| | 1h | -0.103 | -0.028 | -0.076 | -1.285 | -2.321 | 1.036 |
| | 3h | **-0.132** | -0.040 | -0.091 | -1.309 | -1.780 | 0.472 |
| | 6h | **0.206** | 0.080 | **0.126** | 1.953 | 1.263 | 0.690 |
| EUR/JPY | 5min | 0.138 | 0.016 | 0.122 | 2.257 | 5.767 | -3.510 |
| | 10min | 0.055 | 0.056 | -0.001 | 0.858 | 6.223 | -5.366 |
| | 30min | -0.051 | -0.057 | 0.006 | -1.476 | -2.516 | 1.040 |
| | 1h | -0.069 | -0.070 | 0.001 | -3.584 | -2.268 | -1.316 |
| | 3h | 0.105 | 0.028 | 0.076 | 1.632 | 3.910 | -2.278 |
| | 6h | **0.179** | 0.024 | 0.155 | 0.735 | 2.273 | -1.538 |
| EURGBP | 5min | 0.150 | 0.024 | 0.126 | 1.083 | 23.534 | **-22.451** |
| | 10min | -0.173 | -0.006 | -0.167 | -0.209 | -6.771 | 6.562 |
| | 30min | -0.256 | 0.000 | -0.256 | 0.002 | -8.272 | 8.275 |
| | 1h | **-0.292** | -0.001 | **-0.291** | -0.361 | **-8.625** | 8.264 |
| | 3h | -0.147 | -0.018 | -0.129 | -2.092 | -2.900 | 0.808 |
| | 6h | **0.110** | 0.028 | 0.082 | 0.845 | 1.527 | -0.682 |

Table A.3.3: Results of both metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data only on Thursday. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

### A.3.2 Day Effect on Event Time

| | | Kantorovich | | | Lèvy | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 100 | 0.308 | 0.072 | 0.237 | 1.232 | 9.631 | -8.400 |
| | 500 | 0.174 | 0.031 | 0.143 | 0.452 | 5.269 | -4.818 |
| | 1000 | 0.242 | 0.014 | 0.229 | 0.643 | 6.526 | -5.884 |
| | 2000 | 0.121 | 0.033 | 0.088 | 1.759 | 6.029 | -4.271 |
| | 5000 | 0.172 | 0.007 | 0.165 | 0.243 | 5.264 | -5.021 |
| | 9000 | 0.081 | 0.066 | 0.015 | 1.185 | 2.559 | -1.374 |
| GBP/USD | 100 | 0.252 | 0.019 | 0.232 | 1.394 | 2.437 | -1.043 |
| | 500 | 0.117 | 0.018 | 0.099 | 0.654 | 2.592 | -1.938 |
| | 1000 | 0.086 | 0.026 | 0.060 | 1.277 | 1.878 | -0.600 |
| | 2000 | 0.179 | 0.060 | 0.119 | 1.772 | 2.228 | -0.457 |
| | 5000 | **0.224** | 0.003 | **0.221** | 0.379 | **3.899** | -3.520 |
| | 9000 | **0.307** | 0.001 | **0.305** | 0.104 | **3.378** | -3.274 |
| GBP/JPY | 100 | 0.193 | 0.122 | 0.071 | 2.631 | 8.725 | -6.094 |
| | 500 | 0.169 | 0.077 | 0.092 | 0.493 | 6.366 | -5.873 |
| | 1000 | 0.093 | 0.060 | 0.032 | 1.166 | 5.337 | -4.171 |
| | 2000 | 0.122 | 0.025 | 0.097 | 2.184 | 3.765 | -1.581 |
| | 5000 | 0.186 | 0.009 | 0.177 | 0.593 | 7.336 | -6.743 |
| | 9000 | **0.194** | 0.026 | 0.169 | 1.234 | 2.952 | -1.718 |
| EUR/USD | 100 | 0.154 | 0.061 | 0.093 | 2.896 | 1.585 | 1.312 |
| | 500 | 0.097 | 0.060 | 0.038 | 3.609 | 1.622 | 1.987 |
| | 1000 | 0.106 | 0.021 | 0.085 | 2.485 | 1.706 | 0.780 |
| | 2000 | 0.042 | 0.076 | -0.034 | 2.148 | 2.339 | -0.192 |
| | 5000 | 0.055 | 0.023 | 0.032 | 1.322 | 1.196 | 0.126 |
| | 9000 | 0.017 | 0.108 | -0.091 | 1.570 | 4.255 | -2.685 |
| EUR/JPY | 100 | 0.134 | 0.230 | -0.096 | 6.073 | 3.063 | 3.010 |
| | 500 | 0.209 | 0.064 | 0.145 | 2.004 | 3.924 | -1.920 |
| | 1000 | 0.117 | 0.072 | 0.045 | 2.316 | 2.296 | 0.021 |
| | 2000 | 0.040 | 0.073 | -0.033 | 1.833 | 3.426 | -1.593 |
| | 5000 | 0.052 | 0.051 | 0.001 | 2.997 | 2.668 | 0.329 |
| | 9000 | 0.018 | 0.119 | -0.101 | 3.233 | 0.387 | 2.846 |
| EURGBP | 100 | 0.031 | 0.106 | -0.075 | 2.350 | 1.468 | 0.882 |
| | 500 | 0.014 | 0.122 | -0.108 | 3.301 | 1.247 | 2.054 |
| | 1000 | 0.048 | 0.102 | -0.054 | 2.266 | 1.387 | 0.879 |
| | 2000 | 0.015 | 0.049 | -0.035 | 2.822 | 1.183 | 1.639 |
| | 5000 | 0.081 | 0.030 | 0.051 | 2.955 | 3.132 | -0.176 |
| | 9000 | 0.040 | 0.027 | 0.013 | 1.760 | 2.860 | -1.100 |

Table A.3.4: Results of both metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data only on Monday. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

