

**THE REPUBLIC OF TURKEY
BAHCESEHİR UNIVERSITY**

**IDENTIFYING JUMPS AND CO-JUMPS IN
FOREIGN EXCHANGE MARKETS: A
COMPARATIVE ANALYSIS OF NON-
PARAMETRIC JUMP TESTS**

Ph.D. Thesis

SERKAN YEŞİLYURT

ISTANBUL, 2018

**THE REPUBLIC OF TURKEY
BAHÇEŞEHİR UNIVERSITY**

**GRADUATE SCHOOL OF SOCIAL SCIENCES
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Thesis Supervisor: PROF. ÜMIT EROL

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SCIENCES

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We hereby recommend that the dissertation prepared under our supervision by **Serkan YEŞİLYURT** entitled **Identifying Jumps And Co-Jumps in Foreign Exchange Markets: A Comparative Analysis of Non-Parametric Jump Tests** be accepted in partial fulfillment of the requirements for the Doctor of Philosophy Business Administration .


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Istanbul, 2018

Serkan YEŞİLYURT

ABSTRACT

IDENTIFYING JUMPS AND CO-JUMPS IN FOREIGN EXCHANGE MARKETS: A COMPARATIVE ANALYSIS OF NON-PARAMETRIC JUMP TESTS

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This dissertation covers the effect of macroeconomic news announcements on jumps and co-jumps in foreign exchange markets. According to traditional financial theory, asset prices follow a continuous process. However, recent research shows that the high-frequency trading data is characterized by sudden but infrequent changes in asset prices, which are known as “jumps”. We focus on the effect of macroeconomic news announcements especially on developed markets’ cross currency pairs, including also one emerging market’s currency pair. Barndorff-Nielsen and Shephard (2009), and Ait-Sahalia and Jacod (2009) nonparametric jump detection tests and event study methods are used to explore this effect. We use one, five, fifteen, thirty and sixty minutes intervals extracted from high frequency data as it is recommended on USD/CHF, USD/JPY, USD/TRY, EUR/USD, EUR/CHF, EUR/GBP, EUR/TRY, EUR/JPY, GBP/CHF, GBP/JPY and CHF/JPY cross pairs from January 1, 2010 to December 31, 2016. This study shows that scheduled news related to the employment, real economic activities, trade balance, GDP and FOMC rate decisions have a significant effect on jumps and co-jumps.

Keywords: Jump detection models, Co-Jump detection models, high-frequency data, pre-averaging, macroeconomic news, event study approach

ÖZET

DÖVİZ PİYASALARINDA SIÇRAMA VE EŞ SIÇRAMA SÜREÇLERİNİN TANIMLANMASI: PARAMETRİK OLMAYAN SIÇRAMA MODELLERİNİN KARŞILAŞTIRMALI ANALİZİ

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Bu tez finans literatüründeki önemli ve güncel konulardan makroekonomik haberlerin sıçrama ve eş sıçramalar üzerine etkisini incelemektedir. Geleneksel finans teorileri varlık fiyatlarının kesintisiz bir süreç izlediklerini kabul etmektedir. Yüksek frekanslı verilerle yapılan çalışmalar varlık fiyatlarının literatürde “sıçrama” olarak bilinen ani ama seyrek kesintili bir süreç izlediklerini göstermektedir. Bu çalışmada makroekonomik haberlerin gelişmiş ülkeler ve Türkiye döviz piyasalarındaki kurlar üzerinde nasıl sıçrama ve eş-sıçrama etkileri yarattıklarını ortaya çıkarmaktır. Ait-Sahalia ve Jacod (2009) ve Bardorff-Nielsen and Shephard (2009)’ın parametrik olmayan modelleri ve ayrıca makroekonomik haberlerin çapraz kurlar üzerindeki etkileri haber etkisi analizi yaklaşımı ile ortaya konmuştur. Çalışmada bir, beş, onbeş, otuz ve altmış dakikalık frekanslarda USDCHF, USDJPY, USDTRY, EURUSD, EURCHF, EURGBP, EURTRY, EURJPY, GBPCHF, GBPJPY ve CHFJPY kur verileri 1 Ocak 2010’dan 31 Aralık 2016 tarihine kadar incelenmiştir. Açıklama zamanı önceden bilinen istihdam, güncel ekonomik aktiviteler, dış ticaret dengesi, GDP ve FOMC kararları ile ilgili haberlerin sıçrama ve eşsıçramalar üzerine anlamlı etkiler yarattıkları tespit edilmiştir.

Anahtar Kelimeler: Sıçrama yakalama modelleri, Eş-sıçrama yakalama modelleri, yüksek frekanslı veri, ön-ortalama, makroekonomik haberler, haber etkisi analizi yaklaşımı.

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ABBREVIATION

LM	:	Lee and Mykland Jump Model
ABD	:	Andersen, Bollerslev and Diebold Jump Model
BNS	:	Barndorff-Nielsen and Sephard
AJ	:	Ait-Sahalia et.al Jump Model
ADS	:	Andersen et.al Jump Model
CRP	:	Corsi et.al. Jump Model
JO	:	Jiang and Omen Jump Model
RV	:	Realized Variation
BPV	:	Bi-Power Variation
FX	:	Forex Market
US	:	United States of America
UK	:	United Kingdom
STR	:	Two regime smooth transition regression models
ARCH	:	Autoregressive conditional heteroskedasticity model
GARCH	:	Generalized autoregressive conditional heteroskedasticity model
CPI	:	Consumer price index
PPI	:	Producer price index
ACH	:	Autoregressive conditional hazard model
HAR-RV	:	Heterogeneous autoregressive model of the realized volatility
S&P	:	Standart and Poor's
NFP	:	Nonfarm payroll
MPC	:	Mean-cross-product
EMF	:	Efficient market hypothesis

SYMBOLS

s_t	:	Represent the logarithmic price of an asset
μ_t	:	Represent the drift term of the logarithmic asset price
σ_t	:	Represent the volatility process and can be stochastic, which is cadlag
W_t	:	is a standard Brownian motion, Wiener process
$k_t dq_t$	:	Represent the jumps in the price process
q_t	:	Represent the Poisson process counting the number of jumps
k_t	:	Is the logarithmic size of any jump in s_t at the t
IV_t	:	integrated variance at time t
QV_t	:	quadratic variation at time t
RV_t	:	realized variation at time t
j	:	represents the intraday period
t	:	denotes the observation days
r_t	:	denotes daily return
M	:	intraday period
BPV	:	Bipower variation
RJ_t	:	realized jump
TP_t	:	Tree power Quadricity
$\emptyset$	:	the cumulative distribution function of the standard normal distribution
α	:	significance level
$\sqrt{Y_t}$	:	standard error
P	:	price of an asset
$\Delta_i^n p$	:	logarithmic return
$C(t)$	:	jump size
M	:	optimal block size
$C(q)$	:	constant parameter

1. INTRODUCTION

The dynamics of asset prices are characterized by unpredictable price movements. One reason for this random behavior is the efficient market hypothesis (EMH). EMH mainly states that past price history is reflected in current prices. It also states that all available information is embedded by the price movements of the markets.

A central issue of the economics and finance literature is to explore the determinants of asset prices and return distributions. This is an important question which is investigated extensively in the literature. Asset prices can be assumed to be characterized by a continuous process if markets are dominated by normal events, and characterized by Brownian motion process. This is a process which is called continuous-time stochastic process written in the form of the stochastic differential equation below;

$$\frac{dS_t}{S_t} = \mu dt + \sigma dW_t \quad (1.1)$$

S_t = current asset price

μ = the drift/trend term which is constant

σ = annualized volatility – constant

W_t = Standard Wiener process

(Merton, 1976)

This process doesn't allow any discontinuity or "jumps" in the price process.

However, prices of traded assets are subject to the sudden movements which can't be described by a continuous process. Such events mostly generate significant discontinuities, which are called "jumps", in data series (Lee & Mykland, 2008). The jump may differ in terms of its sign (positive or negative), magnitude (large or small) and frequency (recurring or rare) (Zoi, 2016). It is formulated as below;

$$\frac{dS_t}{S_t} = \mu dt + \sigma dW_t + d \sum_{j=1}^{N_t} (Y_j - 1) \quad (1.2)$$

The additional variable $Y_j - 1$ here represents a log normal distribution of a random variable. The jump size, N_t comes from Poisson process¹ with parameter λt and it represents unexpected shocks in price processes. d is the last parameter uses as a constant term.

Jumps are generally associated with a sudden flow of new information but there is no general understanding of which kind of market events can generate discontinuous price movements. Also, much effort has been spent to detect the sudden changes (also called as a structural break) in the time series data (see Basseville and Nikiforov (1993), Shiau (1986), Yin (1988), Wu and Chu (1993), and Wang (1995)). The analysis of structural break shows that they are generated by sudden changes in either drift or volatility (Wong, Ip, & Li, 2001). Asset prices may jump up or down due to the impact of important macroeconomic news or events (Qiu & Yandell, 1998).

The jump and co-jump detection tests have been applied to different asset groups, such as Forex Market (FX), Stock Market, Bond Market, Interest rate markets, derivative markets. The most important research in this area has been done in FX market.

In this dissertation, we applied jump detection tests to extract jumps and co-jumps (simultaneous jumps) from USD, EUR, and CROSS exchange rate pairs. We then symbolize the dynamics of the discontinuities and informally relate them to U.S, U.K, Switzerland, Germany, Japan, France, Italy and Spain, Turkey and Eurozone aggregate macroeconomic news releases. How big and usual are jumps and co-jumps (Qiu & Yandell, 1998) across FX pairs? Do Jumps perform independently? What causes jumps and co-jumps in Forex markets? Does only financial news cause FX jump or other economic releases affect the jumps and co-jumps? Our dissertation alternately answers these questions.

This study is a fundamental attempt to empirically verify the response of prices to new information which is instrumental in price determination and ascertains the microstructure of markets as well as price discovery process. Several studies considered financial price series as a continuous-time diffusion process. Such processes have been

¹ See Neftci, S., (2008), An Introduction To The Mathematics of Financial Derivatives.

investigated by several empirical studies whose goals were to ascertain the sudden and severe price changes leading to violation of Gaussian distributions. According to Balduzzi, Elton, and Green (2001); this type of empirical evidence found in currency markets have critical implications for portfolio applications, hedging, and derivative securities pricing. Moreover, the analysis of macroeconomic news effects is fundamental because they offer an opportunity to determine the ways through which asset prices are related to the wider economy. It may show the leading role of economic fundamentals in the price formulation process of equity and bond markets. However, the economic fundamentals may be insufficient to fully explain the exchange rate movements. Barndorff-Nielsen and Shephard (2004) refers to this problem as a news puzzle and notes that some of the directional impacts are very difficult to be related to specific fundamentals since they are more often likely to be associated with other fundamentals as well.

The isolation problem withstanding; the role of economic fundamentals especially the effect of macroeconomic news on generating jumps and co-jumps is now a well-established fact. Andersen et.al. (2003), for example clearly demonstrate the effect of macroeconomic news in exchange rate markets and the asymmetric patterns generated by such information. This study also put emphasis in the discontinuous aspect (jump process) of the price movements in Exchange rate markets. We see several studies where the irregular behavior of discontinuities incorporated and their dependence on market conditions was analyzed but without openly modeling the jumps in the pricing processes. However, it is also a fact that the incorporation of jump based market information leads to improvement in pricing models as shown by Andersen et.al.(2007) in the case of the bond market. There are also other studies that deal with various asset markets and apply the macroeconomic news announcements approach for different nations showing that there is a huge correlation between discontinuities and news (Lahaye et.al. 2011). Calcagnile et.all (2015) find that it is so hard to say that such discontinuities are only partially related to the scheduled macroeconomic news announcements and their occurrence is largely unpredictable. On the other hand, Bajgrowicz et.al (2016) study show that common detection methods entail a misclassification risk. This issue is the important point of our studies too. The common detection methods have misclassification problem and need to be revised based on the

market types. They claim that jumps are rare and strongly related to the news announcements (scheduled or unscheduled). Scheduled news are the news that releases via the news sources of the data vendors with their expected surveys. On the other hand, there are many unscheduled news which are the speeches that also affect the market dynamics and create a major jump. Furthermore; recent research also point out that the impact of the macroeconomic news might fundamentally be dependent on the background of the current economic state. This is plausible since market agents tend to make different choices in response to similar issues in case of different economic background. Veredas (2006) in his study finds asymmetric responses to negative and positive news at different stages of business cycles. He underlines the fact that the market give an extreme response to negative news. It suggests that investors are very sensitive to the possibility of losing money and they are in quest of a hedging instrument. The hedging instruments protect them not to lose too much money.

There is also an important survey (The Institute for Supply Management Survey index) which show that business cycles must also be considered for more precise economic analysis of jumps since there is a close association between the phase of the cycles and the type of explanations. The problem associated with the inclusion of business cycles in the analysis is the fact that business cycles can be measured in different ways leading to non-overlapping results. Andersen et.al. (2007), states that recession automatically kicks off in case of a decline in nonfarm employment for three subsequent days. Bandi and Russell (2006), on the other hand, focus on the time-varying variance of the unobservable (efficient) returns which is emphasizing the fact that this variance creates equally unobservable microstructure noise in the market and data series. Wang (2015) in his study uses the two-regime transition regression (STR) model developed by Terasvirta (1994) to describe the different business cycles and make the interaction between macroeconomic news and business cycles. The jumps and co-jumps of the exchange rates estimated in this study and the study use the definition of business cycles as the relevant economic background. Many other studies also underline the fact that the impact of macroeconomic news on jumps depends to a large extent on the context and the current state of the economy.

Giving the brief summary of the literature cited above, our dissertation aims to focus on the following points as a possible further contribution to the literature. We start by analyzing the statistical properties and characteristics of the jumps and co-jumps in the FX markets. We utilize non-parametric Barndorff-Nielsen and Shephard (2006) (BNS) and Aith Sahalia and Jacord (2009) (AJ) test to detect the significant jumps and co-jumps (jumps that appear simultaneously) in foreign exchange rate pairs by using different threshold levels. We also applied Jiang and Oomen (2008) JO tests for robustness. In the next stage; we tested the relationship between the identified jumps / co-jumps and the macroeconomic news announcements. Finally, we show the importance of the co-jumps in FX market.

The rest of the thesis is structured as it follows: Chapter 2 examines the current literature on high-frequency price dynamics, jump, co-jumps and price dynamics with the macroeconomic news. It also discusses the measures of variations and microstructure noise in high-frequency financial data series.

Chapter 3 discuss the conceptual framework of the dissertation and quantitative research process that includes data collection and data manipulation processes. One minute Exchange rate data are extracted for eleven currency pairs for seven years from January 1, 2010, to December 31, 2016.

Chapter 4 focus on the jump and co-jump detection tests techniques and their properties. The daily and intraday jump detection methods and co-jump detection methods are discussed.

Chapter 5 find out the empirical results and performance of the jump and co-jump detection models. Which method is good to detect the jumps and co-jumps in different cross pairs. Our null hypothesis is that jumps are not independent of all exchange rate combinations. It means that there are co-jumps between currency pairs. Is there any clustering between jumps (co-jumps) in different currency pairs and if these co-jumps are significantly related to the macroeconomic news? We discussed those issues for eleven currency pairs.

Chapter 6 summarizes the dissertation and draws some conclusions. It also underlines possible directions for the future academic research issues.



2. LITERATURE REVIEW

2.1 INTRODUCTION

Availability of high-frequency data makes possible the jump detection analysis since 1995. Thanks to the availability of high-frequency data, since this date; financial research increasingly started to use intraday data instead of daily data. Assets prices in financial markets are unwavering by two important factors. One factor is the equilibrium prices that reflect the supply and demand of the assets and the other is market microstructure noise that is induced by the frictions that actual trade takes place. Li, Leaven & Vellekoop (2017) suggested that such frictions include discrete observation, tick size, bid-ask spread and trading mechanics. In recent years, the availability of databases that consist of observations documented at ultra-high frequency up to each second and extensive studies to take advantage of such data for noise and volatility estimation and also observe the economic implications of the noise and volatility (Li, Laeven & Vellekoop (2017); Lee & Mykland (2012)). In recent years, asset pricing has experienced jumps that are large and cannot be explained by the simple process of diffusion. Lee & Mykland (2012) shows how to differentiate the large shifts in equilibrium prices from the noise utilizing high data frequency. In this study, a new nonparametric test is used that enables the asymptotic removal of noise for the prices that are observable and also discover the jumps that are fundamental to asset values. The tests are immune to the presence of general noise and provide new empirical evidence.

Financial markets are chaotic and characterized by discontinuities. Assets react to any significant information very quickly. This reaction causes significant price fluctuations and jumps in data series. Recent empirical studies have confirmed that the jumps have a remarkable effect on risk management. They also increase the predictive power of forecasting models.

This chapter reviews the existing high-frequency literature, and it is organized as follows:

First, we focus on the jump detection methods and how they are used with high-frequency data series. The second step discuss the elimination of the microstructural noise

Then explore the co-jumps. The jump detection is a well-known implementation but co-jump detection must be taken into account. Co-jump is defined as a jump, observed in the price series of a financial instrument followed by a jump in the price series of another financial asset. Co-jumps provide valuable information which may be used to predict the exact time of the jumps. Finally, the effects of macroeconomic news on jumps and co-jumps are analyzed.

2.2 JUMP DIFFUSION, JUMP AND CO-JUMP DETECTION TECHNIQUES: EMPIRICAL APPLICATIONS

Jump detection procedure starts by defining the jump-diffusion processes. Continuous jump-diffusion modeling process has a long history in finance literature and dating back to the preliminary study of Merton (1976). This phenomenon has been discussed since Merton's propaedeutic study. Then several studies including Phalm (1998), Andersen at. all (1999), Zhu (1999), Duffy et.al (2000), Cont and Tankov (2004), Bollerslev, Law, and Tauchen (2008) have examined the jump-diffusion process.

Andersen and Bollerslev (1998) characterized the nature of volatility in the Deutsche mark-dollar foreign exchange market. They used an annual sample of five minutes exchange rate returns data. The volatility process of Deutsche mark and dollar from daily to high-frequency returns was a new phenomenon. There are three findings: intraday volatility pattern is dominant, the predictable power of volatility models change (ARCH) which move by more than 25 percent over a 24 hour period. Finally, short-lived announcement effects are prevalent in the high-frequency data analysis. Andersen, Bollerslev, and Diebold (2007a) in their study established both the jumps and cojumps for different kinds of assets that comprise exchange rates and then connected them to macroeconomic news. They implemented their analysis on modeling and forecasting of the return volatilities. Bollerslev and Diebold (2007b) differentiated their studies from the early study through several ways that include offering an absolute articulation of cojumps and jumps in the currency markets through including the jump components the measurement, modeling and forecasting the return volatilities.

Through the above jump and co-jump detection processes, the researchers were able to determine some news of the relative significance in the United States of American macroeconomic news and non-United States of American macroeconomics news in the dynamics of exchange rates. The researchers were also able to examine more recent times that was a period between March 2000 and Nov 2006 which was a period of considerable volatility with regards to the financial markets. Moreover, the researchers go ahead and provided a test regarding the speed of news absorption by making a comparison between the immediate price response of news-times with a time-matched sample of day's benchmark without jumps and news.