| FX Pair | $\Delta t$ | Kantorovich $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | Lèvy $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
|---|---|---|---|---|---|---|---|
| USD/JPY | 100 | 0.230 | 0.045 | 0.185 | 3.305 | 5.804 | -2.500 |
| | 500 | 0.053 | 0.055 | -0.001 | 2.553 | 1.820 | 0.733 |
| | 1000 | 0.099 | 0.072 | 0.028 | 1.935 | 2.169 | -0.234 |
| | 2000 | 0.057 | 0.062 | -0.005 | 0.561 | 2.381 | -1.820 |
| | 5000 | 0.022 | **0.151** | -0.129 | 1.043 | 2.626 | -1.583 |
| | 9000 | 0.015 | **0.186** | -0.172 | 0.677 | 1.527 | -0.850 |
| GBP/USD | 100 | 0.096 | 0.149 | -0.054 | 6.271 | 2.551 | 3.720 |
| | 500 | 0.108 | 0.021 | 0.087 | 1.979 | 1.763 | 0.216 |
| | 1000 | 0.062 | 0.075 | -0.014 | 1.481 | 0.586 | 0.895 |
| | 2000 | 0.096 | 0.062 | 0.034 | 3.649 | 2.458 | 1.191 |
| | 5000 | 0.075 | 0.035 | 0.040 | 1.186 | 1.847 | -0.661 |
| | 9000 | 0.080 | 0.012 | 0.068 | 1.371 | 1.961 | -0.590 |
| GBP/JPY | 100 | 0.203 | 0.096 | 0.107 | 8.955 | 3.468 | 5.488 |
| | 500 | 0.100 | 0.183 | -0.084 | 4.207 | 1.563 | 2.644 |
| | 1000 | 0.045 | 0.177 | -0.132 | 4.033 | 1.286 | 2.748 |
| | 2000 | 0.031 | 0.144 | **-0.113** | 2.965 | 1.737 | 1.227 |
| | 5000 | 0.040 | 0.056 | -0.016 | 2.862 | 1.671 | 1.191 |
| | 9000 | 0.084 | 0.045 | 0.040 | 1.684 | 2.674 | -0.990 |
| EUR/USD | 100 | 0.185 | 0.095 | 0.090 | 7.332 | 8.722 | -1.390 |
| | 500 | 0.168 | 0.062 | 0.106 | 2.913 | 3.131 | -0.217 |
| | 1000 | 0.186 | 0.072 | 0.114 | 3.253 | 3.591 | -0.338 |
| | 2000 | **0.225** | 0.089 | 0.135 | 1.572 | 1.679 | -0.107 |
| | 5000 | **0.131** | 0.053 | 0.078 | 0.965 | 2.143 | -1.177 |
| | 9000 | 0.065 | 0.053 | 0.013 | 0.808 | 1.477 | -0.668 |
| EUR/JPY | 100 | 0.140 | 0.195 | -0.055 | 16.048 | 6.875 | 9.173 |
| | 500 | 0.156 | 0.215 | -0.059 | 4.646 | 5.538 | -0.891 |
| | 1000 | 0.117 | 0.169 | -0.052 | 2.906 | 4.455 | -1.549 |
| | 2000 | 0.119 | 0.136 | -0.017 | 3.166 | **4.364** | -1.198 |
| | 5000 | 0.070 | 0.113 | -0.042 | 1.595 | 2.322 | -0.727 |
| | 9000 | 0.055 | 0.075 | -0.019 | 1.434 | 2.221 | -0.787 |
| EURGBP | 100 | 0.104 | 0.201 | -0.097 | 5.509 | 4.090 | 1.418 |
| | 500 | 0.054 | 0.067 | -0.013 | 0.678 | 3.110 | -2.432 |
| | 1000 | 0.006 | 0.117 | **-0.111** | 1.381 | 1.201 | 0.181 |
| | 2000 | 0.019 | 0.063 | -0.044 | 1.724 | 1.325 | 0.399 |
| | 5000 | 0.018 | 0.091 | **-0.073** | 1.884 | 0.915 | 0.969 |
| | 9000 | 0.013 | **0.088** | -0.074 | **2.072** | 0.334 | **1.738** |

Table A.3.5: Results of both metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data only on Tuesday. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

| | | Kantorovich | | | Lèvy | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 100 | 0.096 | 0.123 | -0.027 | 6.965 | 3.232 | 3.733 |
| | 500 | 0.131 | 0.243 | -0.112 | 4.048 | 2.681 | 1.366 |
| | 1000 | 0.052 | 0.081 | -0.029 | 1.277 | 3.074 | -1.797 |
| | 2000 | 0.028 | 0.107 | -0.079 | 2.112 | 2.241 | -0.130 |
| | 5000 | 0.035 | 0.083 | -0.048 | 0.624 | 2.009 | -1.384 |
| | 9000 | 0.028 | **0.138** | -0.110 | 0.856 | 0.818 | 0.038 |
| GBP/USD | 100 | 0.119 | 0.173 | -0.054 | 2.730 | 3.147 | -0.418 |
| | 500 | 0.116 | 0.127 | -0.011 | 4.188 | 3.774 | 0.414 |
| | 1000 | 0.106 | 0.145 | -0.039 | 3.569 | 3.305 | 0.264 |
| | 2000 | 0.046 | 0.066 | -0.020 | 3.035 | 1.277 | 1.758 |
| | 5000 | 0.052 | 0.039 | 0.013 | 1.024 | 2.424 | -1.399 |
| | 9000 | 0.033 | 0.044 | -0.011 | 1.208 | 1.369 | -0.161 |
| GBP/JPY | 100 | 0.074 | 0.168 | -0.094 | 8.595 | 2.802 | 5.793 |
| | 500 | 0.071 | 0.108 | -0.037 | 3.291 | 2.403 | 0.888 |
| | 1000 | 0.095 | 0.137 | -0.042 | 2.375 | 4.614 | -2.239 |
| | 2000 | 0.065 | 0.161 | -0.096 | 2.326 | 1.460 | 0.866 |
| | 5000 | 0.012 | **0.155** | -0.143 | 2.038 | 1.744 | 0.294 |
| | 9000 | 0.019 | **0.135** | -0.116 | 1.885 | 1.498 | 0.388 |
| EUR/USD | 100 | 0.092 | 0.134 | -0.042 | 5.206 | 4.433 | 0.773 |
| | 500 | 0.067 | 0.123 | -0.057 | 1.713 | 2.135 | -0.422 |
| | 1000 | 0.067 | 0.157 | -0.090 | 0.856 | 4.876 | **-4.020** |
| | 2000 | 0.051 | 0.059 | -0.008 | 2.153 | 1.127 | 1.026 |
| | 5000 | 0.051 | 0.043 | 0.008 | 3.312 | 1.149 | 2.163 |
| | 9000 | 0.019 | 0.045 | -0.026 | 2.645 | 0.618 | 2.027 |
| EUR/JPY | 100 | 0.075 | 0.388 | -0.313 | 9.482 | 1.722 | 7.761 |
| | 500 | 0.023 | 0.158 | -0.135 | 2.378 | 4.598 | -2.220 |
| | 1000 | 0.017 | 0.225 | **-0.208** | 3.303 | 3.208 | 0.096 |
| | 2000 | 0.007 | **0.292** | -0.285 | 2.195 | 1.018 | 1.177 |
| | 5000 | 0.029 | **0.157** | -0.128 | 1.597 | 0.546 | 1.051 |
| | 9000 | 0.003 | **0.173** | -0.170 | 1.303 | 0.959 | 0.344 |
| EURGBP | 100 | 0.069 | 0.057 | 0.013 | 4.174 | 0.992 | 3.182 |
| | 500 | 0.055 | 0.019 | 0.036 | 0.544 | 0.997 | -0.453 |
| | 1000 | 0.065 | 0.063 | 0.002 | 0.648 | 1.420 | -0.772 |
| | 2000 | 0.002 | 0.138 | -0.136 | 1.219 | 0.281 | 0.938 |
| | 5000 | 0.005 | **0.118** | -0.112 | 1.252 | 0.427 | 0.825 |
| | 9000 | 0.023 | **0.074** | -0.051 | 1.414 | 0.496 | 0.919 |

Table A.3.6: Results of both metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data only on Wednesday. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

| | | Kantorovich | | | Lèvy | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 100 | 0.151 | 0.214 | -0.063 | 7.125 | 27.332 | -20.207 |
| | 500 | 0.114 | 0.052 | 0.062 | 1.267 | 5.993 | -4.727 |
| | 1000 | 0.115 | 0.068 | 0.047 | 1.304 | 3.366 | -2.062 |
| | 2000 | 0.080 | 0.131 | -0.051 | 2.033 | 5.328 | -3.295 |
| | 5000 | 0.107 | 0.123 | -0.016 | 0.789 | **4.407** | -3.619 |
| | 9000 | 0.047 | **0.206** | -0.159 | 1.613 | 3.096 | -1.483 |
| GBP/USD | 100 | 0.160 | 0.370 | -0.210 | 21.968 | 3.829 | 18.139 |
| | 500 | 0.093 | 0.123 | -0.031 | 10.459 | 2.759 | 7.700 |
| | 1000 | 0.081 | 0.094 | -0.014 | 7.162 | 1.843 | 5.319 |
| | 2000 | 0.075 | 0.031 | 0.044 | 1.452 | 2.170 | -0.718 |
| | 5000 | 0.105 | 0.069 | 0.037 | 2.703 | 3.012 | -0.309 |
| | 9000 | 0.064 | 0.064 | 0.001 | **4.421** | 0.987 | **3.434** |
| GBP/JPY | 100 | 0.271 | 0.041 | 0.231 | 11.186 | 8.447 | 2.740 |
| | 500 | 0.168 | 0.038 | 0.131 | 5.439 | 2.069 | 3.370 |
| | 1000 | 0.152 | 0.015 | 0.137 | 2.795 | 6.114 | -3.319 |
| | 2000 | 0.143 | 0.004 | 0.139 | 0.718 | 5.570 | -4.852 |
| | 5000 | **0.228** | 0.006 | **0.222** | 0.826 | **5.910** | -5.084 |
| | 9000 | **0.124** | 0.048 | 0.076 | 1.586 | 2.757 | -1.172 |
| EUR/USD | 100 | 0.163 | 0.214 | -0.051 | **16.785** | 12.270 | 4.516 |
| | 500 | 0.097 | 0.153 | -0.055 | 3.620 | 1.584 | 2.036 |
| | 1000 | 0.072 | 0.095 | -0.023 | 2.641 | 2.510 | 0.131 |
| | 2000 | 0.111 | 0.040 | 0.071 | 1.113 | 1.292 | -0.179 |
| | 5000 | **0.097** | 0.025 | 0.073 | 1.654 | 0.846 | 0.808 |
| | 9000 | **0.109** | 0.003 | **0.106** | 0.463 | 1.321 | -0.858 |
| EUR/JPY | 100 | 0.191 | 0.055 | 0.137 | 7.169 | 13.445 | -6.276 |
| | 500 | 0.104 | 0.030 | 0.074 | 1.819 | 4.767 | -2.948 |
| | 1000 | 0.103 | 0.058 | 0.045 | 1.620 | 2.928 | -1.308 |
| | 2000 | 0.063 | 0.057 | 0.006 | 0.552 | 9.108 | -8.556 |
| | 5000 | 0.057 | 0.047 | 0.010 | 0.425 | 6.533 | **-6.108** |
| | 9000 | 0.093 | 0.014 | 0.079 | 0.515 | **6.628** | -6.112 |
| EURGBP | 100 | 0.168 | 0.137 | 0.030 | 12.459 | 25.566 | -13.106 |
| | 500 | 0.096 | 0.053 | 0.042 | 6.032 | 13.747 | -7.715 |
| | 1000 | 0.098 | 0.031 | 0.067 | 2.884 | 7.597 | -4.713 |
| | 2000 | **0.177** | 0.009 | **0.169** | 2.952 | 4.868 | -1.917 |
| | 5000 | **0.179** | 0.011 | **0.168** | 2.002 | 4.224 | -2.222 |
| | 9000 | **0.110** | 0.019 | **0.091** | 1.731 | **4.478** | -2.747 |

Table A.3.7: Results of both metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data only on Thursday. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

| | | Kantorovich | | | Lèvy | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 100 | 0.194 | 0.235 | -0.041 | 13.351 | 6.713 | 6.638 |
| | 500 | 0.085 | 0.202 | -0.116 | 7.516 | 3.962 | 3.555 |
| | 1000 | 0.050 | 0.208 | **-0.158** | 4.727 | 3.314 | 1.414 |
| | 2000 | 0.030 | **0.254** | -0.224 | **4.855** | 2.627 | 2.228 |
| | 5000 | 0.006 | **0.190** | -0.184 | 2.008 | 1.223 | 0.785 |
| | 9000 | 0.039 | 0.101 | **-0.062** | 1.467 | 1.719 | -0.253 |
| GBP/USD | 100 | 0.129 | 0.179 | -0.051 | 11.992 | 14.573 | -2.581 |
| | 500 | 0.146 | 0.058 | 0.088 | 3.567 | 9.395 | -5.828 |
| | 1000 | 0.112 | 0.070 | 0.042 | 2.851 | 3.696 | -0.845 |
| | 2000 | 0.070 | 0.097 | -0.027 | 2.636 | 4.461 | -1.825 |
| | 5000 | 0.042 | 0.088 | -0.045 | 1.644 | 1.036 | 0.608 |
| | 9000 | 0.089 | 0.027 | 0.062 | 2.095 | 0.974 | 1.121 |
| GBP/JPY | 100 | 0.059 | 0.124 | -0.065 | 7.703 | 3.623 | 4.080 |
| | 500 | 0.201 | 0.018 | 0.183 | 1.277 | 2.485 | -1.209 |
| | 1000 | 0.031 | 0.103 | -0.072 | 1.598 | 2.484 | -0.886 |
| | 2000 | 0.000 | **0.318** | -0.317 | 3.327 | 0.202 | 3.124 |
| | 5000 | 0.005 | **0.252** | -0.247 | 2.596 | 0.541 | 2.055 |
| | 9000 | 0.000 | **0.345** | -0.345 | **3.350** | -0.040 | **3.390** |
| EUR/USD | 100 | 0.167 | 0.130 | 0.038 | 4.095 | 10.666 | -6.571 |
| | 500 | 0.196 | 0.042 | 0.154 | 2.341 | **18.309** | -15.968 |
| | 1000 | **0.250** | 0.089 | 0.161 | 5.271 | **12.423** | -7.152 |
| | 2000 | 0.129 | 0.059 | 0.070 | 1.220 | 4.516 | **-3.296** |
| | 5000 | 0.077 | 0.036 | 0.042 | 1.641 | **4.301** | -2.660 |
| | 9000 | **0.079** | 0.022 | 0.058 | 1.430 | 2.499 | -1.069 |
| EUR/JPY | 100 | 0.199 | 0.102 | 0.097 | 5.191 | 6.201 | -1.010 |
| | 500 | 0.190 | 0.017 | 0.173 | 1.115 | 3.698 | -2.582 |
| | 1000 | 0.184 | 0.016 | 0.168 | 1.102 | 7.876 | -6.775 |
| | 2000 | 0.083 | 0.026 | 0.057 | 0.236 | **7.120** | -6.884 |
| | 5000 | 0.118 | 0.004 | 0.114 | 0.197 | 4.149 | -3.953 |
| | 9000 | 0.104 | 0.036 | 0.068 | 0.432 | **4.558** | -4.127 |
| EURGBP | 100 | 0.100 | 0.055 | 0.045 | 3.535 | 1.484 | 2.051 |
| | 500 | 0.107 | 0.037 | 0.070 | 5.989 | 1.326 | 4.663 |
| | 1000 | 0.044 | 0.045 | -0.001 | 3.329 | 1.405 | 1.924 |
| | 2000 | 0.065 | 0.081 | -0.016 | 4.012 | 1.617 | 2.395 |
| | 5000 | 0.051 | 0.045 | 0.006 | 1.797 | 0.671 | 1.126 |
| | 9000 | 0.060 | 0.033 | 0.027 | 2.606 | 0.606 | 2.000 |

Table A.3.8: Results of both metric obtained by comparing the post-release $(t_0^i + \Delta t)$ and pre-release $(t_0^i - \Delta t)$ data only on Friday. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