The importance of jumps is widely accepted in the finance literature. A partial list of research which is published includes tests specification Andersen et.al (1997, 1998), Aith-Sahalia, (2004), Barndorff-Nielsen and Shephard (2004a,2006), Jiang and Omen (2008), Lee and Mykland (2008) and Aith-Sahalia and Jacord (2009) as well as seminal empirical studies of Maheu and Mccurdy (2004), Andersen et.al. (2007), Bollerslev et.al. (2009), Cartea and Karyampas (2010), Corsi et.al. (2010), Podolskij and Ziggel (2010). These are the non-parametric jump detection tests but all these tests tell us on which day the jump occurred. Andersen et.al. (2012), Lee and Mykland (2012), El Quadghiri and Uctum (2016) tests detect the occurrence of the jumps. The problem of non-parametric jump detection test is the existence of the microstructural noise in the data series. It disputes the quality of the detected jumps. Besides the noise, there are also another important factors, such as the threshold levels that affect the jump detection processes. These levels cannot catch up with some important jumps in the market.

Andersen and Bollerslev (1997b) and Andersen et al (2007a) studies define the importance of jumps and periodicity of intraday volatility in the nonparametric estimation and forecasting of volatility. Barndorff-Nielsen and Shephard (2004) examine the jump detection by involving some aspects that were extracted from the noted realized variation and bi-power variations in the literature. Amaya and Vasquez (2011) research explore the impact of the jumps on the pricing of the assets by extracting the average jump size of the individual stock returns. They have also suggested an approach that can be used in ascertaining an accurate timing regarding the

intraday jumps. The earlier studies like those of Andersen and Bollerslev (1998) and Andersen and Bollerslev (1997) entirely relied on a low-frequency daily or monthly data to analyze the role of macroeconomic and monetary news. An example was in Ait-Sahalia and Lo (1998) where the researchers use daily data for nonparametric estimation of state price densities implicitly in financial asset prices.

Since the availability of the intraday data, high-frequency data analysis is conducted by Ait-Sahalia, Mykland, and Zhang (2011). The researchers offered a reliable analyze for the impact of the time series dependence in microstructure noise on the properties of the integrated volatility of an asset price. Andersen, Dobrev, and Schaumburg (2012) propose two new jump estimators of the integrated variance which allow for an asymptotic theory in the absence of the jumps. They make an empirical investigation of Dow Jones 30 stocks and the simulation in their model is corrected that the MinRV and MedRV estimators possess excellent jump robustness.

Moreover, some of the most recent studies incorporate high-frequency data with the aim examining the intraday effects of surprises from scheduled macroeconomic news announcements and unscheduled one-time event news on six foreign exchange rates excess returns (Ouadghiri and Uctum, 2016). The researchers noted that there are two types of news which match the exchange rate jumps at about 34 % and 14 % respectively. The other feature of the study is the extensive range of the macroeconomic announcement geographic regions (US, UK, Eurozone, and China) by contrast to most of the studies where announcements are confined to the US economy.

2.3 ASYMMETRIC BEHAVIOR OF JUMPS

News sometimes trigger jump arrivals in financial time series either as good or bad news with a distinct impact (Kostrzewski, 2014). In their study a double exponential jump distribution is applied to model downward and upward jumps. Dumitru and Urga (2016) analyse the new information role of the trading activity when jumps are realized in US treasury market. They find out that jumps reduce the information asymmetry. There is another important finding of this research. In two and five years of maturities, there is a lower level of information asymmetry prior to jump but followed by a high level during the jump window up to twenty minutes after the jump occurs. Délèze and

Hussain (2014) also examines the jumps and co-jumps in European financial markets on the basis of the US macroeconomic news. They use six years of high frequency data which are stock indices, exchange rates, and interest rate futures. They find out that major US base macroeconomic news announcements cause significant jumps and co-jumps on all asset classes. Europe markets is seen more responsive to the US macroeconomic news. Fatum and Hutchison (2003) used the high-frequency foreign exchange returns data to assess the intraday impacts of the daily Bundesbank and US officials intervention operations. They identified separate intervention episodes and analysed the effects of currency market on the basis of European Monetary Union and United States of America macroeconomic news regarding both the conditional variance and conditional means. The authors indicated that sterilized interventions systematically affects the currency rates especially in the short run. In this study they used event study approach that is widely used in jump and news analysis. Fatum et.al. (2012) in their study investigated possible asymmetric response of five minutes intraday JPY/USD exchange rate to scheduled macroeconomic news announcement between 1999-2006. In this period the Japanese interest rate is close to zero. This effect must be taken into consideration. They find that asymmetric response to news is manifested and linked to macroeconomic news during this period. Ehrmann and Fratzscher (2005) examines the link between economic dynamics and exchange rates by incorporating real-time data. They use US dollar – Eur/Deutsche Mark intraday data between 1993-2002. The findings are a bit different from the previous ones. The other important thing in their study is that; FX rates are seen to respond more strongly to news in the time of large market uncertainty and when negative or large shocks occur. 75% of the monthly directional changes of the US dollar-euro exchange although it does not explain well the magnitude of the exchange rate changes. Huang and Tauchen (2005) run tests for jumps in their analysis based on recent asymptotic results; they interpret the test as Housman did in his early research. They use Monte Carlo methods which provide daily ratio z-statistic with appropriate size, good power and good jump detection capabilities. The theoretical results and Monte Carlo results show that microstructure noise biases the tests against detecting jumps and also basic lagging strategy does correct the strategy. The 7 % of the market variance can be explained by jumps.

Andersen et.al. (2010) point out that the jump detection is important but not enough the anchors also play a main role in the decision making process, in other words, the algorithms applications must go beyond just detecting jumps, in order to be able to detect what is called “market neutral portfolio”. He introduced new proofs showing that the “anchoring” is an important factor of decision making process.

2.4 MARKET MICROSTRUCTURE NOISE

Jumps are unexpected prices changes across any historical financial data, especially in high-frequency sampling. In order to avoid the inaccuracy arising from parametric models; a nonparametric model is applied by Gençay and Fagan (2014), and Lee and Mykland (2007). Gençay and Fagan (2013) also test the asymptotic distribution; assuming that the test is strong and consistent for a variety of price procedures and the given existence of the randomness and repetition of the microstructure noise they run an appropriate test to eliminate the errors.

Jansen and De Haan (2007) use high-frequency Euro-Dollar exchange rates in their study, and examine the effects of policy interventions by Euro area central banking sector’s professionals to verbally support the euro. They found little evidence that European Central Bank (ECB) verbal interventions were strongly effective (unscheduled interventions). Macroeconomic news that coincides with verbal interventions is followed by a lower exchange rate volatility.

However, this study has put a lot of emphasis in the study of jumps or price changes instead of researching much more on ways through which macroeconomic news usually link to asset prices. Kaminsky and Lewis (1996) in their study highlighted the fact that how foreign exchange interventions affect the exchange rate when these interventions are signals to future monetary policy interventions. They underline the fact that central bank signals a more contractionary monetary policy for future monetary policy then the domestic currency is appreciated. The paper empirically assesses these presumptions. On the other hand, they confirmed the earlier studies and they also noted that the estimation and identification of jumps always have a significant implication regarding financial market risk adjustments assessments.

Laakkonen and Lanne (2008) study focuses on the impact of the positive and negative macroeconomic US and European base news announcements under different business cycle phrases on the high-frequency volatility of the EUR/USD exchange rate. They ascertained that bad news generally increase volatility more particularly than the positive news. The result also depends on the state of the economy. The interesting finding is that bad news creates a remarkable increase in volatility more in good times than in bad times. There is no difference between volatility effects of good or bad news in good or bad times.

Nonetheless, jump dynamics have been observed as being predictable and persistent when compared to the continuous elements (Pearce and Solakoglu, 2007). The relationship between dollar/Deutsche mark and dollar/Japanese yen exchange rates macroeconomic news were examined by the authors in their study. They used a 10 year period high-frequency data of mentioned exchange rate pairs. They found out that there are linearity and symmetry of the responses to the news. Dollar rate responds to US-based macroeconomic news announcements within 5 minutes and when measured over 6 hours intervals significance of news are eliminated. They also underline that this result depends on the state of the economy. Piazzesi (2003) identified joint dynamics of bond yields and macroeconomic variables. The forecasting performance of a VAR improves when no-arbitrage restrictions exist. The variance decomposition shows that macroeconomic factors explain more than 85 % of the variation in bond yields.

Jumps and co-jumps are significantly connected to the macroeconomic news for exchange rates, bond futures, and stock index futures markets. The probability of news announcements can only result to a jump in exchange rates that is between one percent and two percent which is less than three percent and four percent for bonds and stocks.

Lahaye et.al. (2011) used tests recently to extract jumps and co-jumps from the three asset groups which are a stock index, bond and exchange rate futures. They also confirmed the significance of jumps and co-jumps in their study and they noted that majority of the jumps are related to some particular macroeconomic news announcements and they have microstructural noises.

Tauchen and Zhou (2011) extend their jump and co-jump detection method using the bipower variation to identify the realized jumps in financial markets and also to estimate parametrically the jump intensity in their study by using mean and variance. They implement their analysis on equity bond and exchange markets data and the results reveal important differences in jump frequency and volatility across asset classes over the time

There is a general acceptance that three percent and four percent of currency jumps are linked to some specific news types either positive or negative. The researchers hypothesized that the jumps that exist in exchange rates are usually small and regular since they focused on United States of America macroeconomic news instead of putting the emphasis on the domestic home currency news. Ouadghiri and Uctum (2016) in their current research found that the most influential scheduled macroeconomic news are globally related to the US job markets, public debt, GDP and rescue plans. Moreover, in a similar study that was concerned with the exchange rates of euro-dollar, the researchers ascertained that verbal communications always results in large kind of jumps for nearly an hour after news announcements, which is an abnormal variation is due to European official's interventions as opposed to the United States of American authorities.

Veredas (2006) analyzed the relationship between macroeconomic surprise and short-term behavior of bond futures. They estimated a Polynomial distributed lag model. They used 10 minutes sampled data for 9 years. They realized that there are limited effects of macroeconomic surprises on bond markets, where the effect is limited to few hours. The observed effects depend also on the business cycle and finally, the release time of the news is always significative.

Lee and Mykland (2008) and Uctum and Ouadghiri (2016) identify jumps in their studies by decomposing realized volatility into discourteous jump martingale components and a continuous local martingale component. They found that for negative volatility shocks have a greater impact on volatility than positive shocks.

Barndorff-Nielsen and Shephard identified jumps during their study by the realized variation (continuous component measure) subtraction from the realized volatility

(isolates the jumps components). Nonetheless, the authors' study was only able to identify the daily jumps as opposed to the intraday jumps. The researchers used high-frequency data with the aim of capturing the instant price response with regards to the macroeconomic news. Similar to Lee and Mykland (2008) and Uctun and Ouadghiri (2016) studies, they utilized a non-parametric statistics technique to identify jumps that are related to the high-frequency data. The problem in their analysis is a technical one. Those relatively small jumps due to low volatility cannot be detected very easily and very quickly when some of superious jumps are removed.

2.5 NEWS EFFECTS ON FINANCIAL VOLATILITY

Barndorff-Nielsen and Shephard (2003) introduced an asymptotic distribution for several non-parametric tests which assumes that asset prices follow a sustained track. They investigate the attitude of the test in a limited dataset utilizing a simulated dataset. Also, by running the test on the exchange rate data, they have discovered that the null hypothesis of a non-discrete sample track is rejected most often, they find that majority of the detected jumps are closely related with the macroeconomic level news. The result of Eraker, Johannes, and Polson (2003) is quite opposite of Barndorff-Nielsen and Shephard (2003) results which show that prices of assets follow a continuous track. Andersen, Bollerslev et.al (2003), who used six years of intraday exchange rate data, macroeconomic expectations, and macroeconomic comprehension, distinguish the tools of U.S dollar spot exchange rate in their research. They found that the shocks cause jumps. High-frequency exchange rate processes are strongly connected to the negative unscheduled news. As evident in what is mentioned so far; several researchers have tried to investigate the relationships that exist between foreign exchange rates and macroeconomic fundamentals. Some of the studies that were conducted earlier began with the low-frequency daily or monthly data. For example, Barndorff-Nielsen and Shephard (2003) used daily data in their analysis. The null hypothesis of continuous sample path is frequently rejected. They find that most of the jumps are associated with the macroeconomic news stemming from the government. Becker, Clements, and White (2007) indicated that the news that is concerned with trade balances always has a contingent impact on the exchange rates. Bollerslev et. al. (2008) used a new test for common jumps that explicitly utilizes the cross-covariance structure in the returns to

identify non diversifiable jumps. They find strong evidence for the fact that the co-jumps may pass through the standard jump detection statistic even at the modest levels.

Capori et.al. (2014) provide clear evidence for the co-jumps. They called their analyses as multivariate jumps analysis. More powerful and economically informative results are taken from the liquid stocks. The co-jump detections mentioned in their recent study investigated the relationship that exists between foreign exchange rates movements and news announcements using intraday high-frequency data. Christensen and Podolskij (2007) present a set of probabilistic laws for quadratic variation of continuous semimartingales estimation with the realized range base variance. They accurately reach a powerfully integrated variance. They solve the downward bias problem that has haunted the range based literature for decades.

In another study conducted by Bollerslev, Law, and Tauchen (2008), the researchers found out that the announcements day shocks do not normally persist completely but instead they are just purely transitory. This study supports the Mixture of Distribution Hypothesis that was introduced by Andersen, Bollerslev, and Diebold (2007a). The Mixture of Distribution Hypothesis implies that volatility persistence is normally only due to the serial correlation in the information process. Also, they outline the risk premium that is concerned with the announcement days which is in line with GARCH-M specification. Andersen, Bollerslev, Diebold, and Vega (2007b) in their study investigated the different impacts on the volatility of the unscheduled versus scheduled announcements by using of five-minute returns or intraday foreign exchange returns data.

Balduzzi, Elton, and Green (2001) suggested that the CPI and PPI inflation measures normally only affect the stock returns level only. The three real factor candidates that include Housing Starts, Balance of Trade and Employment/Unemployment that affect the return's conditional volatility only. Bakshi, Kapadia, and Madan (2003) in their study investigated the impacts of monetary policy announcements regarding stock returns' volatility. The Bakshi, Kapadia, and Madan (2003) research were based on Bali and Weinbaum (2007), and the result of the study showed that the unforeseen monetary policy decisions always significantly boost volatility of the stock markets in the short

run. However, the positive sign surprises always have larger effects on the volatility as expected more than the negative sign surprises as expected. The common setup in all these studies depends on a multiplicative filter with the announcements dummies.

The study carried out by Bali and Weinbaum (2007) suggested that there is always a deterministic shift in the standard diffusion component that defines news process especially on announcement days. This means that the announcement effects are normally modeled as seasonal impacts. On the natural circumstances, the surprise aspect is not normally unexpected as well as being typically connected to a jump in the return process. The new econometric growths around the realized Bates (1996)'s vitality framework have been suggested to be able to filter the significance of jumps to the realized variance measure due to the availability of the high-frequency data. Becker, Clements, and White (2007) found that most of the jumps occur in days of macroeconomic announcements and the largest proportion of jumps occur in days of macroeconomic surprises. The researchers Bollerslev and Tauchen (2008) presents an alternative technique with the aim of characterizing the volatility effect of surprises based on the announcement days by modeling like the application of the jump component in the turning process as well as characterizing jump response intensity to the macroeconomic events.

2.6 OTHER EMPIRICAL APPLICATION

Over the past years, there has been a growing literature that is related to forecasting and modeling the dynamics dependencies within the financial market volatility (Ait-Sahalia 2004). The earlier empirical studies used the coarser or daily frequency data when dealing with the stochastic volatility or GARCH models. Chan and Maheu (2002) outlined that paradigm shift has begun to take place where high-frequency data started to be used entailed in a long-run volatility forecasting and modeling with the increased use of simple and reduced-from time series models that incorporating intraday squared returns and non-parametric daily realized volatility measures (Chan and Maheu 2002). Moreover, the decomposition of the total daily return volatility to discontinuous components and continuous components that concerns with the big-power variations measures developed by Clark (2004) and the David and Veronesi (2008) empirical

results suggested that a chunk of the predictable variation within the volatility stems that is from the dynamic dependencies concerning continuous price path variability is always minor.

Engle and Rangel (2008) takes the analysis further and estimates a separate reduced kind of time series forecasting models for every varied component that forms part of the total price variation. Based on the Ait-Sahalia, Mykland, and Zhang (2011) analysis, the researchers start by decomposing the overall return variability into the variation and continuous sample path variation using bi-power variation measure that was introduced by Andersen and Bollerslev (1997) and Andersen and Bollerslev (1998). The researchers' empirical results regarding the 5th year sample of the T-Bond futures return and high-frequency intraday S&P 500 was in line with the earlier research which indicated that the dynamic dependencies of the daily continuous sample path variability were clearly defined by the accurate long-memory and the Heterogenous AR (HAR) model suggested by Andersen, Bollerslev and Diebold (2007).

According to the study conducted by Suzanne and Per (2012), times between the sizes of jumps and jumps are both auto-correlated unlike the time series of statistically important squared jumps that normally appear to be accurately serially uncorrelated. Suzanne and Per (2012) successfully modeled the dependencies by a combination of an Autoregressive Conditional Hazard (ACH) model with regards to the different intensities of jumps. Those two different model structures that have been mentioned here insufficiently consider variability as an active part of the trading day when the markets are officially open. Nonetheless, Uctum and Ouadghiri (2016) in their study indicated that opening price usually differs from the previous close because of the corresponding overnight return and this usually explains the non-trivial fraction of the total daily return. Therefore, Pearce and Solakoglu (2007) outline the method to tackle with the problems concerning forecasting and modeling realized volatilities by scaling the model forecasts or the intraday measures as a constant factor to make them unconditionally unbiased with regards to the total daily variation

Moreover, another alternative technique that depends on reducing the average square error of the realized variation over a day was advocated by Lee and Mykland (2008).

The authors treated returns as a time series of frequent occurring jumps. The researchers modeled it through a discrete time GARCH model where the conditional variance was completely found to be dependent on the continuous sample path variation against the instant previous active trading daypart. Pearce and Solakoglu (2007) compared both in and out sample daily, weekly and monthly forecasts with those other discrete-time models such as HAR-RV, GARCH models. The results of the research indicated that the more detailed method that was developed by then led to an improved forecast. This research was most likely related to the study that was conducted by Tauchen and Zhou (2011) that examined a discrete-time model that concerns with the dynamic of daily S&P 500 returns, bi-power variation and realized variance. Nonetheless, when these results are compared to those of the earlier studies, the earlier studies did not attempt separately modeling or identifying the jumps dynamics as well as the overnight return components. However, the closely related research results are shown by the independent research that was conducted by Uctum and Ouadghiri (2016). Their research was also related to the coexisting literature of Laakkonen and Lanne (2009) which documented time-varying jump intensities dependent on the test statistics and realized variation measures.