### A.3.3 Time of The Day on Event Time

| | | Kantorovich | | | Lèvy | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 100 | 0.366 | 0.228 | 0.138 | 13.982 | 25.412 | -11.429 |
| | 500 | 0.195 | 0.144 | 0.051 | 5.993 | 7.067 | -1.074 |
| | 1000 | 0.158 | 0.119 | 0.040 | 3.574 | 6.635 | -3.061 |
| | 2000 | 0.123 | 0.090 | 0.034 | 3.592 | 3.924 | -0.333 |
| | 5000 | **0.186** | 0.009 | **0.177** | 0.710 | 3.519 | -2.809 |
| | 9000 | 0.116 | 0.045 | 0.071 | 1.568 | 1.137 | 0.431 |
| GBP/USD | 100 | 0.130 | 0.234 | -0.104 | 23.717 | 11.764 | 11.953 |
| | 500 | 0.148 | 0.080 | 0.068 | 6.295 | 5.399 | 0.896 |
| | 1000 | 0.091 | 0.080 | 0.011 | 5.315 | 3.450 | 1.866 |
| | 2000 | 0.082 | 0.036 | 0.047 | 2.428 | 2.001 | 0.428 |
| | 5000 | 0.078 | 0.034 | 0.044 | 1.722 | 1.288 | 0.434 |
| | 9000 | 0.065 | 0.031 | 0.034 | 2.197 | 1.043 | 1.154 |
| GBP/JPY | 100 | 0.174 | 0.102 | 0.072 | 10.141 | 21.819 | -11.678 |
| | 500 | 0.179 | 0.088 | 0.092 | 4.249 | 5.448 | -1.199 |
| | 1000 | 0.118 | 0.065 | 0.053 | 2.612 | 4.116 | -1.505 |
| | 2000 | 0.054 | 0.081 | -0.027 | 3.190 | 1.287 | 1.903 |
| | 5000 | 0.055 | 0.036 | 0.019 | 0.761 | 3.723 | **-2.962** |
| | 9000 | 0.047 | 0.081 | -0.034 | 2.579 | 2.114 | 0.465 |
| EUR/USD | 100 | 0.151 | 0.131 | 0.020 | 18.617 | 20.438 | -1.821 |
| | 500 | 0.148 | 0.068 | 0.081 | 4.317 | 4.687 | -0.370 |
| | 1000 | 0.141 | 0.078 | 0.062 | 2.937 | 3.432 | -0.495 |
| | 2000 | **0.126** | 0.036 | 0.090 | 0.811 | 2.268 | -1.457 |
| | 5000 | **0.091** | 0.014 | **0.077** | 1.060 | 2.049 | -0.990 |
| | 9000 | **0.074** | 0.018 | **0.056** | 0.616 | 1.460 | -0.845 |
| EUR/JPY | 100 | 0.182 | 0.190 | -0.008 | 19.687 | 13.066 | 6.622 |
| | 500 | 0.177 | 0.079 | 0.099 | 3.129 | 5.912 | -2.783 |
| | 1000 | 0.126 | 0.092 | 0.034 | 2.401 | 5.848 | -3.447 |
| | 2000 | 0.095 | 0.099 | -0.005 | 1.166 | **5.021** | -3.856 |
| | 5000 | 0.076 | 0.059 | 0.017 | 0.812 | 2.471 | -1.659 |
| | 9000 | 0.074 | 0.037 | 0.037 | 0.814 | 2.139 | -1.325 |
| EURGBP | 100 | 0.119 | 0.119 | 0.000 | 22.957 | 18.877 | **4.080** |
| | 500 | 0.079 | 0.038 | 0.041 | 3.696 | 7.625 | -3.928 |
| | 1000 | 0.047 | 0.052 | -0.005 | 2.594 | 4.197 | -1.603 |
| | 2000 | 0.038 | 0.044 | -0.006 | 2.561 | 2.688 | -0.127 |
| | 5000 | 0.026 | 0.021 | 0.005 | 1.938 | 2.024 | -0.087 |
| | 9000 | 0.030 | 0.030 | 0.000 | 1.229 | 1.624 | -0.395 |

Table A.3.9: Results of both metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data only in time period 1. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

| | | Kantorovich | | | Lèvy | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 100 | - | - | - | - | - | - |
| | 500 | - | - | - | - | - | - |
| | 1000 | - | - | - | - | - | - |
| | 2000 | - | - | - | - | - | - |
| | 5000 | - | - | - | - | - | - |
| | 9000 | - | - | - | - | - | - |
| GBP/USD | 100 | 0.094 | 0.353 | -0.259 | **32.964** | 5.621 | 27.343 |
| | 500 | 0.123 | 0.184 | -0.061 | 4.495 | 4.258 | 0.237 |
| | 1000 | 0.119 | 0.125 | -0.006 | 6.075 | 3.327 | 2.748 |
| | 2000 | 0.037 | 0.135 | -0.099 | 3.782 | 1.488 | 2.295 |
| | 5000 | 0.040 | **0.254** | -0.214 | 1.857 | 2.717 | -0.860 |
| | 9000 | 0.009 | **0.234** | -0.225 | 2.702 | 1.423 | 1.279 |
| GBP/JPY | 100 | - | - | - | - | - | - |
| | 500 | - | - | - | - | - | - |
| | 1000 | - | - | - | - | - | - |
| | 2000 | - | - | - | - | - | - |
| | 5000 | - | - | - | - | - | - |
| | 9000 | - | - | - | - | - | - |
| EUR/USD | 100 | 0.122 | 0.394 | -0.272 | 16.421 | 29.791 | -13.370 |
| | 500 | 0.045 | 0.309 | -0.264 | 5.826 | 3.790 | 2.036 |
| | 1000 | 0.042 | 0.241 | **-0.199** | 5.334 | 2.434 | 2.901 |
| | 2000 | 0.009 | **0.248** | -0.239 | 4.164 | 1.413 | 2.752 |
| | 5000 | 0.004 | **0.317** | -0.313 | 3.603 | 0.991 | 2.612 |
| | 9000 | 0.002 | **0.361** | -0.359 | 2.598 | 0.497 | 2.101 |
| EUR/JPY | 100 | 0.807 | 0.010 | 0.797 | 0.191 | 12.467 | -12.276 |
| | 500 | 0.188 | 0.407 | -0.219 | 2.658 | 1.068 | 1.589 |
| | 1000 | 0.068 | 0.356 | -0.288 | 1.485 | 0.887 | 0.598 |
| | 2000 | 0.132 | 0.335 | -0.203 | 6.500 | 1.177 | 5.324 |
| | 5000 | 0.234 | 0.230 | 0.004 | 1.175 | 2.146 | -0.972 |
| | 9000 | 0.176 | 0.243 | -0.067 | 0.828 | 3.846 | -3.018 |
| EURGBP | 100 | 0.563 | 0.022 | 0.541 | 48.105 | 43.542 | 4.563 |
| | 500 | 0.343 | 0.296 | 0.047 | 0.849 | 13.140 | -12.291 |
| | 1000 | 0.106 | 0.246 | -0.139 | 3.292 | 3.154 | 0.138 |
| | 2000 | 0.321 | 0.045 | 0.277 | 2.374 | 9.684 | -7.310 |
| | 5000 | 0.193 | 0.057 | 0.136 | 3.278 | 4.823 | -1.546 |
| | 9000 | 0.174 | 0.055 | 0.118 | 5.081 | 2.183 | 2.898 |

Table A.3.10: Results of both metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data only in time period 2. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used. Results for USD/JPY and GBP/JPY pairs are omitted due to a small number of observations

| | | Kantorovich | | | Lèvy | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 100 | 0.268 | 0.063 | 0.205 | 17.726 | 26.974 | -9.249 |
| | 500 | 0.127 | 0.076 | 0.051 | 5.137 | 3.240 | 1.897 |
| | 1000 | 0.131 | 0.021 | 0.110 | 1.789 | 4.015 | -2.226 |
| | 2000 | 0.037 | 0.059 | -0.022 | 2.135 | 1.104 | 1.031 |
| | 5000 | 0.059 | 0.033 | 0.026 | 1.213 | 1.591 | -0.378 |
| | 9000 | 0.052 | **0.103** | **-0.051** | 1.509 | 1.306 | 0.203 |
| GBP/USD | 100 | 0.213 | 0.071 | 0.141 | 8.565 | **37.649** | -29.084 |
| | 500 | 0.086 | 0.029 | 0.056 | 4.373 | 4.009 | 0.364 |
| | 1000 | 0.057 | 0.060 | -0.003 | 3.274 | 1.864 | 1.410 |
| | 2000 | 0.077 | 0.030 | 0.047 | 2.319 | 1.412 | 0.907 |
| | 5000 | **0.149** | 0.003 | **0.146** | 1.023 | 1.468 | -0.444 |
| | 9000 | **0.214** | 0.005 | **0.209** | 0.869 | 1.510 | -0.641 |
| GBP/JPY | 100 | 0.525 | 0.069 | 0.456 | 6.758 | 7.247 | -0.488 |
| | 500 | 0.064 | 0.362 | -0.298 | 1.434 | 4.883 | -3.448 |
| | 1000 | 0.052 | 0.448 | -0.395 | 1.684 | 2.808 | -1.124 |
| | 2000 | 0.351 | 0.053 | 0.298 | 0.516 | 6.487 | -5.970 |
| | 5000 | 0.436 | 0.015 | 0.422 | 0.373 | 6.899 | -6.525 |
| | 9000 | 0.445 | 0.017 | 0.428 | 0.280 | 6.818 | **-6.539** |
| EUR/USD | 100 | 0.214 | 0.057 | 0.157 | 22.857 | 17.682 | 5.175 |
| | 500 | 0.091 | 0.036 | 0.056 | 2.815 | 3.334 | -0.518 |
| | 1000 | 0.147 | 0.031 | 0.116 | 2.829 | 4.135 | -1.306 |
| | 2000 | **0.146** | 0.022 | 0.124 | 1.594 | 1.461 | 0.133 |
| | 5000 | **0.177** | 0.012 | **0.165** | 3.144 | 1.336 | 1.809 |
| | 9000 | **0.178** | 0.011 | **0.167** | 1.908 | 1.293 | 0.615 |
| EUR/JPY | 100 | 0.142 | 0.756 | -0.614 | 26.731 | 2.748 | 23.983 |
| | 500 | 0.012 | 0.786 | -0.774 | 2.594 | 0.299 | 2.295 |
| | 1000 | 0.246 | 0.300 | -0.054 | 2.148 | 2.288 | -0.141 |
| | 2000 | 0.123 | 0.126 | -0.003 | 3.068 | 0.987 | 2.082 |
| | 5000 | 0.053 | 0.308 | -0.255 | 1.109 | 0.737 | 0.372 |
| | 9000 | 0.012 | **0.620** | -0.609 | 3.742 | 0.278 | 3.463 |
| EURGBP | 100 | 0.133 | 0.119 | 0.014 | 16.049 | 22.912 | -6.863 |
| | 500 | 0.123 | 0.090 | 0.032 | 3.331 | 5.652 | -2.320 |
| | 1000 | 0.142 | 0.045 | 0.097 | 1.034 | 5.968 | -4.934 |
| | 2000 | 0.291 | 0.001 | 0.291 | 0.642 | 3.377 | -2.735 |
| | 5000 | 0.235 | 0.022 | 0.212 | 0.596 | 2.264 | -1.667 |
| | 9000 | 0.193 | 0.042 | 0.151 | 0.612 | 2.900 | **-2.288** |

Table A.3.11: Results of both metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data only in time period 3. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

### A.3.4 News Variable Effect on Event Time

| | | Positive Outcome | | | Negative Outcome | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ |
| USD/JPY | 100 | 0.180 | 0.145 | 0.035 | 0.181 | 0.162 | 0.019 |
| | 500 | 0.119 | 0.084 | 0.035 | 0.080 | 0.209 | -0.129 |
| | 1000 | 0.088 | 0.053 | 0.035 | 0.076 | 0.136 | -0.060 |
| | 2000 | 0.062 | 0.085 | -0.024 | 0.027 | **0.183** | -0.156 |
| | 5000 | 0.055 | 0.063 | -0.008 | 0.024 | **0.180** | -0.157 |
| | 9000 | 0.039 | **0.085** | -0.046 | 0.001 | **0.249** | -0.248 |
| GBP/USD | 100 | 0.125 | 0.213 | -0.088 | 0.184 | 0.175 | 0.009 |
| | 500 | 0.085 | 0.078 | 0.007 | 0.156 | 0.056 | 0.100 |
| | 1000 | 0.057 | 0.081 | -0.024 | 0.138 | 0.078 | 0.060 |
| | 2000 | 0.057 | 0.031 | 0.026 | 0.086 | 0.086 | -0.001 |
| | 5000 | **0.076** | 0.018 | 0.058 | 0.076 | 0.057 | 0.019 |
| | 9000 | **0.097** | 0.005 | **0.092** | 0.050 | 0.064 | -0.015 |
| GBP/JPY | 100 | 0.116 | 0.113 | 0.003 | 0.238 | 0.109 | 0.129 |
| | 500 | 0.079 | 0.084 | -0.006 | 0.222 | 0.047 | 0.175 |
| | 1000 | 0.053 | 0.084 | -0.031 | 0.090 | 0.060 | 0.030 |
| | 2000 | 0.019 | 0.124 | -0.105 | 0.094 | 0.035 | 0.059 |
| | 5000 | 0.050 | 0.068 | -0.018 | 0.063 | 0.022 | 0.041 |
| | 9000 | 0.036 | **0.077** | -0.042 | 0.027 | 0.041 | -0.015 |
| EUR/USD | 100 | 0.157 | 0.131 | 0.026 | 0.146 | 0.159 | -0.013 |
| | 500 | 0.099 | 0.082 | 0.016 | 0.159 | 0.098 | 0.062 |
| | 1000 | 0.100 | 0.075 | 0.025 | 0.180 | 0.096 | 0.084 |
| | 2000 | **0.100** | 0.043 | 0.057 | 0.134 | 0.085 | 0.049 |
| | 5000 | **0.078** | 0.014 | **0.064** | **0.100** | 0.067 | 0.033 |
| | 9000 | **0.044** | 0.008 | 0.036 | **0.088** | 0.051 | 0.038 |
| EUR/JPY | 100 | 0.135 | 0.154 | -0.019 | 0.173 | 0.220 | -0.047 |
| | 500 | 0.126 | 0.067 | 0.059 | 0.111 | 0.105 | 0.006 |
| | 1000 | 0.106 | 0.061 | 0.045 | 0.095 | 0.142 | -0.046 |
| | 2000 | 0.061 | 0.055 | 0.006 | 0.047 | **0.178** | **-0.131** |
| | 5000 | 0.066 | 0.019 | 0.047 | 0.028 | 0.112 | **-0.084** |
| | 9000 | 0.040 | 0.018 | 0.021 | 0.020 | **0.099** | -0.079 |
| EURGBP | 100 | 0.081 | 0.128 | -0.047 | 0.124 | 0.091 | 0.034 |
| | 500 | 0.049 | 0.057 | -0.008 | 0.090 | 0.009 | 0.082 |
| | 1000 | 0.032 | 0.065 | -0.033 | 0.063 | 0.016 | 0.047 |
| | 2000 | 0.026 | 0.040 | -0.014 | 0.070 | 0.024 | 0.046 |
| | 5000 | 0.029 | 0.017 | 0.012 | 0.040 | 0.015 | 0.025 |
| | 9000 | **0.047** | 0.021 | 0.026 | 0.011 | 0.043 | **-0.032** |