The discrete-time GARCH models incorporating Poisson jump processes which are time-varying jump intensities dependent daily data was also estimated by Kaminsky and Lewis (1996) whereas the other research conducted by Jansen and De Haan (2007) outlined the effective benefits that result from eliminating jumps when forecasting volatility through the use of GARCH kind models. At a wider level, the results reported by Jansen and De Haan (2007) belong to the larger finance literature that is concerned with the corresponding parametric models and continuous-time models. Particularly, several subsequent studies and the Huang and Tauchen (2005) entirely relied on the time-variant jump-diffusions thus making all of them contrary in spirit to some empirical findings that are presented in this paper. Consequently, in El Ouadghiri and Uctum (2016) completely gave room to the time-varying jump intensities and also accurately estimated the daily data process. The studies that were previously conducted by Déléze and Hussain (2014), David and Veronesi (2008) and Christensen and Podolskij (2007) were all consistent with this study and ascertained the existence of time-varying jump intensities in case of incorporating more informed choices of data. Several studies have

indeed explored jumps in a process and among those studies are the ones by Caporin, Kolokolov, and Reno (2014) and Chan and Maheu (2002). The researchers Caporin, Kolokolov and Reno (2014) and Chan and Maheu (2002) in their studies developed a parametric model through the addition of Poisson jumps with time-varying intensity to stochastic the volatility diffusions. The researchers used the model with the aim of finding out jumps in the daily equity-index returns. Bauwens, Ben and Giot (2005) and Busch, Christensen, and Nielsen (2011) conducted a similar research that imposed criteria function on the transaction responsibilities thus identifying jumps from the discrete-time sampled data.

Becker, Clements, and White (2007) in their study introduced a new variation measure they referred to as the big power variation and it was identified as robust to a limited number of jumps as well as being able to separate the continuous section from the quadratic variation. The researchers Bollerslev, Law, and Tauchen (2008) later suggested some kind of the non-parametric tests that are dependent on the asymptotic distribution theory. Andersen, Bollerslev, and Diebold (2007) and Andersen, Bollerslev, Diebold and Vega (2007) also developed a test that was based on the hedging error of a variance swap replication strategy. On the other hand, the researchers Andersen, Bollerslev and Diebold (2007) also developed a non-parametric test that was evaluated by simulation. All the non-parametric tests examined above aimed at ascertaining jumps in a univariate price process. The researchers El Ouadghiri and Uctum (2016) did a recent research to determine jumps in the multivariate price processes. The researchers tested non-diversifiable jumps in a broad portfolio of stocks. Fatum and Hutchison (2003) also considered the bivariate process in their study and tested whether or not these have even a single jump that takes place concurrently. Nonetheless, best on facts, there has not been any recent research that has suggested any technique that can be used to detect the existence of even a single jump in a multivariate price process that is referred to as a cojump by considering the correlation into consideration. In their recent studies, the researchers Fatum, Hutchison, and Wu (2012) put a lot of focus on the issue of ascertaining whether or not a cojump at a time in multi-asset returns would follow multivariate processes.

In order to develop a cojump detection method, the authors, Huang and Tauchen (2005) began by finding a persistent estimator to the local multivariate returns covariation. The researchers proved its persistence by estimating the local covariance matrix when the discrete time interval was approaching zero. Based on the mentioned estimator, the researchers designed a test statistic that standardized the return vector through the use of the local covariation. Huang and Tauchen (2005) were able to ascertain that even in the absence of jumps at a time (t_i), the test statistic $L(t_i)$ could still obey a chi-square distribution alongside levels of freedom similarly as multivariate processes dimensions (Huang and Tauchen 2005). The researchers studied the test statistic extreme distribution and later suggested a non-parametric test to deduce jumps. Fratzscher (2009) applied Monte Carlo simulation in their research with the aim of exploring the effectiveness of multivariate test in the rest of their studies. Consequently, in using the univariate Jump test for a single asset, Engle and Rangel (2008) found out in their study that in case of the occurring jumps at a given time (t_i), the change in prices at a similar time (t_i) is always a reality and becomes much greater as compared to the regular continuous settings. However, in case the price movements are observed in the continuous periods then a jump is easily observed through the identification of the continuous prices path. Délèze and Hussain (2014) in their study ascertained that asset prices are always found disjointedly. Therefore, during discrete periods, a broad price change at giving time (t_i) is likely to occur due to either a jump occurring at that time (t_i) or when there is no jump; however, the immediate volatility would still be high thus leading to hiking of the prices. Therefore, in detecting a jump, researchers simply look at the observed realized returns which are able to overestimate the number of jumps (Délèze and Hussain 2014). Consequently, the second case is eliminated by standardizing the realized return through a measure that is able to outline the local variation from the continuous form of the process.

3. CONCEPTUAL FRAMEWORK OF THE DISSERTATION

Owing to enormous advance in data processing technology, the high-frequency data becomes an important area of financial econometrics in the world. It increases the prediction power of the forecasting model so that many econometric methods use high-frequency financial data. The availability of high-frequency data made jump detection analysis possible since 1995. Thanks to the availability of high-frequency data, nature of the analysis evolved from investigating daily data to that of highly frequent intraday data. In this part, we will explain the aim of the thesis, qualitative and quantitative methods and research questions.

3.1 THE AIM OF THE DISSERTATION AND MOTIVATION

The literature on jump mainly consists of researchers detecting jumps but too little has yet been done regarding the detection of co-jumps and macroeconomic release analysis in case of Forex market returns. Although there have been many individual asset class-based studies carried especially with the widely-used non-parametric jump detection methods including tests developed by Barndorf-Nielsen and Sephard (2006) BNS method, Andersen et.al (2012) ADS method, Ait-Sahalia and Jacord (2009) AJ method, Lee-Mykland (2008-2012) LM method, Andersen et.al (2007) ABD method, Jiang and Omen (2008) JO method, Corsi et.al. (2010) CPR method. The first attempt of the dissertation is to measure the performance of the existing BNS and AJ jump detection methods. In addition to detecting the jumps the co-jumps are detected among eleven foreign exchange currency pairs and we will discuss their relationship with macroeconomic news announcements.

Mathematical properties of jump detection models make them powerful tools for analyzing the high-frequency data. So we used 1-minute, 5-minute, 15-minute and 30-minute and 60-minute frequency return data (mid-price calculated as the average of high and low price) of eleven currency pairs in Forex Markets.

One of the most important problems in jump detection process is to determine the optimal sampling frequency. The theory requires high-frequency data to confirm structural continuity whereas high-frequency intraday data leaves room available for the

market microstructure noise (Dungey, M., Sayeed, A., M., and Tao, 2014). Market microstructure noise can be explained as the deviation from the observed asset prices (Band, F.M., and Russell, 2007). The optimal frequency problem is solved by graphical tool method which is known as volatility signature plot developed by Andersen et.al (2007). This method reveals the effect of sampling frequency on volatility by plotting sampling intervals on the horizontal axis and volatility on the vertical axis (Dungey, M., Sayeed, A., M., and Tao, 2014). The logic behind the plot is that the variance of a price process is independent of the frequency. When we observe a distortion on the variance (realized one) measure for a certain frequency, then it can be said that microstructure noise causes a distortion at the frequency. The optimal frequency level is founded as 5 and 15 minutes by using this method. We also tested the 30 and 60 minutes frequencies as alternatives.

We implement different frequencies and different models mentioned above to find out if 5-minutes and 15-minutes frequencies are optimal frequency levels for all cross pairs. In the second part of the analysis besides the ABD and AJ methods, we implemented JO tested for robustness and tested the model power by changing the threshold levels². The general acceptance is that when the data frequency level increases, the models detect a lower percentage of jumps.

The second dimension of this dissertation is to find out the co-jump while measuring the performance of the existing jump detection methods. Jumps simultaneously occur in different cross pairs. This is a very important information which is used by risk managers and practitioners in financial markets. Do co-jumps provide valuable information for the market practitioner? Do risk managers use the jumps or co-jumps for hedging strategies? Do co-jumps provide significant signals? These are the questions that we are trying to answer here. The other contribution of this dissertation is that we used macroeconomic news from United States, United Kingdom, Switzerland,

² We tested the power of the models to detect the jumps. So we changed the models threshold levels. For example: Andersen et al (2003) make an empirical investigation on Dow Jones 30 stocks and the simulation corrected that the MinRV and MedRV estimators possess excellent jump robustness. We changed the MinRV and MedRV and find the new metric and new threshold levels. Based on this level we implemented our tests again.

Germany, France, Italy, Aggregate Eurozone, China, India and even Turkey. The pool here is unique and never used before. We try to find out which macroeconomic news has a significant effect on jumps and jump sizes.

There are many jump detection analysis which is run on developed markets, but there are few studies dedicated to emerging markets. This study will be a unique study since it also includes emerging ones.

The dissertation aims to answer the following questions in the rest of the sections:

- i. What are the differences between jump detection methods?
- ii. Do jumps have long-term memory?
- iii. Which type of event has more effect on foreign exchange markets? Do US-based news have more effects on any market?
- iv. Can any practitioners make abnormal returns by forecasting the jumps?
- v. Do co-jumps provide valuable information for the market practitioner?
- vi. Do risk managers use the jumps or co-jumps for hedging strategies?
- vii. Do co-jumps provide the significant signals?

3.2 QUANTITATIVE RESEARCH

3.2.1 Data Collection and Description

US, Germany, United Kingdom, Switzerland, and Japan are represented as developed markets while Turkey is represented as developing country in Eastern Europe. We conduct our analysis on Foreign Exchange market, the research data begins from January 1, 2010, and ends up on December 31, 2016, which is seven years of available high-frequency data. The high-frequency exchange rate data, extracted from www.histdata.com and Bloomberg data vendors, includes tick by tick tradable quotes for best bid and best ask spot exchange rates and size. Each quote is time-stamped to seconds with two decimals in Greenwich Mean Time to Eastern Standard Time (GMT), starting from 00.00.00 EST to 23:59:59 GMT. Therefore there are 1440 1-Minute, 288 5-minute, 96 15-minute, 48 30-minute and 24 60-minute intervals during the 24-hour foreign exchange market. The outliers aren't remove the data set. There are two ways to remove the outliers from the data set. First, we use Andersen & Bollerslev (1998) and

Bauwen, Ben Ommrane and Giot (2005) methods which delete the returns from the first interval for each day. The first return contains the overnight effects, especially the first day of the week, Monday morning. Besides this, another problem is the weekend anomalies. We also don't exclude the weekends from the data set. It means that we don't remove the data after 21:00:00 on Friday to 00.00.00 on Sunday. The data after 21:00:00 on Friday to 00.00.00 on Sunday has lower quoting activity.

3.2.2 Exchange Rate Data

We use the following currency pairs with the corresponding tickers in this study. The developed and emerging markets' currency pairs are representing as:

USDCHF Currency, United States Dollar / Swiss Franc Cross: The Swiss franc is the official United States of America.

USDJPY Currency, United States / Japanese Yen Cross: The Japanese yen is the official currency of Japan. The US dollar is the official currency of the United States of America.

EURCHF Currency, Euro / Swiss Franc Cross: The euro is the official currency of the European Economic & Monetary Union. The Swiss franc is the official currency of Switzerland.

EURJPY Currency, Euro / Japanese Yen Cross: The euro is the official currency of the European Economic & Monetary Union. The Japanese yen is the official currency of Japan.

EURGBP Currency, Euro / British Pound Cross: The euro is the official currency of the European Economic & Monetary Union. The British Pound Sterling is the official currency of The United Kingdom.

EURUSD Currency, Euro / United States Dollar Cross: The euro is the official currency of the European Economic & Monetary Union. The US dollar is the official currency of the United States of America.

GBPCHF Currency, British Pound / Swiss Franc Cross: The British Pound Sterling is the official currency of The United Kingdom. The Swiss franc is the official currency of Switzerland.

GBPJPY Currency, British Pound / Japanese Yen Cross: The British Pound Sterling is the official currency of The United Kingdom. The Japanese yen is the official currency of Japan.

CHFJPY Currency, Swiss Franc / Japanese Yen Cross: The Swiss franc is the official currency of Switzerland. The Japanese yen is the official currency of Japan.

On the other hand, we chose only one emerging market country from Eastern Europe which is represented by the following tickers:

USDTRY Currency, United States / Turkish Lira Cross: The Turkish lira is the official currency of the Republic of Turkey. The US dollar is the official currency of the United States of America.

EURTRY Currency, Euro / Turkish Lira Cross: The euro is the official currency of the European Economic & Monetary Union. The Turkish lira is the official currency of the Republic of Turkey.

We employ high frequency (1-minute, 5-minutes, 15-minutes, 30-minutes and 60-minutes intervals) of realized log return of mid prices (average of the bid and ask prices) for each currency pairs.

3.2.3 Communication Data

Many monetary authorities have moved away from implementing actual interventions and have used communication as their primary policy instrument to influence exchange rates when deemed necessary and desirable (Fratzscher, 2005). Is an exchange rate communication an effective policy tool or not? This is a question that many scholars have discussed since 2000 (Dewachter, Erdemlioglu, Gnabo, & Lecourt, 2014) and (Fratzscher, 2005). In constructing the communication data, we first collect the released Forex Exchange rate (FX) news from the real-time financial database, Bloomberg. In this study, we don't use the communication data. The communication data is defined as verbal statements, speeches, and comments, related to the exchange rate, by policymakers in the mentioned region. We accept the communication data as an accelerator in this study. It means that the effect of macroeconomic news is accelerated by the communication data and the effect is becoming more rather than the initial magnitude.

In the literature, we may see the dynamic effects of new information on exchange rates (Evans, Dc, & Berkeley, 2005). Key results from the previous studies showed that exchange rate communications have a statistically significant effect on forwarding exchange rates in 6 months period (Fratzscher, 2005). The effectiveness of the intervention gauge by using event study approach. The advantage of using event study approach is that it can avoid the noise problem which affects the precision of time series estimation success or failure.

3.2.4 Scheduled Macroeconomic Data

Intraday volatility and occurrence of the jumps tend to be related to the macroeconomic news. The level of volatility is not constant but depend on the time of the day. We extract the realized macroeconomic fundamentals from Bloomberg ECO service. The macroeconomic news is classified as National Accounts, Prices, Labor Market, Retail and Whole Sale Sector, Service Sector, Surveys/Cyclical Indicators, Housing and Real Estate, Personal Household Sector, Intl Trade and BoP, Government Finance and Debt, Money Sector and lastly Financial Indicators. We collect 46880 news announcements with their exact date and timing and rank them based on a relevancy factor and use 10850 of them in the final stage.

3.3 MARKET MICROSTRUCTURE NOISE

The price deviation from the fundamental values is called as market microstructure noise. Microstructural noise is categorized into two groups according to Hansen and Lunde (2006) and Ait-Sahalia et.al. (2011) as discrete microstructural noise and residual microstructural noise. The first type of noise refers to tick size (bid-ask bounce effect), the second one, residual microstructural noise refers to order arrival latency, block trades, asymmetry of information and discreteness of price changes.

Those are the main reasons that lead to a noise in the market. The first effect of the noise is the fact that it makes high-frequency estimates of some parameters very unstable. This effect is worse for kurtosis (high order moments) when increasing the risk for good estimation when using high-frequency data. The presence of the noise also

creates the problem of choosing the appropriate sampling frequency when studying with high-frequency data (Fan, 2016). There are many methods that are used to correct the sampling frequency for the destination.

The noise in the price process can be depicted as;

$$Y_t = X_t + \epsilon_t \quad (3.1)$$

Where;

Y_t = *observed transaction price*

X_t = *unobservable efficient price*

ϵ_t = *noise component*

ϵ measures the microstructure effects not only of informational kind but also bid-ask bounces, discreteness of price changes, differences in trade sizes or informational content of price changes, the gradual response of prices to a block trade, the strategic component of the order flow, inventory control effects, etc (Aït-Sahalia, Jacod, & Li, 2012).

A symbolic problem of high-frequency financial econometrics is to forecast the integrated volatility of the price process, X_t , (Li, Laeven, & Vellekoop, 2017). High frequency data facilitate the analysis of volatility estimators in the presence of microstructure noise. Several methods have been developed when estimating integrated variance such as Zhang et.al. (2005 and 2006) which provides a consistent estimator for integrated volatility in the absence of the microstructure noise. Barndorff Nielsen et.al. (2003) develops the kernel base estimator which allows the endogenous noise, this method is extended by Zhoo (2007) and Hansen and Lunde's (2006) studies. Ait-Sahalia et.al.(2005) initiates the likelihood approach by assuming constant volatility and this work is extended by Xiu (2010) by allowing the stochastic volatility. The famous method, pre-averaging, is developed by Podolskij and Vetter (2009a, 2009b) and Jacod et.al.(2009, 2010), Hautsch and Podolskij (2013) and lastly Christensen et.al. (2014).

In our study, we allow noise to be really dependent in a general setting. We haven't imposed any parametric special restriction on the distribution of noise which means that our approach is essentially nonparametric. We first derive a stochastic limit of the

realized volatility after defined lags which is depicted as j^3 . Then the consistent estimators of variance and covariance of noise are developed. Our aim is to explore the dependence structure of microstructure noise. To extinguish the noise effect we use the pre-averaging method.



³ It will be explained in the model description part.

4. JUMP DETECTION METHODS AND METHODOLOGY

4.1 JUMP DETECTION

4.1.1 Introduction

There are many non-parametric jump detection methods as daily nonparametric and intraday nonparametric methods which exist in jump literature. The developed jump detection techniques are listed as Barndorff-Nielsen and Sephard (2004a-2006) BNS method, Andersen et.al (2012) ADS method, Ait-Sahalia et.al (2009) AJ method, Lee-Mykland (2008) LM method, Andersen et.al (2007) ABD method, Jiang and Omen (2008) JO method, Corsi et.al. (2010) CPR method, Wavelet jump detection method and Neural Network method. The existing test statistics are based on robust to jumps measures of variation in the price processes. All are estimated by using one of the following types of estimators in their analysis methods: realized multi-power variations is used by Barndorff-Nielsen et al., (2006) Works, Macini (2009) Works used the threshold estimators method, the median or the minimum realized variation is used by Andersen et al., (2009), the corrected realized threshold multipower variation is used by Corsi et al., (2010) work. Andersen et al. (2007) and Lee and Mykland (2008) tests have the null hypothesis of continuity of the sample path which allows for the exact identification of the time of a jump in their analysis. The other tests have a null of continuity within a certain time period, such as a trading day (Dumitru & Urga, 2011). We concentrated here for testing the presence of jumps and co-jumps here.

4.1.2 Daily Nonparametric Tests

4.1.2.1 Barndorff – Nielsen and Shephard –(2004a-2006) (BNS)

They present a daily jump detection technique which is based on comparing the statistical differences between realized Variance (RV) and Bipower Variation (BPV), the null hypothesis is that there is no jump in a mentioned day. This technique was expanded by Huang and Tauchen in (2005) with the set of plausible test statistics and called as adjusted ratio statistics of Barndorff-Nielsen and Shephard (2006). Each day in a given time interval is expected discrete times. Huang and Tauchen (2005) focused on

fractional differences between RV and BPV. They recommended a new concept known as relative jump measure.

The model starts with some notations. Imagine that $h > 0$ is a fixed time period and the log price of an asset is displayed as $y^*(t)$ for $t \geq 0$. The i th low frequency return is written;

$$y_i = y^*(ih) - y^*((i-1)h), i = 1, 2, \dots, N. \quad (4.1)$$

We refer to the equation above the i th period and day too. The high-frequency return is constituted;

$$y_{k,i} = y^*((i-1)h + hkM^{-1}) - y^*((i-1)h + h(j-1)M^{-1}), \quad k = 1, 2, \dots, M \quad (4.2)$$

Price is recorded at M equally spaced time points during the i th day.