Table A.3.12: Results of Kantorovich metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data by focusing on previous value outcomes only. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

| | | Positive Outcome | | | Negative Outcome | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 100 | 6.284 | 25.369 | -19.085 | 12.682 | 15.565 | -2.883 |
| | 500 | 1.575 | **15.169** | -13.594 | 5.392 | 2.638 | 2.754 |
| | 1000 | 0.721 | 8.672 | -7.951 | 2.693 | 2.597 | 0.096 |
| | 2000 | 1.348 | 5.860 | **-4.511** | 3.069 | 0.840 | 2.229 |
| | 5000 | 0.381 | **4.898** | -4.517 | 1.950 | 0.967 | 0.983 |
| | 9000 | 0.393 | 3.372 | -2.979 | 2.410 | 0.173 | 2.238 |
| GBP/USD | 100 | 15.166 | 9.960 | 5.206 | 12.175 | 12.220 | -0.045 |
| | 500 | 4.971 | 4.829 | 0.143 | 2.433 | 7.036 | -4.604 |
| | 1000 | 4.898 | 2.583 | 2.315 | 1.221 | 2.759 | -1.538 |
| | 2000 | 2.388 | 1.094 | 1.294 | 2.348 | 2.478 | -0.130 |
| | 5000 | 0.803 | 2.482 | -1.679 | 0.888 | 1.941 | -1.054 |
| | 9000 | 0.653 | 0.944 | -0.291 | 2.057 | 1.562 | 0.495 |
| GBP/JPY | 100 | 9.745 | 4.873 | 4.873 | 9.859 | 7.677 | 2.182 |
| | 500 | 1.879 | 2.944 | -1.065 | 3.173 | 3.030 | 0.144 |
| | 1000 | 1.202 | 6.036 | -4.834 | 1.854 | 1.683 | 0.171 |
| | 2000 | 2.842 | 4.298 | -1.456 | 0.962 | 1.560 | -0.598 |
| | 5000 | 1.305 | **7.205** | -5.900 | 1.723 | 3.771 | -2.048 |
| | 9000 | 1.434 | 1.766 | -0.332 | 1.920 | 1.203 | 0.717 |
| EUR/USD | 100 | 9.943 | 9.662 | 0.281 | 14.287 | 9.509 | 4.779 |
| | 500 | 2.499 | 5.451 | -2.953 | 3.568 | 7.123 | -3.555 |
| | 1000 | 2.631 | 2.874 | -0.243 | 2.815 | **6.475** | **-3.660** |
| | 2000 | 1.008 | 2.880 | -1.872 | 2.111 | 2.862 | -0.751 |
| | 5000 | 0.764 | 1.041 | -0.278 | 2.011 | 2.282 | -0.271 |
| | 9000 | 0.537 | 2.173 | -1.637 | 1.272 | 1.366 | -0.094 |
| EUR/JPY | 100 | 4.454 | 8.646 | -4.192 | 14.582 | 11.160 | 3.422 |
| | 500 | 1.021 | 8.450 | -7.428 | 5.999 | 4.454 | 1.545 |
| | 1000 | 1.735 | 5.019 | -3.284 | 4.782 | 4.192 | 0.590 |
| | 2000 | 0.725 | 12.855 | -12.131 | 1.979 | **4.170** | -2.191 |
| | 5000 | 0.495 | **13.533** | -13.038 | 1.056 | 1.153 | -0.097 |
| | 9000 | 0.806 | 4.935 | -4.129 | 1.347 | 1.308 | 0.039 |
| EURGBP | 100 | 10.456 | 15.470 | -5.014 | 3.378 | 10.404 | -7.026 |
| | 500 | 3.637 | 9.330 | **-5.692** | 1.461 | 4.166 | -2.705 |
| | 1000 | 3.064 | 4.065 | -1.001 | 0.637 | 1.766 | -1.130 |
| | 2000 | 2.333 | **4.540** | -2.207 | 0.929 | 2.143 | -1.214 |
| | 5000 | 2.182 | 2.898 | -0.716 | 1.023 | 1.787 | -0.763 |
| | 9000 | 1.103 | 1.836 | -0.733 | 1.477 | 0.599 | 0.878 |

Table A.3.13: Results of Lèvy metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data by focusing on previous value outcomes only. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

| | | Positive Outcome | | | Negative Outcome | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ |
| USD/JPY | 100 | 0.174 | 0.159 | 0.015 | 0.174 | 0.155 | 0.019 |
| | 500 | 0.103 | 0.096 | 0.007 | 0.094 | 0.180 | -0.086 |
| | 1000 | 0.081 | 0.051 | 0.030 | 0.077 | 0.163 | -0.085 |
| | 2000 | 0.048 | 0.084 | -0.036 | 0.059 | **0.213** | -0.154 |
| | 5000 | 0.040 | 0.066 | -0.027 | 0.057 | **0.220** | -0.163 |
| | 9000 | 0.037 | **0.085** | -0.048 | 0.003 | **0.289** | -0.287 |
| GBP/USD | 100 | 0.136 | 0.191 | -0.055 | 0.157 | 0.265 | -0.108 |
| | 500 | 0.095 | 0.070 | 0.025 | 0.123 | 0.096 | 0.027 |
| | 1000 | 0.059 | 0.073 | -0.013 | 0.119 | 0.126 | -0.006 |
| | 2000 | 0.045 | 0.029 | 0.016 | 0.103 | 0.106 | -0.004 |
| | 5000 | 0.060 | 0.020 | 0.040 | 0.087 | 0.065 | 0.022 |
| | 9000 | **0.084** | 0.008 | **0.077** | 0.048 | 0.055 | -0.007 |
| GBP/JPY | 100 | 0.130 | 0.094 | 0.036 | 0.187 | 0.161 | 0.026 |
| | 500 | 0.095 | 0.072 | 0.023 | 0.159 | 0.078 | 0.081 |
| | 1000 | 0.065 | 0.088 | -0.022 | 0.043 | 0.074 | -0.031 |
| | 2000 | 0.019 | 0.110 | **-0.091** | 0.064 | 0.081 | -0.017 |
| | 5000 | 0.036 | 0.087 | -0.051 | 0.119 | 0.010 | 0.109 |
| | 9000 | 0.027 | **0.096** | -0.069 | 0.050 | 0.020 | 0.031 |
| EUR/USD | 100 | 0.166 | 0.140 | 0.026 | 0.127 | 0.139 | -0.013 |
| | 500 | 0.113 | 0.076 | 0.037 | 0.136 | 0.108 | 0.028 |
| | 1000 | 0.112 | 0.065 | 0.047 | 0.158 | 0.111 | 0.047 |
| | 2000 | **0.103** | 0.036 | 0.067 | 0.129 | 0.086 | 0.043 |
| | 5000 | **0.077** | 0.015 | **0.062** | 0.093 | 0.076 | 0.017 |
| | 9000 | **0.048** | 0.009 | 0.039 | **0.086** | 0.055 | 0.031 |
| EUR/JPY | 100 | 0.146 | 0.167 | -0.021 | 0.142 | 0.199 | -0.057 |
| | 500 | 0.148 | 0.067 | 0.081 | 0.070 | 0.090 | -0.020 |
| | 1000 | 0.114 | 0.066 | 0.048 | 0.084 | 0.115 | -0.031 |
| | 2000 | 0.076 | 0.057 | 0.019 | 0.046 | **0.176** | -0.130 |
| | 5000 | 0.058 | 0.029 | 0.030 | 0.038 | 0.091 | -0.053 |
| | 9000 | 0.052 | 0.013 | 0.040 | 0.017 | **0.116** | -0.098 |
| EURGBP | 100 | 0.075 | 0.144 | -0.070 | 0.159 | 0.051 | 0.108 |
| | 500 | 0.052 | 0.071 | -0.019 | 0.138 | 0.002 | 0.135 |
| | 1000 | 0.034 | 0.074 | -0.041 | 0.062 | 0.008 | 0.054 |
| | 2000 | 0.022 | 0.068 | **-0.045** | 0.096 | 0.001 | 0.095 |
| | 5000 | 0.011 | 0.042 | **-0.032** | **0.105** | 0.001 | **0.104** |
| | 9000 | 0.022 | 0.037 | -0.015 | 0.060 | 0.019 | 0.042 |