$y_{k,i}$ = the k th intra h return for the i th day. (e.g if $= 288$, this is the return for j th 5 minute period on the i th day)

$$\sum_{k=1}^M y_{k,i}$$

(Barndorff-Nielsen, 2004)

Realized Variance and Bipower Variation

The jump detection technique of BNS (2006) is based on the difference between realized variance and bi-power variation.

The log price represented by s and the general diffusion process has price dynamics given by

$$ds_t = \mu_t dt + \sigma_t dW_t + k_t dq_t, \quad 0 \leq t \leq T, \quad (4.3)$$

s_t = represent the logarithmic price of an asset

μ_t = represent the drift term of the logarithmic asset price

σ_t = represent the volatility process and can be stochastic, which is cadlag

W_t = is a standart Brownian motion, Wiener process

$k_t dq_t$ = represent the jumps in the price process

q_t = represent the Poission process counting the number of jumps

k_t = is the logoratomic size of the any jump in s_t at time t

The basic rule is that; $dq_t = 1$ indicates a jump at time t , and $dq_t = 0$ shows there is no jump at time t , with the k_t process describing the logarithmic size of the jump.

Integrated Variance

The integrated variance in day t is represented as IV_t ;

$$IV_t = \int_{t-1}^t \sigma^2(s) ds \quad (4.4)$$

IV_t Equations contains the variation of the continuous component. This is written for one interval of time from $t-1$ to t .

Quadratic Variation

We start by recalling the well-known connections between quadratic variation process in equation (1) depicted;

$$QV^{[0,T]} = \int_0^T \sigma^2 dp + \sum_{0 < p \leq T} K_p^2 \quad (4.5)$$

This equation can be rewritten as

$$QV_t = IV_t + \sum_{0 < p \leq T} K^2(s) \quad (4.6)$$

The integrated variance includes a variation of the jump components for day t and squared jumps are summarized in equation (5). It also measures the variation recognized in one day. Prices move either up or down for two reasons; diffusion or jump. The negative or positive movements caused by diffusion recognized in the first term IV_t , while the positive or negative movements are realized in the second term. The

differences between two terms IV_t and QV_t bring to light the jumps jump contribution to price variation.

Realized Variance and realized based variance

Realized variance, RV_t , measures the price movement. We observe the asset price at discrete time intervals in every Δ^n . The high frequency return series can be written as

$$\Delta^n r_{t,j,N} = s_j - s_{j-1}, j = 1, 2, \dots, M \quad (4.7)$$

where

r_t = each daily return, which is the sum of the N intraday returns

M = counts the number of intraday period

t = denotes the observation days

j = denotes the intraday period

(Andersen & Bollerslev, 1998)

Andersen and Bollerslev (1998), Andersen et.al.(2001), and Andersen et.al.(2003)

premeditate the realized variance $RV_t(N)$ in day t as

$$RV_t(M) = \sigma_{t,N}^2 = \sum_{j=1}^M r_{t,j,N}^2, \quad t = 1, 2, \dots, T, \quad (4.8)$$

There is another realized bipower variation expression by (Barndorff-Nielsen and Shephard, 2004), defined as

$$BPV_{[0,T]} = \mu - 2Y|\Delta_{nj}S|2, \quad j = 1 \quad (4.9)$$

The $\mu = s_2/\pi = \mathcal{E}(|Z|)$ depicts the mean of the absolute value of the standard random variable, represents as Z . When $\Delta^n \rightarrow 0$, $BPV^{[0,T]}$ converges to the contribution to QV from the components, $\int_0^T \sigma^2 ds$, in the presence of jumps. The jump contribution to

Quadratic Variation can be calculated by taking the differences between Realized Variance and Bipower Variation depicted as;

$$(RV - BPV)^{[0,T]} \xrightarrow{s} \sum_{0 < p \leq T} K^2 \alpha p \Delta^n \rightarrow 0 \quad (4.10)$$

(Dungey, M., Sayeed, A., M., and Tao, 2014)

The differences between RV_t and BPV_t provides consistent estimate of contribution of the jump part to the total variation (Chatrath, 2014). The works of (Dungey, M., Sayeed, A., M., and Tao, 2014) extended BNS method by applying the Huang and Tauchen in 2005 plausible test statistics and it is called as adjusted ratio test statistics. The new jump detection test statistics is given by

$$J = \frac{1}{\sqrt{\Delta^n}} \times \frac{1}{\sqrt{\emptyset \cdot \max(1, DV^{[0,T]} / (BV^{[0,T]})^2)}} \times \left(\frac{BV^{[0,T]}}{RV^{[0,T]}} - 1 \right) \quad (4.11)$$

where

$$DV^{[0,T]} = \sum_{j=1}^{\lceil \frac{T}{\Delta^n} - 3 \rceil} |\Delta_j^n s| |\Delta_{j+1}^n s| |\Delta_{j+2}^n s| |\Delta_{j+3}^n s| \text{ and } \emptyset = \frac{\pi^2}{4} + \pi - 5. \quad (4.12)$$

If there are no jumps; the test statistics J explained above follows a standard normal distribution (Dungey, M., Sayeed, A., M., and Tao, 2014). Consequently under the null hypothesis of no jumps, which depicts;

$$J^* \rightarrow N^L(0,1), \Delta^n \rightarrow 0 \quad (4.13)$$

This null hypothesis can be rejected if the test statistics is significantly negative. Given the complicated calculation above; we can summarize the Huang and Tauchen (2005), ratio statistic for detecting jumps as:

They used the notation RJ_t for the realized jump.

$$RJ_t = \frac{RV_t - BPV_t}{RV_t}, \text{ where } RJ_t \text{ is realized jump} \quad (4.14)$$

This representation converges to the standard normal distribution depends on its own asymptotic variance (Chatrath, 2014) and so the new threshold level proposed by Huang and Tauchen (2005) as

$$ZJ_t = \frac{RJ_t}{\sqrt{[(\frac{\pi}{2})^2 + \pi - 5] \frac{1}{M} \max(1, \frac{TP_t}{BV_t^2})}} \xrightarrow{d} N(0,1) \quad (4.15)$$

From this equation the test statistic is

$$z_t = \frac{RJ_t}{\sqrt{Y_t}} \quad (4.16)$$

$$Y_t = cN^{-1} \max\left(1, \frac{TP_t}{BV_t^2}\right), c \cong 0,609 \quad (4.17)$$

TP_t is called as Tri Power Quadrivity mentioned by Barnorff Nielsen and Shephard (2004), and depicted as

$$TPQ_t = M\mu_{\frac{4}{3}}^{-3} \frac{M}{M-2} \sum_{j=3}^M |r_{j,t}|^{\frac{4}{3}} |r_{j,t-1}|^{\frac{4}{3}} |r_{j,t-2}|^{\frac{4}{3}}, d \cong 0.831^{-3} \quad t = 1, 2, 3, \dots, T, \quad (4.18)$$

The gamma function here is shown as $M\mu_{\frac{4}{3}} 2^{\frac{2}{3}} \varphi(\frac{7}{6}) / \varphi(\frac{1}{2})$. Hence with the significance levels, there is a jump in day t if $ZJ_t > \phi_{\alpha}^{-1}$. It is meant that the jump is detected when the $|z_t|$ is very large.

ϕ = cumulative distribution function of standart normal distribution

α = significance level

The intraday jumps and timing of the jumps are defined with this definition. (Chatrath, 2014).

Christian and Podolskij (2007) present a jump which has the same methodology with BNS method. The major differences are that they used RRV- Re realized variation and range based BV and the power of the test is good but the size of the test is worse when it is compared with the BNS test. They use pre-averaging variance estimators in 2009 and also Jiang and Oomen (2009) introduce the variance swap based jump detection technique similar to BNS one. Those are the daily base jump detection tests in the literature. There is also another type of jump detection techniques called as intraday nonparametric jump tests (Fan, 2016).

4.1.3 Intraday nonparametric Jump Test

4.1.3.1 Andersen, Bollerslev, and Dobrev (2007b) ABD test and Lee and Mykland (2008) LM test

Andersen et.al (2007b) and Lee Mykland (2008) constructed a jump detection model which employ to detect jumps at individual return observations rather than a given time span. Their test statistic is based on calculating the ratio of the return at each observation to a local volatility measure which includes variance over a number of returns predicting that return (Dungey, M., Sayeed, A., M., and Tao, 2014).

ABD and LM tests use a different type of distributions in their hypothesis (the null hypothesis which is there are no jumps in the realization of the process at a certain time). During the test, they are observing whether the return is a jump by comparing test statistic with the threshold. The exact timing of the jumps and as well as the number of the jumps can be identified for users. This test is called as intraday jump test in which jumps occur anytime during any trading day, whereas the other tests examine only the discontinuity of the return process in the daily base (Dumitru & Urga, 2011).

The starting point for ABD and LM test is to compute the local volatility estimate which is robust to jumps and then standardize the intraday returns. The intraday returns at the

time t_i is representing by r_i and the local volatility estimate is depicted as V_i , from this notations the following statistics can be defined;

$$z_i = \frac{r_i}{\sqrt{\hat{V}_i}} \quad (4.19)$$

Computation of $\hat{V}_i$ is proposed in both papers as the properly scaled realized bi-power variation;

$$\hat{V}_i = \frac{BPV_{t_i}}{K - 2} \quad (4.20)$$

K represents the windows size on which BPV_{t_i} is calculated

(Dumitru & Urga, 2011).

z_i is accepted as asymptotically normal in this model and one can attempt to identify jumps by comparing it to a normal threshold which is recommended by Andersen et al. (2007). The authors proposed using a new approach (Sidak approach) in order to deal with the false discovery rate in their analysis. α represents the nominal daily size which is accepted as fixed, the size for each intraday test is depicted as $\beta = 1 - (1 - \alpha)^\delta$.

The null hypothesis of continuity of the sample path is rejected if $z_i > \Phi_{1-\beta/2}$.

The LM (2008) model used a the slightly different approach in their test. % 95 and % 99 confidence intervals from the Gaussian distribution prove too permissive and result in an over the rejection of the null hypothesis. To come to grips with the problem, Lee and Mykland suggest using critical values from the limit distribution of the maximum of the test statistics. This maximum converges to a Gumbel variable for $\delta \rightarrow 0$;

$$\frac{\max(z_i) - C_n}{S_n} \xrightarrow{L} \varepsilon, \quad P(\varepsilon) = \exp(-e^{-\tau}) \quad (4.21)$$

$$\text{Where; } C_n = \frac{(2 \log n)^{1/2}}{\mu_1} - \frac{\log \pi + \log(\log n)}{2\mu_1(2 \log n)^{1/2}} \text{ and } S_n = \frac{1}{\mu_1(2 \log n)^{1/2}} \quad (4.22)$$

The test statistic can be conducted by comparing z_i , *standardized* as $\max(z_i)$, to the critical values. There is no suggestion for sample size by Andersen et.al. (2007) but LM

(2008) instead of proposes computing $\hat{\sigma}_i$ on a window size K observations which pioneer time t_i . K represents the sampling frequency and LM suggest to take as $K = \sqrt{252 * n}$, where n represents the daily number sampling, 252 is the number of working days. Besides this the ABD test requires very low nominal size as 10^{-5} .

4.1.4 Other Nonparametric Jump Tests

4.1.4.1 The Ait-Sahalia and Jacod (2009) test (AJ)

Their test is constructed based on the power variation sampled at different frequencies. It examines the presence of jumps in high-frequency data series.

The logic behind this method is to compare the multipower variation of equispaced returns computed at a fast time scale $h, r_{t,i} (i = 1, \dots, N)$ and it is computed at the slower time scale $kh, y_{t,i} (i = 1, \dots, \frac{N}{k})$.

In their study, they realized that limit (for $N \rightarrow \infty$) of the realized power variation is invariant for different sampling group and also their ratio is 1 in any case of jumps and $k^{p/2} - 1$ if no jumps. Hence the Aith-Sahalia and Jacord test, (henceforth is called as AJ test) detects the jumps using the ratio of realized power variation sampled which is from the two scales. This represents the null hypothesis, that there are no jumps.

In AJ test functions return three results:

- a. Z-test value: which is the threshold level to detect the jumps,
- b. Critical value: is used the defined whether there is jump or not under the level of 95 % and,
- c. P-value: significance of the detected jumps.

Imagine that we have N equispaced returns in period T . $t_{t,i}$ depicts the return process of the pricing process (with $i = 1, \dots, N$) in period T .

There is also N/k equispaced returns in period T . Let $y_{t,i}$ be a return (with $i = 1, \dots, N/k$) in period T .

Based on the above restriction the AJ jump detection test is performed as;

$$AJ\ Test_{t,N} = \frac{S_t(pik, h) - k^{\frac{p}{2}-1}}{\sqrt{V_{t,N}}} \quad (4.23)$$

The unknown components of the models are depicted below:

$$S_t(p, h, k) = \frac{PV_{t,M}(p, kh)}{PV_{t,M}(p, h)} \quad (4.24)$$

$$PV_{t,N}(p, kh) = \sum_{i=1}^{N/k} |y_{t,i}|^p \quad (4.25)$$

$$PV_{t,N}(p, h) = \sum_{i=1}^N |r_{t,i}|^p \quad (4.26)$$

$$V_{t,N} = \frac{N(p, k)A_{t,N(2p)}}{N A_{t,N(p)}} \quad (4.27)$$

$$N(pik) = \frac{1}{\mu_p^2} (k^{p-2}(1+k))\mu_{2p} + k^{p-2}(k-1)\mu_p^2 - 2k^{\frac{p}{2}-1}\mu_{k,p} \quad (4.28)$$

$$A_{t,n(2p)} = \frac{(1/N)^{\frac{1-p}{2}}}{\mu_p} \sum_{i=1}^N |r_{t,i}|^p \text{ for } |r_j| < \alpha(\frac{1}{N})^\omega \quad (4.29)$$

$$\mu_{k,p} = E(|U|^p U + \sqrt{k-1}V|p) \quad (4.30)$$

$h = \frac{1}{N}$; p, k, α, ω are the parameters and U and V are the independent normal random variables.

(Aït-Sahalia et al., 2012)

The theoretical background of the jump test is defined by X_t which belongs to the Brownian semimartingales, it can be written as;

$X = (X_t)_{t \geq 0}$ is accepted as a one dimensional underlying process which is sampled at discrete time intervals depicted as $i\Delta_n$ in a given interval $[0, T]$ with a time lag that asymptotically goes to “Zero” (Aït-Sahalia et al., 2012).

$$X_t = \int_0^t a_u du + \int_0^t \sigma_u dW_u + J_t \quad (4.31)$$

a depicts the drift term,

σ depicts tspot volatility process,

W depicts the standart Brownian motion process,

J depicts the jump process,

The jump process is defined as;

$$J_t = \sum_{i=1}^{N_t} k_j \quad (4.32)$$

k_j is representing the nonzero random variables. The counting process can be accepted finite or infinite for any finite or infinite jump activities.

From that point; the Ait-Sahalia and Jacod jump test is implemented as;

The presence of the jump is depicted by using the convergence properties of power variation and its dependence, which is a new variable of Ait-Sahai and Jacod and they defined the jumps when this defined new variable converge to 1.

Consider the following equation depicts the power variation;

$$B(m, \delta)_t = \sum_{j=1}^{[t/\delta]} |r_j|^m, m > 0 \quad (4.33)$$

It is realized that jumps are present when $m > 0$ and $B(m, \delta)_t$ is invariant to sampling scale (Dumitru & Urga, 2011). A test statistics is developed by Ait-Shalia and Jacod (2008) to compare realized power variations computed on data sampled with two different scales as δ and $k\delta, k \in \mathbb{N}$.

The expected m, k, δ is defined as:

$$S(\widehat{m, k, \delta})_t = \frac{B(\widehat{m, k, \delta})_t}{B(m, \delta)_t} \xrightarrow{\delta \rightarrow 0} k^{\frac{m}{2}-1}, \text{ when } m > 2 \text{ and } k \geq 2. \quad (4.34)$$

Then a test statistics for null hypothesis of no jumps can be developed as;

$\frac{S(\widehat{m, k, \delta})_t - k^{\frac{m}{2}-1}}{\sqrt{V_{n,t}}} \xrightarrow{L} N(0,1)$, $\sqrt{V_{n,t}}$ = measures the variance of the test statistic. It is estimated by multivariate variations or threshold estimators that mentioned in the introduction part of the dissertation.

4.1.4.2 Jiang and Oomen (2008) JO method

A new robust jump test which is based on the differences between simple and logarithmic returns is developed by Jiang and Oomen (2008). The new jump measure uses the jump sensitive measure instead of the comparing the realized volatility. The new test statistic depicted below, use a new methodology which is implemented by taking the accumulated difference between simple and logarithmic returns which approaches one half of the integrated variance (Dungey, M., Sayeed, A., M., and Tao, 2014).

$$SwV = 2 \sum_{j=2}^{[T/\Delta^n]} (r_i - \Delta_i^n p) \xrightarrow{p} \int_0^T \sigma^2 ds \quad (4.35)$$

Where;

r_i depicts the i th arithmetic intraday return $(\frac{P_i - P_{i-1}}{P_{i-1}})$

P represents the price of the asset

$\Delta_i^n p$ represents the j th logarithmic return

If there is no jump the differences between SwV and the realized variance becomes “Zero”. The jump between this differences shows as;

$$SwV_t - RV_t \xrightarrow{p} 2 \sum_{t_j \in [0, T]} (\exp(K_j)) - K_j - 1 - \sum_{t_j \in [0, T]} K_j^2 \quad (4.36)$$

The equation below depicts the alternative format that use the exponential form to capture the jumps by taking difference $SwV - RV$. The test statistic is written as;

$$JO_t = \frac{[T/\Delta^n]BPV_t}{\sqrt{\varphi_{SwV}}} \left(1 - \frac{RPV_t}{SwV_t}\right) \xrightarrow{L} N(0,1) \quad (4.37)$$

Where;

$$\varphi_{SwV} = \frac{\mu_p}{9} \frac{[T/\Delta^n]^3 \mu_{3/2}^{-4}}{[T/\Delta^n] - 3} \sum_{i=5}^n |\Delta_j^n p|^{3/2} |\Delta_{j-2}^n p|^{3/2} |\Delta_{j-3}^n p|^{3/2} \quad (4.38)$$

μ_p depicts the p th moment of the absolute value of a variable which is defined as;

$$\mu = E(|U|^p) = \pi^{-\frac{1}{2}} 2^{\frac{p}{2}} \Gamma\left(\frac{p+1}{2}\right), \quad (4.39)$$

Γ depicts the gamma distribution.

The JO method defines the jump in the presence of the large returns. It means that if the test statistic becomes very large a jump can be detected.

(Dungey, M., Sayeed, A., M., and Tao, 2014).

4.1.4.4 Lee and Mykland (2012) LM method

Microstructural noise shows frictions which can disrupt the trading process at a very high frequency (e.g. transaction costs or liquidity shortages) (Lee & Mykland, 2012). To overcome the effect of noise from the high-frequency data; Lee and Mykland proposed a test technique which removes the noise from the observed log price to determine the noise-free log price or directly has jump (Ouadghiri & Uctum, 2016). This test follows a Gumbel distribution mentioned in Glambos's study in 1987. In the given test size, it is possible to control if there is or not a standardized return which is meaningful with jumps.

The continuous jump-diffusion process is defined in (Lee & Mykland, 2008) as;

$$dp_{(t)} = \mu(t)dt + \sigma(t)dW(t) + C(t)dJ(t) \quad (4.40)$$

$p(t)$ = unobservable equilibrium log price at time t

$\mu(t)$ = denotes the drift term

$\sigma(t)$ = is the instantaneous volatility process

$W(t)$ = is the standart Brovnian Motion

$C(t)dJ(t)$ = is representing the pure jump component follow poission process

$J(t)$ = represents the continuous process

$C(t)$ = is a jump size

t = denoting the trading day

(t_i) = represents the i th observation of the day t .

$p(t_i)$ = denotes the intraday asset log price

(Ouadghiri & Uctum, 2016)

In Lee Mykland methodology $W(t)$, $C(t)$ and $J(t)$ are mutually independent. The equation 11 below shows the true log price and market microstructure and the noise distribution is assumed stationary.

$$\widetilde{p}t_i = pt_i + ut_i \quad (4.41)$$

The stationary means that all noise follows a general process with “zero” mean standard deviation.

When σ (standat deviation) is zero, ut_i (market microstructure noise) is equal to $E(u(t_i))$ ant it also equal to zero too. At the end we have frictionless market in which the equilibrium asset price can be directly observed (Lee & Mykland, 2012). There is high, low, bid and ask price in quotation system of any asset classes. The Lee and Mykland’s 2012 work follows the pre-averaging method which is calculated as high price plus low price divided by two. This method asymptotically remove the noise from the observed data. When we look at the previous empirical works (Hansen and Lunde, 2006) which shows that micro structure noise is somehow time dependent. The order of the noise is not observable thing, Lee and Mykland suggest to use lag order of the autocorrelation function of the observed data.

This methodology allows us to remove the noise from the given log prices. To denoise data, we use equation (12).

$$\widehat{p(t_j)} = \frac{1}{M} [\widehat{p(t_j)} + \widehat{p(t_{j+k})} + \dots + \widehat{p(t_{j+k(m-1)})}] \quad (4.42)$$

Where;

$k - 1$ is representing the numbers of the lags,

$i = 0, k, 2k, \dots$

M represents the optimal block size,

$\widehat{p(t_i)}$ is the number of observations calculated from the pre

– averaging methods

$j \in J = (0, kM, 2kM \dots \dots)$.

The resampling process guarantee that the noise doesn't come from any abnormal variation between $\widehat{p(t_j)}$ and $p(t_{j+kM})$. Equation 12 also determine the block size which

$$M = C(q) \left(\frac{n}{k}\right)^{1/2} \text{ when } n \rightarrow \infty. \quad (4.43)$$

Where;

n = number of observations

$C(q)$ is constant parameter. Authors provides list of constant values for this parameter.⁴

Lee and Mykland also present a robust estimator for the presence of the jumps. It is depicted as;

$$\hat{q} = \frac{1}{\sqrt{2}} [\sum_{s=1}^{n-k} (\hat{p}(t_{s+k}) - \hat{p}(t_s))^2]^{1/2} \quad (4.44)$$

(Ouadghiri & Uctum, 2016).

In order to simplify their study in their paper, they standardize the test statistics $\gamma(t_i)$.

The expected value of $\gamma(t_i)$ is equal to zero and variance, $\text{var } \sqrt{M} \gamma(t_i)$ has its limit.

$$\gamma(t_i) \equiv \hat{p}(t_{j+kM}) - \hat{p}(t_j), j \in J = (0, kM, 2kM \dots \dots) \quad (4.45)$$

⁴ For constant parameters See Lee and Mykland (2012)

Equation 47 is used to test the presence of the jumps in the equilibrium prices between $t_{(j+kM)}$ and (t_j) . The null hypothesis of $\phi(t_j) = \gamma(t_i)/\sqrt{V(\gamma(t_i))}$ is standart normal distribution and $\vartheta_n = (\max|\phi(t_j)| - A_n)/B_n$ follows the Gumbel distribution is depicted as

$$A_n = \sqrt{C_n} - \frac{\log(\pi) + \log(\log(\frac{n}{kM}))}{2\sqrt{C_n}} \quad (4.46)$$

The cumulative distribution is representing a function of ϑ_n which is

$$P(\vartheta_n \leq \frac{G_n - A_n}{B_n}) = \exp \left[- \exp \left(- \frac{G_n - A_n}{B_n} \right) \right]$$

(Ouadghiri & Uctum, 2016)

Where;

$$C_n = (2\log(\frac{n}{kM}))^{1/2}$$

$$B_n = \frac{1}{\sqrt{C_n}}.$$

G_n is a positive real number.

The critical value for rejecting the null hypothesis, $G_{n,\alpha}$, is used at the $100\alpha\%$ significance level is such that

$$P(\vartheta_n \leq \frac{G_n - A_n}{B_n}) = 1 \text{ which implies } G_{n,\alpha} = -\log(-\log(1 - \alpha))B_n + A_n.$$

4.2 METHODOLOGY

4.2.1 Jump Identification

The jump detection tests are developed in the last decade. The first seminal study on jump detection nonparametric method is developed by Bardorff-Nielsen and Shephard. This method compare the two realized measures of volatility:

- i. The power variation
- ii. Quadratic variation

Then after, different alternative jump detection tests are developed.

We can mainly divide the jump detection methods into two family groups. The first family group is the BNS family group:

All tests are constructed on bipower variation and alternative measure which is robust to jump volatility.

BNS type jump detection methods are later developed by Corsi, Pirino, and Ren`o (2010), Andersen, Dobrev, and Schaumburg (2012) and Podolskij and Ziggel (2010).

The second family group of jump detection is the Lee and Mykland (2008). In this family group:

Jumps can be identified when a return exceeds a certain threshold which determined according to instantaneous volatility (Zoi, 2016).

Andersen, Bollerslev, and Diebold (2007b), Bollerslev et al. (2013) and Bormetti et al. (2015) studies are the Lee and Mykland type jump detection methods but they differentiate with their methodology about volatility and threshold levels. Besides these two families there is other jump detection methods such as Jiang and Oomen (2008) which use the swap variation and the test of Aith-Sahalia and Jacod (2009) which is based on absolute return moments calculated at different sampling frequencies (that we use in our analysis).

There are no common results in jump detection tests. This fact is empirically shown in Schwert (2010) study. He used the different identification methods and can generally get different conclusions on jump results. We also empirically tested the different family group jump detection tests and utilized the same results parallel to current literature.

4.2.1.1 The BNS jump detection method

Though their power and size in finite samples can be negatively affected by violent volatility shocks, this jump detection models are very flexible and consistent in presence of volatility jumps (Zoi, 2016). The test statistic is not so complicated and use some volatility metrics to compute the test statistics: It starts by the Realized variance metric:

$$RV_t = \sum_{i=1}^M r_{t,i}^2 \quad (4.47)$$

In Andersen et.al. (2010) study RV_t metric converges to the quadratic variation. ($MM \rightarrow \infty$)

$$p \lim_{M \rightarrow \infty} RV_t = QV_t = \int_{t-1}^t \sigma_s^2 ds + \int_{t-}^t J_s^2 dN_s \quad (4.48)$$

If there is no jump in the time series data the QV_t corresponds the integrated variance (IV_t).

$$IV_t = \int_{t-1}^t \sigma_s^2 ds \quad (4.49)$$

To split the contribution of the continuous price variation from the contribution of the jump part, Barndorff-Nielsen and Shephard introduces the bipower variation which is written as;

$$BPV_t \equiv \mu_{11}^{-2} \left(\frac{M}{M-1} \right) \sum_{i=2}^M |r_{t,i-1}| |r_{t,i}| \quad (4.50)$$

If there is a jumps, the joint distribution of BV_t and IV_t normally distributed, is written as;

$$\sqrt{M} \begin{pmatrix} RV_t & \rightarrow & IV \\ BV_{t,M} & \rightarrow & IV \end{pmatrix} \vec{D} \rightarrow \left(0, \begin{bmatrix} 2 & 2 \\ 2 & 2,62 \end{bmatrix} IQ_t \right) \quad (4.51)$$

The integrated quarticity (IQ_t) = $\int_{t-1}^t \sigma_s^4 ds$.

Besides those statistical computations BNS is recommended another alternative statistics which is a common and robust one;

$$RJ_t = \frac{RV_t - \widehat{IV}_t}{RV_t} \quad (4.52)$$

$\widehat{IV}_t$ shows the jump robust measure of the IV_t .

We use this method with some modifications:

- i. We first remove the zero intraday returns as recommended by Rognlie (2010). Zero return day increase the noise in the data.

- ii. We use the mid-price which is calculated (intraday high price + intraday low price/2).
- iii. We use the Holm-Bonferroni correction method is only proved to work if the p values are independent, although simulations have indicated that it works in correlated cases as well. Hence the Holm method is the default.

4.2.1.2 Aith-Sahalia and Jacord jump detection methods

Their test is constructed based on the power variation sampled at different frequencies. It examines the presence of jumps in high-frequency data series.

The logic behind this method is to compare the multipower variation of equispaced returns computed at a fast time scale $h, r_{t,i} (i = 1, \dots, N)$ and it is computed at the slower time scale $kh, y_{t,i} (i = 1, \dots, \frac{N}{k})$.

In their study, they realized that limit (for $N \rightarrow \infty$) of the realized power variation is invariant for different sampling group and also their ratio is 1 in any case of jumps and $k^{p/2} - 1$ if no jumps. Hence the Aith-Sahalia test, (henceforth is called as AJ test) detects the jumps using the ratio of realized power variation sampled which is from the two scales. This represents the null hypothesis, if no jumps.

In AJ test functions return three results:

- i. Z-test value: which is the threshold level to detect the jumps,
- ii. Critical value: is used the defined whether there is jump or not under the level of 95 % and,
- iii. P-value: significance of the detected jumps.

Imagine that we have N equispaced returns in period T . $t_{t,i}$ depicts the return process of the pricing process (with $i = 1, \dots, N$) in period T .

There is also N/k equispaced returns in period T . Let $y_{t,i}$ be a return (with $i = 1, \dots, N/k$) in period T .

Based on the above restriction the AJ jump detection test is performed as;

$$AJ Test_{t,N} = \frac{S_t(pik, h) - k^{\frac{p}{2}-1}}{\sqrt{V_{t,N}}} \quad (4.53)$$

We use this method with some modifications:

- i. We first remove the zero intraday returns as recommended by Rognlie (2010). Zero return day increase the noise in the data.
- ii. We use the mid-price which is calculated (intraday high price + intraday low price/2).
- iii. We use the Holm-Bonferroni correction method is only proved to work if the p values are independent, although simulations have indicated that it works in correlated cases as well. Hence the Holm method is the default

4.2.1.3 Jiang and Oomen (2008) JO method

A new robust jump test which is based on the differences between simple and logarithmic returns is developed by Jiang and Oomen (2008). The new jump measure uses the jump sensitive measure instead of the comparing the realized volatility. The new test statistic depicted below, use a new methodology which is implemented by taking the accumulated difference between simple and logarithmic returns which approaches one half of the integrated variance (Dungey, M., Sayeed, A., M., and Tao, 2014).

$$SwV = 2 \sum_{j=2}^{[T/\Delta^n]} (r_i - \Delta_i^n p) \xrightarrow{p} \int_0^T \sigma^2 ds \quad (4.35)$$

Where;

r_i depicts the i th arithmetic intraday return $(\frac{P_i - P_{i-1}}{P_{i-1}})$

P represents the price of the asset

$\Delta_i^n p$ represents the j th logarithmic return

If there is no jump the differences between SwV and the realized variance becomes “Zero”. The jump between this differences shows as;

$$SwV_t - RV_t \xrightarrow{p} 2 \sum_{t_j \in [0, T]} (\exp(K_j)) - K_j - 1) - \sum_{t_j \in [0, T]} K_j^2 \quad (4.36)$$

The equation below depicts the alternative format that use the exponential form to capture the jumps by taking difference $SwV - RV$. The test statistic is written as;

$$JO_t = \frac{[T/\Delta^n]BPV_t}{\sqrt{\varphi_{SwV}}} \left(1 - \frac{RPV_t}{SwV_t}\right) \xrightarrow{L} N(0,1) \quad (4.37)$$

Where;

$$\varphi_{SwV} = \frac{\mu_p}{9} \frac{[T/\Delta^n]^3 \mu_{3/2}^{-4}}{[T/\Delta^n] - 3} \sum_{i=5}^n |\Delta_j^n p|^{3/2} |\Delta_{j-2}^n p|^{3/2} |\Delta_{j-3}^n p|^{3/2} \quad (4.38)$$

μ_p depicts the p th moment of the absolute value of a variable which is defined as;

$$\mu = E(|U|^p) = \pi^{-\frac{1}{2}} 2^{\frac{p}{2}} \Gamma\left(\frac{p+1}{2}\right), \quad (4.39)$$

Γ depicts the gamma distribution.

The JO method defines the jump in the presence of the large returns. It means that if the test statistic becomes very large a jump can be detected.

(Dungey, M., Sayeed, A., M., and Tao, 2014).

4.2.1.4 Jumps and macroeconomic news: Event study analysis

We choose to implement the Dewachter et.al (2014) event study approach with some modifications to realize the effects of macroeconomic news on jumps. We assume that news announcement cause jumps rather than jumps cause macroeconomic news. This is the preliminary assumption of this event study approach. We collect the news from Bloomberg ECO page with their significance level. Then we ranked all news in according to their relevance level. We use the news whose relevance level is over 50 (this is the relevance ranking system of Bloomberg from 0 to 100). In order to see how the news announcement (the actualized news) influence jumps, we analyze the jump dynamics at the time of event. We don't use the event and pre-event study windows.

First we construct our conditional probability equation:

$$P(\text{jump}|\text{event}) = \frac{\text{number of event match the jumps}}{\text{total number of events}} \quad (4.54)$$

We also construct the alternative probability equation which is unconditional probability equation:

$$P(\text{jump}|\text{event}) = \frac{\text{jumps occurs in the sub sample}}{\text{total number of the observation}} \quad (4.55)$$

Then we set up our null hypothesis:

$$H_0 = P(\text{jump}|\text{event}) = \text{jump}$$

$$H_1 = P(\text{jump}|\text{event}) \neq \text{jump}$$

H_0 implies that jump caused by an event is identical to H_1 , jump occurs without any event.

4.2.1.5 Macroeconomic news announcements

Our hypothesis is that the intraday volatility and the occurrence of the jumps are related to macroeconomic news announcements. The average volatility level is not constant (which is given) but it depends on the time of the day and creates a significant variation between the Exchange rate pairs (Fan, 2016). There is a U-shaped variation in which price starts high, comes down in the middle of the day and goes up at the end of the days. On the other hand, volatility responds to the important scheduled macroeconomic news announcements and tend to increase either positive or negative direction.

There are many studies which have very significant results that show the strong relationship between important scheduled macroeconomic news announcements and jumps. Evans (2011) studies on S&P500, 10 –year US Treasury Bond and EURUSD futures market and their relations with the major US macroeconomic news announcements (Fan, 2016). Another important study was done again by Evans and Speight (2011); they use news release from US, UK, Japan and Eurozone and explore their relationship with 5-minutes EUR/USD, EUR/GBP, and EUR/JPY Exchange rates. They find very significant results. Fan, (2016) and Wang (2015) examine the macroeconomic news effects on Exchange rate jumps and co-jumps. They found out that macroeconomic news announcements do impacts on forex jumps and co-jumps.

The scheduled macroeconomic news announcements are extracted from Bloomberg data vendor with the exact date and time. The local time is used for all countries. Some news like GDP released quarter over quarter, but Personal income, CPI and Employment is announced monthly. For a few cases some of the news like US Continuing Claims is released weekly.

The scheduled news announcements affect the future performance of the exchange rate pairs. We have three effects on news announcement like pre-announcement and post-announcement effects. Pre-announcement reflects the investor expectations on assets. Announcement effect is an effect which is hard to catch up this effect on time. It most probably shows its effect after the announcement. So the post-announcement is becoming more important than the announcement time.

We searched the post-announcement effects of the scheduled macroeconomic news so we examined the time interval which is 30-minutes after the news announcement. In this interval we try to catch up the jumps and co-jumps.

4.3 CO-JUMPS

We detect the jumps with implementing BNS and AJ tests in the previous section. There are many studies on jump detection but few studies on co-jump detection. Co-jump is defined as simultaneous jumps in any individual assets, exchange rate pairs in our case.

4.3.1 Co-Jump Test Method

Barndorff-Nielsen and Sephard (2006) test for co-jump detection is empirically hard to implement. Remember that they extend their univariate bipower approach to a multivariate one to detect co-jump between return pairs⁵. A co-jump occurs when the threshold levels detect any jumps simultaneously in two or more currency pairs. In this dissertation, we have evaluated the Gobbi and Mancini (2007) works on threshold levels, the extended works of Jacob and Todorow (an extension of the Ait-Sahalis-2009) which based on the bivariate case. Instead of this previous methods; we decided to implement the mean-cross-product (mpc) statistic of Bollerslev (2008) in which the intraday high-frequency return depicted;

⁵ See Barndorff-Nielsen and Sephard (2004b)

$$mcp_{t,j} = \frac{2}{n(n-1)} \sum_{i=1}^{n-1} \sum_{k=i+1}^n r_{i,t,j} r_{k,t,j}, \quad j = 1, 2, 3, \dots \dots N \quad (4.56)$$

We assume that there are N intraday returns for each of n exchange rate pairs. Then the test statistic turn to frequency mean and standard deviation is written as;

$$Z_{mcp,t,j} = \frac{mcp_{t,j} - \overline{mcp}_t}{S_{mcp,t}}, \quad j=1, 2, 3, \dots, N. \quad (4.57)$$

The $\overline{mcp}_t$ is defined as

$$\overline{mcp}_t = \frac{1}{N} mcp_t = \frac{1}{N} mcp_{t,j} \quad (4.58)$$

The $S_{mcp,t}$ is calculated as

$$S_{mcp,t} = \sqrt{\frac{1}{N} \sum_{j=1}^N (mcp_{t,j} - \overline{mcp}_t)^2} \quad (4.59)$$

We don't identify an asymptotic distribution for this statistic like in Bollerslev et.al.(2008) but we use a bootstrap to get the distribution under the null of no jumps.

5. DATA ANALYSIS AND EMPIRICAL RESULTS

5.1 INTRODUCTION

In this part, we first analyze the statistical properties and characteristics of jumps and co-jumps of eleven Foreign Exchange rate pairs between 2010 to 2016 and macroeconomic news effects on jumps and co-jumps. The nonparametric Barbdorff-Nielsen and Diebold (BNS) and Aith-Sahalia and Jacord (AJ) jump detection tests are employed to detect the significant jumps and co-jumps (jumps that appear simultaneously) from foreign Exchange rate pairs. After detecting the jumps and co-jumps we analyze the relationship between jumps and co-jumps and macroeconomic news announcements. We also use the event study model which match the jumps and co-jumps with the macroeconomic news announcements and lastly we interpret how news announcements affect jumps and co-jumps in Exchange rate return series.

This empirical part is constructed for a deeper understanding of jumps and co-jumps which has practical implications for academicians, high-frequency traders, algorithmic traders and other traders. We choose exchange rate market because the news effect can be realized first in FX market (especially in FX Future) then spill over to the other markets. And also when examining the existing literature there are several studies on U.S Equity indices, bond markets but few studies on the foreign exchange markets.