Table A.3.14: Results of Kantorovich metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data by focusing on released value outcomes only. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

| FX Pair | $\Delta t$ | Positive Outcome $\breve{L}$ | Positive Outcome $\breve{L}_D$ | Positive Outcome $\Delta\breve{L}$ | Negative Outcome $\breve{L}$ | Negative Outcome $\breve{L}_D$ | Negative Outcome $\Delta\breve{L}$ |
|---|---|---|---|---|---|---|---|
| USD/JPY | 100 | 8.268 | 25.375 | -17.107 | 5.492 | **20.020** | -14.528 |
| | 500 | 2.178 | **15.170** | -12.992 | 3.087 | 3.262 | -0.175 |
| | 1000 | 1.094 | 8.734 | -7.641 | 1.621 | 2.766 | -1.145 |
| | 2000 | 1.298 | **6.289** | **-4.991** | 2.500 | 2.379 | 0.121 |
| | 5000 | 0.541 | **4.578** | -4.037 | 1.157 | 2.212 | -1.056 |
| | 9000 | 0.563 | 3.153 | **-2.589** | **2.552** | 0.382 | 2.170 |
| GBP/USD | 100 | 13.665 | 9.461 | 4.205 | 11.607 | 11.084 | 0.523 |
| | 500 | 4.432 | 11.015 | **-6.583** | 3.381 | 4.993 | -1.612 |
| | 1000 | 4.542 | 7.474 | -2.932 | 2.600 | 2.464 | 0.136 |
| | 2000 | 1.933 | 2.808 | -0.875 | 3.460 | 1.908 | 1.552 |
| | 5000 | 0.763 | 3.201 | -2.438 | 1.366 | 1.728 | -0.361 |
| | 9000 | 0.792 | **3.542** | -2.750 | 1.941 | 1.085 | 0.856 |
| GBP/JPY | 100 | 9.751 | 4.548 | 5.203 | 10.673 | 9.591 | 1.082 |
| | 500 | 1.609 | 3.335 | -1.726 | 3.614 | 2.099 | 1.516 |
| | 1000 | 1.337 | 4.225 | -2.887 | 1.435 | 2.351 | -0.915 |
| | 2000 | 2.850 | 4.294 | -1.444 | 1.532 | 1.837 | -0.306 |
| | 5000 | 1.211 | **7.204** | -5.993 | 1.500 | **4.146** | -2.645 |
| | 9000 | 1.669 | 1.702 | -0.033 | 1.250 | 0.951 | 0.299 |
| EUR/USD | 100 | 10.033 | 10.185 | -0.152 | 14.046 | 6.426 | 7.619 |
| | 500 | 2.098 | **13.869** | -11.771 | 4.028 | 4.756 | -0.728 |
| | 1000 | 2.333 | 8.820 | **-6.487** | 2.761 | 4.265 | -1.504 |
| | 2000 | 0.977 | 3.184 | -2.208 | 1.345 | 2.131 | -0.786 |
| | 5000 | 0.840 | 1.694 | -0.853 | 1.738 | 1.622 | 0.117 |
| | 9000 | 0.582 | 2.337 | -1.754 | 1.189 | 1.557 | -0.368 |
| EUR/JPY | 100 | 5.774 | 8.611 | -2.837 | 14.442 | 8.901 | 5.541 |
| | 500 | 1.370 | 5.558 | -4.188 | 4.775 | 3.246 | 1.530 |
| | 1000 | 1.866 | 5.028 | -3.162 | 2.897 | 4.136 | -1.239 |
| | 2000 | 0.813 | 13.074 | -12.261 | 1.834 | 4.115 | -2.281 |
| | 5000 | 0.552 | **13.964** | -13.412 | 0.982 | 1.350 | -0.368 |
| | 9000 | 0.963 | 5.498 | -4.535 | 1.190 | 1.187 | 0.003 |
| EURGBP | 100 | 10.225 | 14.838 | -4.613 | 4.008 | 10.386 | -6.378 |
| | 500 | 3.698 | 8.702 | **-5.004** | 1.369 | 5.990 | -4.621 |
| | 1000 | 2.840 | 3.602 | -0.763 | 0.305 | 3.059 | -2.754 |
| | 2000 | 2.927 | 2.941 | -0.014 | 0.369 | 2.650 | -2.281 |
| | 5000 | 2.735 | 1.632 | 1.103 | 0.165 | 3.039 | -2.874 |
| | 9000 | 1.412 | 1.075 | 0.337 | 0.971 | 1.633 | -0.662 |

Table A.3.15: Results of Lèvy metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data by focusing on released value outcomes only. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