Table 5.10 provides a general view of the largest jumps matched with macroeconomic news⁶. It elaborates the detail information about how significant exchange rate jumps match the scheduled macroeconomic fundamentals. We use macroeconomic news from United States, United Kingdom, Switzerland, Japan, Germany, Italy, France, Aggregate Eurozone and even Turkey. Bloomberg ECO page is used to collect the economic news announcements in accordance to their relevancy. The relevancy is given by Bloomberg data vendor from 100 to 0. This analyses employed on the absolute jump size by time of the day. In total there are 10,850 scheduled macro news announcements is used out of 45,880 news based on the relevancy ranking of Bloomberg. We elaborate the

⁶ We analyze only the effects of scheduled fundamental news announcements on jump and co-jumps. However, there is also unscheduled news announcement and speeches are strongly related to the jump and co-jump occurrence.

relationship between jump dynamics and macroeconomic news. We listed the most meaningful seventeen events categories in Table 5.10 Parallel to literature, US base news match more than the other country's news with the most significant jumps size. We find that; news related to monetary policy (FOMC rate decision, ECB Interest rate, BOJ balance rate), employment (US employment change, Initial job claims, Labor costs), prices (CPI Ex Food and Energy, House price index, Bloomberg GDP YoY, New home sales,), current account (Current account balance, General budget debt), and sentiment (ADP confidence index, Bloomberg global index, Business climate index) have more potential to jumps.

We also notice that when a large jump occurs in one market it matches with to jumps at least one macroeconomic news announcement. Besides this we can easily say that the big jump in one market quite possibly is correlated with a jump in another currency pairs or in another market like stock or bond⁷ it is verified by correlation analysis depicted in Table 5.1. It is also clearly seen from the table 5.10 that both number and size of the jumps are relatively higher around 07:30 – 15:15.

Calcagnile et.all (2015) found that it is so hard to say that such discontinuities are only partially related to the scheduled macroeconomic news announcements and their occurrence is largely unpredictable. On the other hand Bajgrowicz et.al (2016) study show that common detection methods entail a misclassification risk. They claim that jumps are rare and strongly related to the news announcements (scheduled or unscheduled).

5.1 JUMP ANALYSIS

Understanding the dynamics of volatility and correlation is an important issue in jump and co-jump detections. Recent literature developed more sophisticated estimates of volatility and it is associated with jump and diffusion component. Research shows that the proportion of jumps and co-jumps directly affects the volatility and correlation.

⁷ See co-jump analysis

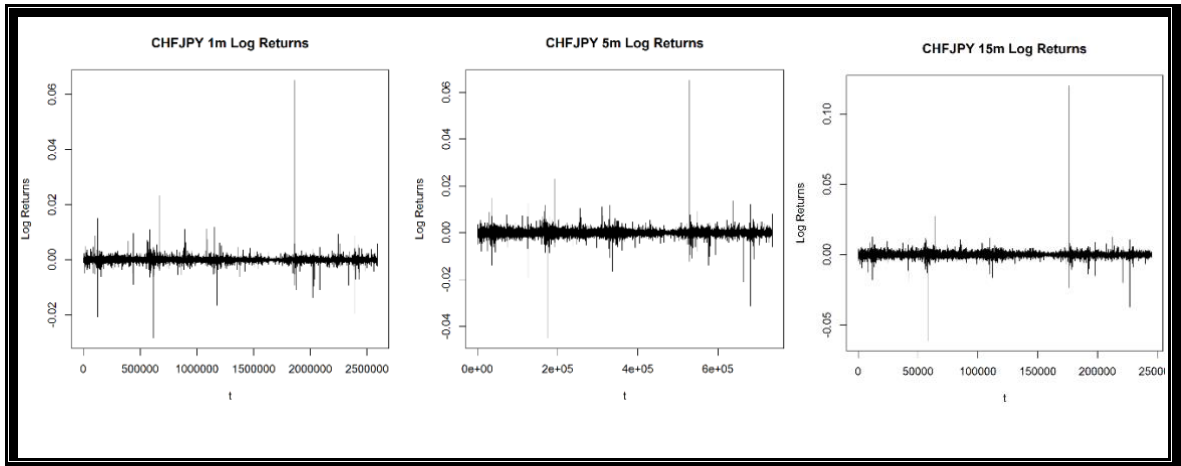
Table 5.1: Correlation matrix between currency pairs

Currency_1m	CHFJPY	EURCHF	EURJPY	EURTRY	EURUSD	GBPCHF	GBPJPY	USDCHF	USDJPY	USDTRY	EURGBP
CHFJPY	100.0%	-89.0%	-61.5%	81.1%	-80.7%	-87.6%	37.8%	17.0%	86.3%	83.7%	-65.4%
EURCHF	-89.0%	100.0%	90.7%	-84.0%	96.1%	93.7%	-3.8%	-36.7%	-88.0%	-91.6%	30.8%
EURJPY	-61.5%	90.7%	100.0%	-70.1%	91.4%	81.3%	28.7%	-47.4%	-72.2%	-80.8%	-36.5%
EURTRY	81.1%	-84.0%	-70.1%	100.0%	-86.9%	-82.6%	8.6%	52.1%	89.6%	98.1%	5.1%
EURUSD	-80.7%	96.1%	91.4%	-86.9%	100.0%	85.4%	-3.1%	-61.1%	-94.1%	-94.9%	-61.7%
GBPCHF	-87.6%	93.7%	81.3%	-82.6%	85.4%	100.0%	11.5%	-18.8%	-77.7%	-86.6%	-34.9%
GBPJPY	37.8%	-3.8%	28.7%	8.6%	-3.1%	11.5%	100.0%	-0.2%	29.3%	6.7%	-76.1%
USDCHF	17.0%	-36.7%	-47.4%	52.1%	-61.1%	-18.8%	-0.2%	100.0%	64.3%	57.1%	57.0%
USDJPY	86.3%	-88.0%	-72.2%	89.6%	-94.1%	-77.7%	29.3%	64.3%	100.0%	94.3%	44.1%
USDTRY	83.7%	-91.6%	-80.8%	98.1%	-94.9%	-86.6%	6.7%	57.1%	94.3%	100.0%	33.0%
EURGBP	-65.4%	30.8%	-36.5%	5.1%	-61.7%	-34.9%	-76.1%	57.0%	44.1%	33.0%	100.0%
Currency_5m	CHFJPY	EURCHF	EURJPY	EURTRY	EURUSD	GBPCHF	GBPJPY	USDCHF	USDJPY	USDTRY	EURGBP
CHFJPY	100.0%	82.2%	95.1%	69.7%	93.8%	-21.8%	86.9%	-97.2%	62.8%	50.0%	91.0%
EURCHF	82.2%	100.0%	95.8%	53.8%	95.8%	20.1%	90.6%	-78.7%	55.2%	31.1%	89.1%
EURJPY	95.1%	95.8%	100.0%	64.7%	99.4%	-0.3%	92.9%	-91.7%	61.8%	42.5%	94.4%
EURTRY	69.7%	53.8%	64.7%	100.0%	61.1%	-47.0%	44.7%	-62.3%	62.2%	96.5%	74.9%
EURUSD	93.8%	95.8%	99.4%	61.1%	100.0%	2.3%	93.1%	-93.0%	52.7%	38.1%	93.2%
GBPCHF	-21.8%	20.1%	-0.3%	-47.0%	2.3%	100.0%	29.2%	20.3%	-15.9%	-55.1%	-26.5%
GBPJPY	86.9%	90.6%	92.9%	44.7%	93.1%	29.2%	100.0%	-85.0%	53.5%	21.3%	75.6%
USDCHF	-97.2%	-78.7%	-91.7%	-62.3%	-93.0%	20.3%	-85.0%	100.0%	-43.0%	-41.7%	-86.8%
USDJPY	62.8%	55.2%	61.8%	62.2%	52.7%	-15.9%	53.5%	-43.0%	100.0%	55.0%	61.8%
USDTRY	50.0%	31.1%	42.5%	96.5%	38.1%	-55.1%	21.3%	-41.7%	55.0%	100.0%	56.4%
EURGBP	91.0%	89.1%	94.4%	74.9%	93.2%	-26.5%	75.6%	-86.8%	61.8%	56.4%	100.0%
Currency_15m	CHFJPY	EURCHF	EURJPY	EURTRY	EURUSD	GBPCHF	GBPJPY	USDCHF	USDJPY	USDTRY	EURGBP
CHFJPY	100.0%	61.4%	87.6%	54.8%	87.6%	14.5%	67.4%	-69.2%	41.0%	32.7%	59.3%
EURCHF	61.4%	100.0%	91.8%	23.8%	80.4%	71.7%	88.1%	-8.6%	68.5%	0.0%	30.8%
EURJPY	87.6%	91.8%	100.0%	42.3%	93.0%	51.1%	87.7%	-40.0%	62.4%	16.7%	48.4%
EURTRY	54.8%	23.8%	42.3%	100.0%	52.7%	-28.8%	9.8%	-58.3%	-3.7%	95.7%	70.3%
EURUSD	87.6%	80.4%	93.0%	52.7%	100.0%	25.7%	68.7%	-66.1%	29.4%	26.1%	68.3%
GBPCHF	14.5%	71.7%	51.1%	-28.8%	25.7%	100.0%	82.8%	47.4%	79.2%	-41.3%	-44.1%
GBPJPY	67.4%	88.1%	87.7%	9.8%	68.7%	82.8%	100.0%	-4.0%	82.2%	-12.0%	0.4%
USDCHF	-69.2%	-8.6%	-40.0%	-58.3%	-66.1%	47.4%	-4.0%	100.0%	37.3%	-43.6%	-75.5%
USDJPY	41.0%	68.5%	62.4%	-3.7%	29.4%	79.2%	82.2%	37.3%	100.0%	-13.8%	-19.6%
USDTRY	32.7%	0.0%	16.7%	95.7%	26.1%	-41.3%	-12.0%	-43.6%	-13.8%	100.0%	56.9%
EURGBP	59.3%	30.8%	48.4%	70.3%	68.3%	-44.1%	0.4%	-75.5%	-19.6%	56.9%	100.0%

Hence the impact of jumps and co-jumps on correlations increased and the appropriate estimation of jumps and co-jumps is becoming crucial step in understanding dependence in exchange rate markets. Table 5.1 summaries the result of correlation for CHFJPY, EURCHF, EURJPY, EURTRY, EURUSD, GBPCHF, GBPJPY, USDCHF, USDJPY, USDTRY and EURGBP currency pairs. It is obviously seen that there is a strong positive and negative relationship between currency pairs. We test the power of the relation in different frequencies, 1-minute, 5-minute and 15-minute. Furthermore, a strong positive correlation was defined between EURUSD and EURCHF ($r = 0,96$). In addition, another positive strong correlation was exhibit between EURCHF and EURUSD ($r = 0,96$). USDTRY and EURUSD has negative strong correlation ($r = -0,95$).

Then we analyze the return series. We try to find out the outliers in the data sets. The outliers is an important metric that signals for the structural break in time and also is a signal of major bad or good news. Figure 5.1 shows the results for CHPJPY pair and picture are very similar for eleven currency pairs. These data have outliers and groups around a mean.

Figure 5.1: Results for CHPJPY Log Returns



Tables 5.14 to 5.35 provides the summary of the significant jumps based on the BNS and AJ methods. The jump detection was utilized based the z scores and p-values. We found many jump days and with higher size but they are not significant. We haven't counted them as jump in the statistical tables. The jump size is an important indicators

that shows the market volatility. The increasing jump size is a signal of the volatility increasing. Based on the good and bad news from the US and Euro zone the market volatility changes in developed and emerging markets. Among the eleven exchange rates USDJPY shows more volatile jumps with the jump size of -2.87 on 31 of October 2011 at 21:30. The reason of this jump is the intervention of the Bank of Japan to the market. Tables from 5.14 to 5.35 provides the summary statistics of significant jumps based on the 1-minute, 5-min, 15-min, 30-min and 60-min frequencies. Jump detection analysis consists of six different parts which provide a brief overview of the significant jumps in return series. The first part has four explanatory terms. The first one is the **number of observations**: We originally have 1-minute data and convert them to 5, 15 and 30-minutes and 60-minutes dataset too. The second term, **E(|abs(return)|)**, shows the absolute value of the returns. Annualized standard deviation of intraday returns is given as **Annualized SD** in the third term. The last one in that section is the **number of days** which represents the number of sample days in the analysis.

The second parts of the tables cover three explanatory terms which are shown in order; **Number of Jumps days**, shows the total number of the days with at least one jump, **P (jump day) (%)**, the probability of a jump day calculated as $(P(\text{Jump day}) = 100 * (\# \text{jump days} / \# \text{days}))$, and the **E (jumps|jump day) (%)** the number of jumps per jump day $((E(\# \text{jump} | \text{jump day}) = (\# \text{jumps} / \# \text{jump days})))$.

Another part of the descriptive statistic table on significant jumps, part three, has four components which are; **Number of Jumps**, provides the total number of jumps, **P(jump) (%)** shows the percentage of the jumps calculated as $(P(\text{jumps}) = 100 * (\# \text{jumps} / \# \text{ of observation}))$, and **E(|jumpsize|)**, refer to the absolute jump mean.

Part four and five in the statistical table help to understand the sign of the jumps either positive or negative. **# jump > 0** shows the positive jumps and **# jump < 0** executes the negative jumps. The last part, panel six, express the percentage of negative jumps in the statistics, $(100 * (\# \text{jumps} < 0 / \# \text{jumps}))$ and it associated with the standard error.

Table 5.2 provide a brief overview of eleven foreign exchange rate's return significant jump days for different frequencies. It can be said that the jump sizes have become

larger when the frequency increases from 1-minute to 30-minutes. This shows that the market volatility increase with the increasing frequency.

Table 5.2: Significant Jump days⁸

1 Minute			5 Minutes			15 Minutes			30 Minutes		
	b_ztest	b_pvalue	Date	b_ztest	p_pvalue	Date	b_ztest	b_pvalue	Date	b_ztest	p_pvalue
5/3/2010	8.6828	3.9E-18	11/19/2015	21.857	0		43.0589	0	4/22/2016	43.0589	0
7/30/2013	7.72504	1.1E-14		22.552	0	3/20/2015	21.7723	4.3E-105	2/5/2014	21.7723	4.3E-105
12/5/2011	5.37245	7.8E-08	3/20/2015	21.549	3E-306		18.442	6.04E-76	12/22/2016	18.442	6.04E-76
5/2/2012	4.85348	1.2E-06	6/6/2011	19.611	1.2E-85	5/27/2015	13.5899	4.6E-42	3/28/2014	13.5899	4.6E-42
4/20/2016	4.10226	4.1E-05	10/3/2013	13.882	8.1E-44	12/10/2012	10.6902	1.13E-26	6/4/2012	10.6902	1.13E-26
12/16/2011	3.99435	6.5E-05		13.197	9.1E-40		10.6856	1.19E-26	7/22/2016	10.6856	1.19E-26
3/29/2016	-3.7334	0.00019	12/30/2013	12.515	6.2E-36	8/5/2013	8.67462	4.15E-18	11/30/2012	8.67462	4.15E-18
	3.61966	0.00029	8/5/2013	12.059	1.7E-33		8.14873	3.68E-16	9/1/2015	8.14873	3.68E-16
9/7/2015	-3.6176	0.0003	1/6/2016	11.129	9.1E-29	10/3/2013	7.93527	2.1E-15	1/25/2013	7.93527	2.1E-15
2/24/2015	3.51839	0.00043		10.966	5.5E-28	12/30/2013	7.70796	1.28E-14	3/29/2013	7.70796	1.28E-14
	3.45019	0.00056	5/3/2016	10.735	7E-27	3/22/2012	7.54789	4.42E-14	11/18/2011	7.54789	4.42E-14
7/23/2014	-3.4052	0.00066	3/11/2013	9.0002	2.3E-19	1/5/2016	7.29002	3.1E-13	8/18/2014	7.29002	3.1E-13
10/9/2014	3.22995	0.00124		8.8444	9.2E-19	10/25/2011	7.15092	8.62E-13	7/27/2011	7.15092	8.62E-13
6/3/2010	3.18998	0.00142	1/5/2016	8.6356	5.8E-18	11/5/2015	7.02271	2.18E-12	7/7/2014	7.02271	2.18E-12
4/1/2015	-3.1398	0.00169	12/5/2013	8.5095	1.7E-17		6.7613	1.37E-11	8/13/2015	6.7613	1.37E-11
7/26/2010	-3.1133	0.00185	9/28/2016	8.2505	1.6E-16	3/22/2016	6.37866	1.79E-10	10/21/2014	6.37866	1.79E-10
	-3.0844	0.00204	4/15/2013	7.5292	5.1E-14	5/8/2014	6.28087	3.37E-10	6/27/2013	6.28087	3.37E-10
7/5/2011	-3.0476	0.00231		7.3202	2.5E-13	7/29/2014	6.24836	4.15E-10	8/23/2013	6.24836	4.15E-10
5/28/2015	-3.0441	0.00233		7.2075	5.7E-13		5.98479	2.17E-09	9/8/2015	5.98479	2.17E-09
2/10/2011	-3.0408	0.00236		7.1514	8.6E-13		5.91076	3.41E-09	6/5/2015	5.91076	3.41E-09
8/4/2010	-3.0004	0.0027	12/23/2011	6.5477	5.8E-11	3/11/2013	5.77713	7.6E-09	8/9/2012	5.77713	7.6E-09
	-2.9565	0.00311	9/17/2013	6.3059	2.9E-10	10/29/2015	5.71529	1.1E-08	7/1/2014	5.71529	1.1E-08
11/6/2015	-2.9536	0.00314		6.1043	1E-09	11/2/2015	5.71529	1.1E-08	7/3/2014	5.71529	1.1E-08
1/7/2011	2.9522	0.00316	11/6/2013	6.0574	1.4E-09		5.70534	1.16E-08	1/15/2016	5.70534	1.16E-08
5/5/2016	-2.9368	0.00332	12/13/2016	6.0438	1.5E-09	9/9/2015	5.62439	1.86E-08	6/3/2014	5.62439	1.86E-08
	-2.9081	0.00364	7/22/2016	5.9473	2.7E-09	10/26/2012	5.57926	2.42E-08	4/30/2012	5.57926	2.42E-08
5/25/2010	-2.8984	0.00375		5.6232	1.9E-08		5.53886	3.04E-08	8/18/2016	5.53886	3.04E-08
9/25/2012	-2.8677	0.00413	7/9/2013	5.5625	2.7E-08	7/22/2015	5.5197	3.4E-08	5/7/2014	5.5197	3.4E-08
12/30/2011	-2.8624	0.0042	4/12/2016	5.5179	3.4E-08		5.41261	6.21E-08	2/4/2016	5.41261	6.21E-08
8/18/2011	-2.8236	0.00475	7/12/2012	5.4657	4.6E-08	2/23/2015	5.33973	9.31E-08	1/17/2014	5.33973	9.31E-08
1/23/2013	-2.7876	0.00531	2/6/2014	5.3471	8.9E-08	10/19/2015	5.29882	1.17E-07	6/20/2014	5.29882	1.17E-07
	2.77887	0.00545	4/17/2015	5.3076	1.1E-07		5.22985	1.7E-07	7/13/2015	5.22985	1.7E-07

Annualized returns show the volatility between the exchange rate pairs. Among the exchange rate pairs, GBP/JPY currency pair is the most volatile one with an annualized standard deviation of 22.30⁹. Then looking at the whole sample size¹⁰ only a small proportion of the returns are detected as jumps. Our test compares 1-minute, 5-minutes, 15-minutes, and 30-minutes and 60-minutes frequency returns with a critical values and threshold levels of the jump tests. The threshold level of BNS and AJ tests are different.

⁸ This table shows the some of the significant jump days. It doesn't include the all days.

⁹ It is the highest annualized returns observed in 5, 15 and 3 minutes frequency. See the table from 5.14 to 5.35

¹⁰ 1minute data: 2,587,655, 5-minute data: 735,264, 5-minute data: 245,088, 30-minute data: 122,544 and 60-minute data: 61,272

Based on the threshold level the number of detected jump changing over time. Table 5.3 summarize the frequency of the jumps between currency pairs. The number of detected jumps ranges from 986 in EURJPY market to 1565 in GBPJPY market. Lahaye et.al (2011) indicates that foreign exchange rate markets have more jumps than the other such as stock and bond markets, because theoretically it has 24 hours trading interval in a day.

Table 5.3: Frequency of Jump days

	1-min	5-min	15-min	30-min	60-min	Currency
AJ/ n of Jump Days	1433	1209	1257	1258	1289	GBPCHE
BNS-S / n of Jump Days	1136	1330	1350	1258	1336	GBPCHE
AJ/ n of Jump Days	1198	1301	1216	1254	1242	GBPCHE
BNS-S / n of Jump Days	1198	1301	1216	1254	1216	GBPCHE
AJ/ n of Jump Days	1565	1332	1269	1242	1354	GBPJPY
BNS-S / n of Jump Days	1565	1332	1269	1242	1236	GBPJPY
AJ/ n of Jump Days	1155	1358	1277	1302	1273	USDCHF
BNS-S / n of Jump Days	1155	1358	1277	1302	1429	USDCHF
AJ/ n of Jump Days	1253	1158	1001	1332	1193	USDJPY
BNS-S / n of Jump Days	1168	1413	1057	1332	1241	USDJPY
AJ/ n of Jump Days	1458	1383	1263	1358	1356	USDTRY
BNS-S / n of Jump Days	1450	1466	1258	1263	1368	USDTRY
AJ/ n of Jump Days	1477	1355	1204	1254	1323	EURCHF
BNS-S / n of Jump Days	1117	1355	1204	1301	1244	EURCHF
AJ/ n of Jump Days	1260	1143	1216	1307	1158	EURGBP
BNS-S / n of Jump Days	1381	1326	1233	1252	1298	EURGBP
AJ/ n of Jump Days	1257	1254	1103	986	1121	EURJPY
BNS-S / n of Jump Days	1229	1415	1129	1173	1260	EURJPY
AJ/ n of Jump Days	1332	1301	1258	1254	1286	EURTRY
BNS-S / n of Jump Days	1258	1355	1452	1028	1219	EURTRY
AJ/ n of Jump Days	1242	1332	1301	1242	1279	EURUSD
BNS-S / n of Jump Days	1433	1216	1258	1433	1336	EURUSD

Then looking at the whole sample only small proportion of the returns are detected as jumps. The number of observation for frequencies are; 2,587,655 for 1-minute, 735,264 for 5-minutes, 245,088 for 15-minutes 122,544 for 30-minutes and 61,272 for 60-minutes intervals. However, the largest jump day is observed as 1,565¹¹ days of GBP/JPY, but the percentage of the whole observation is only 0,0006 %. The absolute jump size is depicted in Tables 5.14-5.35 and changing over time. The size of the jumps are depend on the critical values and significance levels. Based on the chosen methods the size of the jump is changing.

The Labor market news play a key role in that volatility fluctuation. El Ouadghiri and Uctum (2016) current study support this finding. They underlined that the most influential scheduled macroeconomic news are globally related to the US job markets, public debt, GDP and rescue plans (especially Obama's rescue plan). Moreover, during the similar study that was concerned with the exchange rates of euro-dollar, the researchers ascertained that verbal communications always results in large kind of jumps for nearly an hour after news announcements, an abnormal variation which the authors might have noted is a result of European official's interventions as opposed to the United States of American authorities.

The number of jump days is accounting from 68 % to 48 % fluctuation between currency pairs. The highest one is realized in USDJPY in 5-min returns and the lowest one utilized in EURJPY in 1-minute. Foreign exchange rate markets have more jump days rather than the other financial markets like bond and stock markets. The main reason is that FX markets in theory have 24 trading hours in a day (Lahaye et.al, 2011).

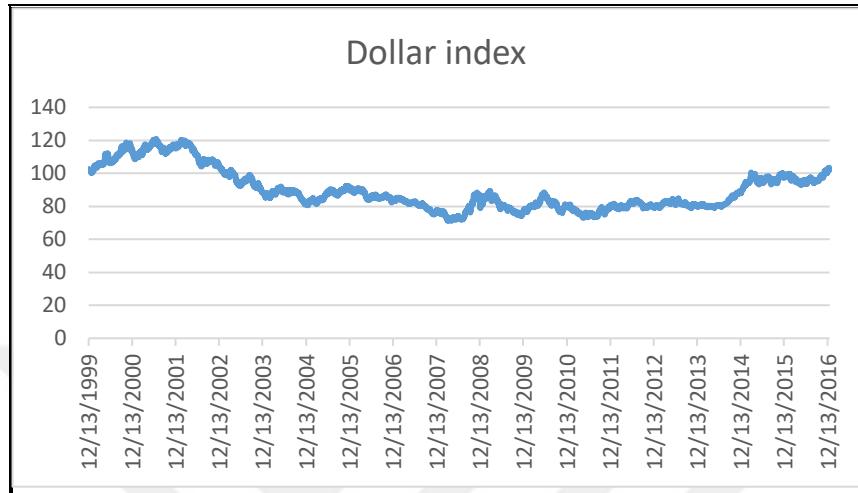
To analyze whether there is asymmetry between positive and negative jumps, we separate the jumps into positive and negative jump categories. Contrary to Wang (2015) study especially USDJPY pair has the more positive jumps together with the EURGBP one in all frequency levels. Except EURGBP, USDJPY, EURCHF and EURTRY, we find more negative jumps than positive jumps during the observation periods¹². The reason of this asymmetry may be due to decrease in dollar and Euro indexes. The U.S. Dollar Index(USDIX) indicates the general initial value of the USD. The USDIX is an

¹¹ See table 3.

¹² See Tables 5.14-5.35.

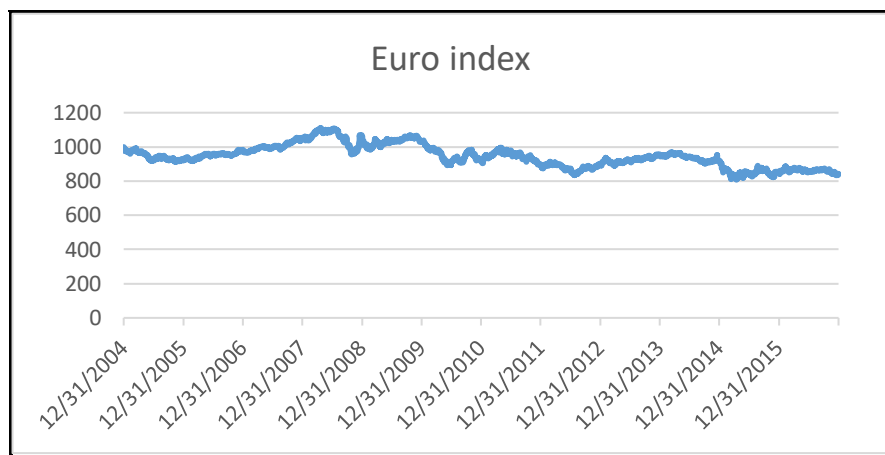
index and is calculated by averaging the exchange rates between the USD and major world currencies.

Figure 5.2: Dollar index (2010-2016)



The Bloomberg Euro Index tracks the performance of EUR versus a basket of leading global currencies. Each currency in the basket and their weight is determined annually based on their share of international trade and liquidity. The index starts from 31 December 2004 with a base level of 1000. 2017 Weights: USD 47.6% GBP 14.9% CHF 7.4% JPY 11.3% SEK 4.5% RUB 4.3% CAD 3.6% CNH 3.0% TRY 3.5%. It also prove the asymmetry between negative and positive jumps.

Figure 5.3: Euro index (2010-2016)



On the other hand comparing the positive and negative jumps we can say that there is an obvious asymmetry between exchange rate pairs. It is depicted in Tables 5.4, 5.5 and 5.6.

Table 5.4: Number of positive jumps

		1-min	5-min	15-min	30-min	60-min	Currency
AJ/ n of Jump Days	# jump>0	698	586	626	605	656	GBPCHF
BNS-S / n of Jump Days	# jump>0	565	672	756	598	623	GBPCHF
AJ/ n of Jump Days	# jump>0	543	651	563	429	439	GBPCHF
BNS-S / n of Jump Days	# jump>0	470	562	711	750	633	GBPCHF
AJ/ n of Jump Days	# jump>0	632	783	572	592	645	GBPJPY
BNS-S / n of Jump Days	# jump>0	640	642	765	739	670	GBPJPY
AJ/ n of Jump Days	# jump>0	571	617	700	704	473	USDCHF
BNS-S / n of Jump Days	# jump>0	573	716	576	797	826	USDCHF
AJ/ n of Jump Days	# jump>0	724	553	641	642	640	USDJPY
BNS-S / n of Jump Days	# jump>0	693	811	764	783	763	USDJPY
AJ/ n of Jump Days	# jump>0	806	734	651	617	702	USDTRY
BNS-S / n of Jump Days	# jump>0	794	686	755	651	722	USDTRY
AJ/ n of Jump Days	# jump>0	701	643	597	750	673	EURCHF
BNS-S / n of Jump Days	# jump>0	542	743	678	562	631	EURCHF
AJ/ n of Jump Days	# jump>0	683	516	711	704	653	EURGBP
BNS-S / n of Jump Days	# jump>0	723	715	618	646	676	EURGBP
AJ/ n of Jump Days	# jump>0	596	630	485	490	493	EURJPY
BNS-S / n of Jump Days	# jump>0	573	635	726	561	623	EURJPY
AJ/ n of Jump Days	# jump>0	642	562	1255	750	802	EURTRY
BNS-S / n of Jump Days	# jump>0	755	743	806	296	576	EURTRY
AJ/ n of Jump Days	# jump>0	739	783	562	592	669	EURUSD
BNS-S / n of Jump Days	# jump>0	659	711	662	686	493	EURUSD

Table 5.5: Number of negative jumps

		1-min	5-min	15-min	30-min	60-min	Currency
AJ/ n of Jump Days	# jump<0	735	623	631	653	633	GBPCHF
BNS-S / n of Jump Days	# jump<0	571	658	594	660	713	GBPCHF
AJ/ n of Jump Days	# jump<0	655	650	653	501	803	GBPCHF
BNS-S / n of Jump Days	# jump<0	728	739	505	504	583	GBPCHF
AJ/ n of Jump Days	# jump<0	933	549	697	650	709	GBPJPY
BNS-S / n of Jump Days	# jump<0	925	690	504	503	566	GBPJPY
AJ/ n of Jump Days	# jump<0	584	741	1277	598	800	USDCHF
BNS-S / n of Jump Days	# jump<0	582	642	701	505	603	USDCHF
AJ/ n of Jump Days	# jump<0	529	605	360	690	553	USDJPY
BNS-S / n of Jump Days	# jump<0	475	602	293	549	478	USDJPY
AJ/ n of Jump Days	# jump<0	652	649	612	741	654	USDTRY
BNS-S / n of Jump Days	# jump<0	656	780	503	612	646	USDTRY
AJ/ n of Jump Days	# jump<0	776	712	607	504	650	EURCHF
BNS-S / n of Jump Days	# jump<0	575	612	526	739	613	EURCHF
AJ/ n of Jump Days	# jump<0	577	627	505	603	505	EURGBP
BNS-S / n of Jump Days	# jump<0	658	611	615	606	622	EURGBP
AJ/ n of Jump Days	# jump<0	661	624	618	496	628	EURJPY
BNS-S / n of Jump Days	# jump<0	656	780	503	612	637	EURJPY
AJ/ n of Jump Days	# jump<0	690	739	3	504	484	EURTRY
BNS-S / n of Jump Days	# jump<0	503	612	652	732	643	EURTRY
AJ/ n of Jump Days	# jump<0	503	549	739	650	610	EURUSD
BNS-S / n of Jump Days	# jump<0	774	505	596	747	843	EURUSD

Table 5.6: Asymmetry in positive and negative jumps

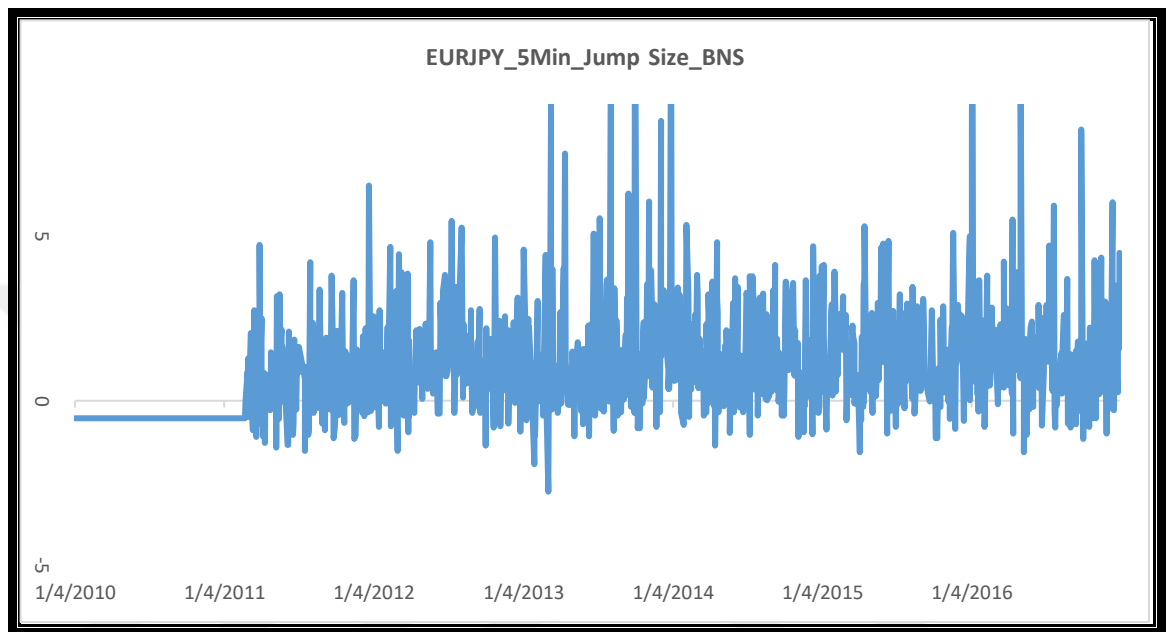
		1-min	5-min	15-min	30-min	60-min	Currency
AJ/ n of Jump Days	# jump +/-	0	0	0	0	1	GBPCHF
BNS-S / n of Jump Days	# jump +/-	0	1	1	0	0	GBPCHF
AJ/ n of Jump Days	# jump +/-	0	1	0	0	0	GBPCHF
BNS-S / n of Jump Days	# jump +/-	0	0	1	1	1	GBPCHF
AJ/ n of Jump Days	# jump +/-	0	1	0	0	0	GBPJPY
BNS-S / n of Jump Days	# jump +/-	0	0	1	1	1	GBPJPY
AJ/ n of Jump Days	# jump +/-	0	0	0	1	0	USDCHF
BNS-S / n of Jump Days	# jump +/-	0	1	0	1	1	USDCHF
AJ/ n of Jump Days	# jump +/-	1	0	1	0	1	USDJPY
BNS-S / n of Jump Days	# jump +/-	1	1	1	1	1	USDJPY
AJ/ n of Jump Days	# jump +/-	1	1	1	0	1	USDTRY
BNS-S / n of Jump Days	# jump +/-	1	0	1	1	1	USDTRY
AJ/ n of Jump Days	# jump +/-	0	0	0	1	1	EURCHF
BNS-S / n of Jump Days	# jump +/-	0	1	1	0	1	EURCHF
AJ/ n of Jump Days	# jump +/-	1	0	1	1	1	EURGBP
BNS-S / n of Jump Days	# jump +/-	1	1	1	1	1	EURGBP
AJ/ n of Jump Days	# jump +/-	0	1	0	0	0	EURJPY
BNS-S / n of Jump Days	# jump +/-	0	0	1	0	0	EURJPY
AJ/ n of Jump Days	# jump +/-	0	0	1	1	1	EURTRY
BNS-S / n of Jump Days	# jump +/-	1	1	1	0	0	EURTRY
AJ/ n of Jump Days	# jump +/-	1	1	0	0	1	EURUSD
BNS-S / n of Jump Days	# jump +/-	0	1	1	0	0	EURUSD

Note: If positive jumps > negative jumps, the value is “1” otherwise “0”.

Figure 5.4 depicts a visual view of the jump distribution within a day. It shows the jump frequency and mean absolute jump size by time of the day. It is clear that both the number and the size of the jumps are higher between 08:30 and 15:15, corresponding to

the macroeconomic news announcements. The jumps in FX market is strongly related to the macroeconomic news.

Figure 5.4: EURJPY 5minutes Jump size-BNS method



There are many anomalies in finance. Day of the week is a most meaningful one for FX market. Monday and Wednesday have the highest jump's days. Monday's jumps have accumulation effect. We can say that there is weekend effect here. Scheduled macroeconomic news are the ones which mostly affect the jumps but there are unscheduled news like speeches which have also more effect on jumps. In this study we haven't given more focus on unscheduled news but it has significant effect on jumps. It increases the magnitude of the jumps.

In order to draw attention to jump and macroeconomic news announcement, we chose 10 largest jumps of EURUSD and match them to the macroeconomic news announcements. It shows that at least one macroeconomic news announcement is associated with the jumps. We can notice that the largest jumps are matched at least one macroeconomic news announcements. When there is a big jump occurs in one FX market, it is quite possible see the jump which occurs in other markets too. We have

focused only on the scheduled news announcements but the unscheduled news exist in the markets. These unscheduled news have also significant effects on jumps.

Table 5.7 shows how closely exchange rates jumps match with the scheduled macroeconomic news announcement. There are 10,850 scheduled news announcement in total. Some of them are related to the jumps but some of them are not related to jumps.