| | | Positive Outcome | | | Negative Outcome | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ | $\breve{\kappa}$ | $\breve{\kappa}_D$ | $\Delta\breve{\kappa}$ |
| USD/JPY | 100 | 0.179 | 0.131 | 0.048 | 0.238 | 0.187 | 0.051 |
| | 500 | 0.114 | 0.079 | 0.035 | 0.102 | 0.197 | -0.095 |
| | 1000 | 0.089 | 0.050 | 0.038 | 0.085 | 0.132 | -0.046 |
| | 2000 | 0.053 | 0.073 | -0.020 | 0.040 | **0.230** | -0.190 |
| | 5000 | 0.047 | 0.072 | -0.026 | 0.032 | **0.216** | -0.184 |
| | 9000 | 0.044 | **0.087** | -0.043 | 0.000 | **0.324** | -0.324 |
| GBP/USD | 100 | 0.129 | 0.189 | -0.060 | 0.177 | 0.238 | -0.061 |
| | 500 | 0.104 | 0.064 | 0.039 | 0.120 | 0.064 | 0.057 |
| | 1000 | 0.070 | 0.062 | 0.009 | 0.130 | 0.106 | 0.024 |
| | 2000 | 0.065 | 0.034 | 0.031 | 0.087 | 0.107 | -0.020 |
| | 5000 | 0.062 | 0.028 | 0.033 | 0.073 | 0.068 | 0.005 |
| | 9000 | **0.078** | 0.012 | 0.066 | 0.047 | 0.059 | -0.011 |
| GBP/JPY | 100 | 0.115 | 0.086 | 0.029 | 0.212 | 0.095 | 0.118 |
| | 500 | 0.110 | 0.054 | 0.055 | 0.203 | 0.073 | 0.130 |
| | 1000 | 0.067 | 0.076 | -0.010 | 0.094 | 0.073 | 0.021 |
| | 2000 | 0.022 | 0.123 | -0.101 | 0.045 | 0.117 | -0.071 |
| | 5000 | 0.026 | 0.092 | -0.066 | 0.055 | 0.029 | 0.025 |
| | 9000 | 0.021 | **0.114** | -0.093 | 0.013 | 0.063 | -0.049 |
| EUR/USD | 100 | 0.152 | 0.138 | 0.015 | 0.183 | 0.128 | 0.054 |
| | 500 | 0.106 | 0.073 | 0.034 | 0.180 | 0.095 | 0.086 |
| | 1000 | 0.108 | 0.073 | 0.035 | 0.219 | 0.086 | 0.133 |
| | 2000 | **0.106** | 0.042 | 0.064 | **0.147** | 0.066 | 0.081 |
| | 5000 | **0.087** | 0.023 | **0.064** | 0.088 | 0.053 | 0.034 |
| | 9000 | 0.040 | 0.017 | 0.023 | 0.080 | 0.036 | 0.043 |
| EUR/JPY | 100 | 0.133 | 0.149 | -0.015 | 0.183 | 0.200 | -0.017 |
| | 500 | 0.136 | 0.052 | 0.085 | 0.083 | 0.078 | 0.006 |
| | 1000 | 0.112 | 0.049 | 0.063 | 0.114 | 0.106 | 0.008 |
| | 2000 | 0.062 | 0.056 | 0.006 | 0.043 | 0.171 | -0.128 |
| | 5000 | 0.065 | 0.034 | 0.030 | 0.016 | 0.119 | -0.103 |
| | 9000 | 0.045 | 0.031 | 0.014 | 0.010 | **0.115** | -0.106 |
| EURGBP | 100 | 0.084 | 0.121 | -0.037 | 0.096 | 0.059 | 0.037 |
| | 500 | 0.060 | 0.065 | -0.005 | 0.059 | 0.007 | 0.052 |
| | 1000 | 0.035 | 0.077 | -0.042 | 0.051 | 0.009 | 0.042 |
| | 2000 | 0.022 | 0.075 | **-0.053** | 0.069 | 0.009 | 0.060 |
| | 5000 | 0.012 | 0.049 | **-0.037** | 0.044 | 0.020 | 0.025 |
| | 9000 | 0.014 | **0.044** | -0.029 | 0.049 | 0.040 | 0.009 |

Table A.3.16: Results of Kantorovich metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data by focusing on forecast value outcomes only. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.

| | | Positive Outcome | | | Negative Outcome | | |
|---|---|---|---|---|---|---|---|
| FX Pair | $\Delta t$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ | $\breve{L}$ | $\breve{L}_D$ | $\Delta\breve{L}$ |
| USD/JPY | 100 | 7.060 | 24.382 | -17.322 | 12.391 | 20.638 | -8.246 |
| | 500 | 1.732 | **14.520** | -12.787 | 6.052 | 3.298 | 2.754 |
| | 1000 | 0.799 | 8.651 | -7.852 | 2.862 | 2.852 | 0.010 |
| | 2000 | 0.985 | 2.644 | -1.658 | 3.849 | 1.328 | 2.520 |
| | 5000 | 0.311 | **4.600** | -4.289 | 2.298 | 1.682 | 0.616 |
| | 9000 | 0.382 | 2.865 | -2.483 | **3.319** | -0.013 | **3.333** |
| GBP/USD | 100 | 9.733 | 3.852 | 5.880 | 13.165 | 9.440 | 3.725 |
| | 500 | 3.203 | 3.311 | -0.108 | 3.004 | 7.157 | -4.153 |
| | 1000 | 3.913 | 1.936 | 1.976 | 2.583 | 3.543 | -0.960 |
| | 2000 | 2.577 | 1.094 | 1.483 | 2.946 | 3.174 | -0.227 |
| | 5000 | 1.179 | 0.767 | 0.412 | 1.086 | 1.947 | -0.861 |
| | 9000 | 1.048 | 0.926 | 0.122 | 1.951 | 1.299 | 0.652 |
| GBP/JPY | 100 | 8.781 | 3.000 | 5.781 | 7.853 | 3.870 | 3.983 |
| | 500 | 1.823 | 2.804 | -0.981 | 3.495 | 2.727 | 0.768 |
| | 1000 | 1.494 | 2.979 | -1.485 | 1.880 | 2.924 | -1.045 |
| | 2000 | 3.367 | 4.262 | -0.895 | 1.752 | 1.719 | 0.033 |
| | 5000 | 1.298 | 4.427 | -3.129 | 1.471 | **4.306** | -2.834 |
| | 9000 | 2.068 | 1.417 | 0.651 | 1.700 | 0.681 | 1.019 |
| EUR/USD | 100 | 10.202 | 11.088 | -0.887 | 15.428 | 7.404 | 8.024 |
| | 500 | 2.574 | 4.799 | -2.225 | 3.360 | 8.241 | -4.881 |
| | 1000 | 2.677 | 3.254 | -0.576 | 1.575 | 4.837 | -3.263 |
| | 2000 | 1.010 | 3.147 | -2.137 | 1.395 | 2.717 | -1.322 |
| | 5000 | 1.189 | 1.481 | -0.292 | 1.473 | 1.876 | -0.404 |
| | 9000 | 0.723 | 2.317 | **-1.594** | 1.308 | 1.748 | -0.440 |
| EUR/JPY | 100 | 4.493 | 8.586 | -4.093 | 16.217 | 6.146 | 10.071 |
| | 500 | 1.253 | 8.379 | -7.126 | 5.503 | 2.502 | 3.002 |
| | 1000 | 2.051 | 5.487 | -3.436 | 2.352 | 4.133 | -1.781 |
| | 2000 | 1.238 | 11.561 | -10.323 | 1.559 | 4.455 | -2.896 |
| | 5000 | 0.627 | **11.664** | -11.037 | 1.085 | 0.874 | 0.212 |
| | 9000 | 1.148 | 5.198 | -4.050 | 0.871 | 1.074 | -0.203 |
| EURGBP | 100 | 3.449 | 6.934 | -3.485 | 4.258 | 8.926 | -4.669 |
| | 500 | 4.861 | 9.411 | -4.550 | 1.102 | 1.418 | -0.316 |
| | 1000 | 2.898 | 4.376 | -1.477 | 0.975 | 2.404 | -1.429 |
| | 2000 | 3.472 | 2.994 | 0.477 | 0.571 | 2.374 | -1.803 |
| | 5000 | 3.040 | 2.653 | 0.388 | 0.555 | 2.918 | -2.363 |
| | 9000 | 1.724 | 1.091 | 0.633 | 0.789 | 0.691 | 0.098 |

Table A.3.17: Results of Lèvy metric obtained by comparing the post-release ($t_0^i + \Delta t$) and pre-release ($t_0^i - \Delta t$) data by focusing on forecast value outcomes only. Values in bold identify statistically significant results at 5% error level. Presented values are scaled by $10^5$. $\Delta t$ refers to the $t_0^i \pm \Delta t$ value used.