Table 5.7: Descriptive statistics of jump and news (BNS Method)

	CHFJPY	GBPCHF	GBPJPY	USDCHE	USDJPY	USDTRY	EURCHF	EURGBP	EURJPY	EURTRY	EURUSD
# observations	735,264	735,264	735,264	735,264	735,264	735,264	735,264	735,264	735,264	735,264	735,264
# of days	2555	2555	2555	2555	2555	2555	2555	2555	2555	2555	2555
# news	10850	10850	10850	10850	10850	10850	10850	10850	10850	10850	10850
# news days	2355	2355	2355	2355	2355	2355	2355	2355	2355	2355	2355
P (news) %	0.922	0.922	0.922	0.922	0.922	0.922	0.922	0.922	0.922	0.922	0.922
# Jumps	1136	1198	1565	1155	1168	1450	1117	1381	1229	1258	1433
# Jumps-matches news	258	254	273	277	235	342	309	315	267	348	357
P (jump/news) (%)	2.38	2.34	2.52	2.55	2.17	3.15	2.85	2.90	2.46	3.21	3.29
P (News/Jump) (%)	22.71	21.20	17.44	23.98	20.12	23.59	27.66	22.81	21.72	27.66	24.91
P (jump/news) (%)	0.035	0.035	0.037	0.038	0.032	0.047	0.042	0.043	0.036	0.047	0.049

When we look at the descriptive statistics the probability of unconditional announcements is 0.92 %. It means that 0.92 % intraday intervals have at least one macroeconomic announcement occurrence. The critical question is that whether news announcements causes a jump? We calculate the occurrence of the jumps within the 30 minutes after the news announcement (calculated as # of the jump match news). EURUSD, EURTRY and USDTRY have the more jumps corresponding to the macroeconomic news announcements while the GBPCHE has the least number of matched-jumps, 254. $P\{jumps|news\}$ shows the probability of the jump conditional on a macroeconomist news announcement. The range for $\{jumps|news\}$ from 2.17 to 3.29 indicate that there is not a big differences between eleven currency pairs. $P\{news|jumps\}$ says how many jumps are related to the macroeconomic news

announcement. It is fluctuated from 17.44 % to 27.66 % and this results indicates that the many of the existing forex jumps probably emerge from the macroeconomic news announcement. The last part, $P\{jumps|news\}$ indicates that the percentage of the jump-news match within the total observation. The highest $P\{jumps|news\}$ rate is 0,049 and the lowest one is 0,032. This shows that there is not a big differences between the highest and lowest probabilities.

When we are examming the category of the news announcements, we realized that ABD Consumer Confidence, Bloomberg Global Confidence, ABD Employment Change, Business Climate index, New Home Sales, ECB announcement Interest Rate, CPI Ex Food and Energy, Current Account Balance, Labor Costs SA, Trade Balance, FOMC Rate Decision, BOJ Basic Balance Rate, Initial Job Claims, Chamber Votes Confidence on Deficit Cuts, House Price Index, General Government Debt and Bloomberg GDP Monthly Estimate have more potential relevance to the jumps.

Table 5.8 provides the more details about the how closely exchange rate jumps match the scheduled macroeconomic news announcement. In total, there are 10,850 scheduled news announcements. To clarify whether news announcement causes jumps, we should consider the lag effect of the announcements. It means that when the announcement occur the possible effect is utilized after or before the news announcement.

Table 5.8: Largest EURUSD Jumps matched with macroeconomic news

MERGE EURUSD WITH NEWS							
Time	Country	News	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
01.06.10 10:00	United States	ABD Consumer Confidence	0.534603	0.5300978	2.218841	0.3857545	0.854854
02.10.10 14:00	United States	Bloomberg Global Confidence	0.482391	0.8733484	0.1381038	0.0331457	0.2327889
01.04.11 14:20	United States	ABD Employment Change	1.267094	0.228312	0.26268	0.3487291	1.429528
01.07.11 04:00	China	Business Climate Index	1.363586	0.9343289	1.052548	1.10969	0.3957099
02.08.11 10:00	United States	New Home Sales	0.315577	1.140027	0.6688684	0.6887274	0.1378783
01.12.11 11:00	Eurozone	ECB Announcement Interest Rate	0.964051	0.7619185	0.8878731	0.8513959	2.419744
04.04.13 08:35	United States	CPI Ex Food and Energy	0.232815	3.366511	3.385785	0.969689	1.786926
12.07.16 09:45	France	Current Account Balance	1.02768	0.8020738	1.21229	0.8465937	0.5529328
12.09.16 09:00	Germany	Labor Costs SA QoQ	2.01471	0.3159773	0.8802566	0.3338352	1.588172
05.12.16 14:30	United States	Trade Balance	1.094689	3.141009	0.3551635	0.1333704	1.094689
01/17/11 14:25	United States	FOMC Rate Decision	0.531507	0.9104603	0.3176433	0.806296	0.0327121
01/29/16 07:38	Japan	BOJ Basic Balance Rate	1.963759	0.4420359	1.69314	3.67733	0.2846371
05/25/11 08:35	United States	Initial Job Claims	0.132368	0.7366009	1.361477	0.3367218	1.308521
07/27/10 16:00	Italy	Chamber Votes Confidence on Deficit Cuts	0.964835	0.2660378	0.6627792	0.2255138	0.3686878
12/13/16 11:30	United Kingdom	House Price Index YoY	0.116775	0.5893646	0.5316566	1.719844	0.3653325
12/15/16 11:30	Italy	General Government Debt	1.606214	1.655951	1.606214	0.3488216	0.6064087
20/01/15 10:00	China	Bloomberg GDP Monthly Estimate YoY	0.91323	1.0433784	1.0772075	0.8009661	0.84122

5.2 Co-Jumps between the dollar rates and corresponding cross pairs

In this section we define a co-jump when there are two or three jumps that occur at the same time among the two/three exchange rate pairs. Figure 5.9 and 5.11 shows the number of the co-jumps between currency pairs from 2010 to 2016 using BNS method. Table 5.11 shows the detail of frequency, detected co-jumps, percentage and conditional probabilities of co-jumps among exchange rates pairs detected from BNS test. The null hypothesis states that jumps are independent. If the null hypothesis is true, the probability of the co-jump should be zero. Result indicates that jumps are not independent so we reject the null hypothesis (jumps are independent). The co-jumps are positive for all the combinations. We investigate the conditional probability of co-jumps in dollar, euro or corresponding cross rates to show the jump dependency. We constructed four cases and explain the existing of the co-movements between currency pairs.

The first case explain the relationship between USD and TRY. Second case explain the core relationship between USD, EUR and CHF. GBP, USD and EUR relationship is discussed in case three. Lastly in case four we find out the USD, EUR and JPY pairs relationship. We used three frequencies 1-min, 5-min and 15-min for this analysis. The dollar rate EURUSD and the corresponding cross rate USDTRY have the largest number of co-jumps in 1-min frequencies.

Table 5.9: Descriptive statistics of co-jumps (1-Minute)

1-Minute						
Case 1 -All	#of observations	# of coj.	Pcoj %	P(coj jump) (%)		
				USDTRY	EURUSD	EURTRY
USDTRY-EURUSD	263643	19	0.0008857	6.01	11.27	-1
USDTRY-EURTRY	263643	77	0.0037714	24.74	-1.00	27.099
EURTRY-USDTRY	309582	77	0.0031571	24.74	-1.00	27.099
USDTRY-EURTRY-EURUSD	263643	7	0.0003429	2.30	4.18	2.499
Case 2 -All	#of observations	# of coj.	Pcoj %	P(coj jump) (%)		
				USDTRY	EURUSD	EURTRY
USDCHF-EURUSD	361593	55	0.002143	31.76	33.55	-1.00
USDCHF-USDJPY	361593	28	0.001100	15.30	-1.00	12.18
EURUSD-EURCHF	309582	10	0.000400	-1.00	6.99	5.57
EURUSD-EURCHF-USDCHF	366404	4	0.000157	1.81	1.92	2.27
Case 3 -All	#of observations	# of coj.	Pcoj %	P(coj jump) (%)		
				USDTRY	EURUSD	EURTRY
EURUSD-EURGBP	366404	27	0.0010429	12.82	18.01571429	-1
EURGBP-GBPCHF	360013	68	0.0027143	32.15	-1.00	31.22
EURUSD-GBPCHF	366404	17	0.0006571	-1.00	9.62	7.58
GBPCHF-EURGBP-EURUSD	369853	9	0.0003571	4.18	5.11	3.97
Case 4 -All	#of observations	# of coj.	Pcoj %	P(coj jump) (%)		
				USDTRY	EURUSD	EURTRY
USDJPY-EURUSD	353809	33	0.001300	13.83	18.36	-1
EURJPY-USDJPY	370055	45	0.001729	21.50	-1.00	27.89
EURUSD-EURJPY	366404	28	0.001100	-1.00	19.06	16.21
EURUSD-EURJPY-USDJPY	366404	7	0.000271	2.99	4.29	4.38

The USDTRY and the corresponding cross rate EURTRY have 77 co-jumps. There are also 7 co-jumps which occurs at the same time among the two dollar and cross and parallel cross rates. 9 co-jumps occur Euro and cross exchange rate in one frequency level.

The conditional probabilities of co-jumps in the dual exchange rate pairs change from 5.57 % to 32.15 %. The highest rate is detected between EURGBP and GBPCHF combination (32.15 % and 31.22 %) and the lowest one EURUSD and EURCHF combinations (6.99 % and 5.57 %). When we look at the conditional probabilities of trio

exchange rate pairs USDTRY-EURTRY-EURUSD, EURUSD-EURCHF-USDCHF, GBPCHF-EURGBP-EURUSD and EURUSD-EURJPY-USDJPY respectively we find a bit lower value ranging from 1.81 up to 4.38. These results shows that euro, dollar and corresponding cross rates are closely related each other and affect the other currency pairs. Table 5.10 shows the detail of 5-minutes frequency, detected co-jumps, percentage and conditional probabilities of co-jumps among exchange rates pairs detected from BNS test.

Table 5.10: Descriptive statistics of co-jumps (5-Minutes)

5-Minutes						
Case 1 -All	#of observations	# of coj.	Pcoj %	P(coj jump) (%)		
				USDTRY	EURUSD	EURTRY
USDTRY-EURUSD	91639	496	0.077829	49.31	47.15	-1.00
USDTRY-EURTRY	91639	611	0.093529	59.07	-1.00	64.63
EURTRY-USDTRY	91645	611	0.093529	59.07	-1.00	64.63
USDTRY-EURTRY-EURUSD	91639	347	0.055643	35.28	32.85	38.36
Case 2 -All	#of observations	# of coj.	Pcoj %	P(coj jump) (%)		
				USDCHF	EURUSD	EURCHF
USDCHF-EURUSD	104613	673	0.091857	65.73	63.83	-1.00
USDCHF-USDJPY	104613	528	0.072086	51.94	-1.00	49.65
EURUSD-EURCHF	91645	512	0.069929	-1.00	49.11	51.62
EURUSD-EURCHF-USDCHF	104613	359	0.049029	35.46	34.42	36.22
Case 3 -All	#of observations	# of coj.	Pcoj %	P(coj jump) (%)		
				EURGBP	EURUSD	GBPCHF
EURUSD-EURGBP	104613	562	0.076743	57.66	53.43	-1.00
EURGBP-GBPCHF	104613	603	0.082329	61.73	-1.00	64.83
EURUSD-GBPCHF	104613	513	0.070043	-1.00	48.87	55.23
GBPCHF-EURGBP-EURUSD	104613	369	0.050357	37.82	34.98	39.76
Case 4 -All	#of observations	# of coj.	Pcoj %	P(coj jump) (%)		
				USDJPY	EURUSD	EURJPY
USDJPY-EURUSD	104613	539	0.073600	50.69	51.43	-1.00
EURJPY-USDJPY	104613	605	0.082600	56.65	-1.00	61.29
EURUSD-EURJPY	104613	583	0.079586	-1.00	55.45	59.11
EURUSD-EURJPY-USDJPY	104613	358	0.048871	33.71	34.08	36.37

The dollar rate EURUSD and the corresponding cross rate USDCHF have the largest number of co-jumps of 673 in 5-minutes frequencies. EURUSD and corresponding USDTRY pairs have the lowest co-jump of 496. The sum of co-jumps and also jumps between dollar, euro and cross rates approximately equal in both testing methods, BNS and AJ. Five minutes frequencies is the appropriate frequencies to detect significant jumps and co-jumps. It is because when the macroeconomic news announced, we will see three effects. Pre news, news and post news effects. News affect the existing and timing of the jumps and co-jumps. So we can summaries that the significant jump and co-jump detection can be handle in 5 or 15 minutes frequencies instead of 1-minutes frequency (Andersen 2009, Barndorf-Nielsen and Shephard, 2005). We have more number of zero return days and noise in 1-minute frequency data.

When we look at the conditional probabilities of trio exchange rate pairs USDTRY-EURTRY-EURUSD, EURUSD-EURCHF-USDCHF, GBPCHF-EURGBP-EURUSD and EURUSD-EURJPY-USDJPY respectively we find ranging from 32.85 % up to 39.76 %. This results strongly display that euro, dollar and corresponding cross rates are closely related each other and affect the other currency pairs.

Table 5.11 shows the detail of 15-minutes frequency, detected co-jumps, percentage and conditional probabilities of co-jumps among exchange rates pairs detected from BNS test. The dollar rate EURUSD and the corresponding cross rate USDCHF have the largest number of co-jumps of 340 in 15-minutes frequencies as is in the previous analyses. EURUSD and corresponding EURCHF pairs have the lowest co-jump of 166. The sum of co-jumps and also jumps between dollar, euro and cross rates approximately equal in both testing methods, BNS and AJ.

Table 5.11: Descriptive statistics of co-jumps (15-Minutes)

15- Minutes						
Case 1 -All	#of observations	# of coj.	Pcoj %	P(coj jump) (%)		
				USDTRY	EURUSD	EURTRY
USDTRY-EURUSD	30547	186	0.095471	36.33	27.49	-1
USDTRY-EURTRY	30547	234	0.101357	38.82	-1.00	45.68
EURTRY-USDTRY	30549	234	0.101343	38.82	-1.00	45.68
USDTRY-EURTRY-EURUSD	30547	92	0.043171	16.41	13.48	20.89
Case 2 -All	#of observations	# of coj.	Pcoj %	P(coj jump) (%)		
				USDCHF	EURUSD	EURCHF
USDCHF-EURUSD	34871	340	0.139186	56.65	50.55	-1
USDCHF-USDJPY	34871	187	0.076586	31.77	-1.00	28.74
EURUSD-EURCHF	30549	166	0.068000	-1.00	25.15	31.90
EURUSD-EURCHF-USDCHF	34871	92	0.037657	15.27	13.54	17.54
Case 3 -All	#of observations	# of coj.	Pcoj %	P(coj jump) (%)		
				EURGBP	EURUSD	GBPCHF
EURUSD-EURGBP	34871	249	0.101971	46.18	37.10	-1.00
EURGBP-GBPCHF	34871	243	0.099486	45.45	-1.00	48.40
EURUSD-GBPCHF	34871	190	0.077800	-1.00	28.33	38.10
GBPCHF-EURGBP-EURUSD	34871	125	0.051143	22.95	18.03	24.87
Case 4 -All	#of observations	# of coj.	Pcoj %	P(coj jump) (%)		
				USDJPY	EURUSD	EURJPY
USDJPY-EURUSD	34871	224	0.091757	34.67	33.91	-1.00
EURJPY-USDJPY	34871	252	0.103186	38.41	-1.00	42.56
EURUSD-EURJPY	34871	283	0.115886	-1.00	42.80	47.78
EURUSD-EURJPY-USDJPY	34871	125	0.051186	19.30	18.76	21.04

When we look at the conditional probabilities of trio exchange rate pairs USDTRY-EURTRY-EURUSD, EURUSD-EURCHF-USDCHF, GBPCHF-EURGBP-EURUSD and EURUSD-EURJPY-USDJPY respectively we find ranging from 13.48 % up to 24.87 %. This results verify that euro, dollar and corresponding cross rates are closely related each other and affect the other currency pairs. Table 5.12 depicts the co-jumps and news relationship between currency pairs.

Table 5.12: Summary of dates and times, news of eleven currency pairs co-jumps together from 2010 to 2016.

Date	Time	5 Min Frequency jump size	News	Co-jumps pairs	List of the Foreign Exchange Rates co-jumps
01.06.10	10:00	0.9449793	ABD Consumer Confidence	5	EURUSD, USDCHF, USDJPY, USDTRY, EURTRY
02.10.10	14:00	0.5009884	Bloomberg Global Confidence	8	EURUSD, USDCHF, USDJPY, USDTRY, EURTRY, EURCHF, EURGBP, EURJPY
01.04.11	14:20	0.8471014	ABD Employment Change	11	EURUSD, USDCHF, USDJPY, USDTRY, EURTRY, EURCHF, EURGBP, EURJPY, EURTRY, GBPCHE, GBPJPY
01.07.11	4:00	0.4343213	Business Climate Index	4	EURUSD, USDTRY, USDJPY, USDCHF
02.08.11	10:00	1.67138	New Home Sales	11	EURUSD, USDCHF, USDJPY, USDTRY, EURTRY, EURCHF, EURGBP, EURJPY, EURTRY, GBPCHE, GBPJPY
01.12.11	11:00	0.6473476	ECB Announcement Interest Rate	6	GBPCHE, EURUSD, GBPJPY, EURTRY, USDTRY, EURJPY
04.04.13	8:35	0.6778346	CPI Ex Food and Energy	3	EURUSD, EURCHF, EURGBP
12.07.16	9:45	1.044866	Current Account Balance	11	EURUSD, USDCHF, USDJPY, USDTRY, EURTRY, EURCHF, EURGBP, EURJPY, EURTRY, GBPCHE, GBPJPY
12.09.16	9:00	1.100795	Labor Costs SA QoQ	6	GBPCHE, EURUSD, GBPJPY, EURTRY, USDTRY, EURJPY
05.12.16	14:30	1.716249	Trade Balance	11	EURUSD, USDCHF, USDJPY, USDTRY, EURTRY, EURCHF, EURGBP, EURJPY, EURTRY, GBPCHE, GBPJPY
01.17.2011	14:25	1.770236	FOMC Rate Decision	11	EURUSD, USDCHF, USDJPY, USDTRY, EURTRY, EURCHF, EURGBP, EURJPY, EURTRY, GBPCHE, GBPJPY
1.29.2016	12:00	0.9826409	BOJ Basic Balance Rate	3	USDJPY, EURJPY, GBPJPY,
5.25.2011	8:35	1.322415	Initial Job Claims	11	EURUSD, USDCHF, USDJPY, USDTRY, EURTRY, EURCHF, EURGBP, EURJPY, EURTRY, GBPCHE, GBPJPY
7.27.2010	16:00	1.586547	Chamber Votes Confidence on Deficit Cuts	3	USDJPY, EURJPY, GBPJPY,
12.13.2016	11:30	0.9026144	House Price Index YoY	6	EURUSD, USDCHF, USDTRY, EURTRY, EURGBP, GBPCHE
12.15.2016	11:30	0.620504	General Government Debt	11	EURUSD, USDCHF, USDJPY, USDTRY, EURTRY, EURCHF, EURGBP, EURJPY, EURTRY, GBPCHE, GBPJPY
20.01.2015	10:00	1.219037	Bloomberg GDP Monthly Estimate YoY	11	EURUSD, USDCHF, USDJPY, USDTRY, EURTRY, EURCHF, EURGBP, EURJPY, EURTRY, GBPCHE, GBPJPY

Andersen et.al (2007) find that the predictability in volatility is mainly related to continuous diffusion and that jumps are not important. In contrast to the univariate case,

predictability in average volatility across a group of assets can be linked to the occurrence of co-jumps. It is said that volatility rise subsequent to co-jump occurring. Another thing is that level of volatility doesn't influence the probability of co-jump occurring. However, the negative and positive jumps affect the volatility in different magnitudes. Table 5.13 shows how positive and negative jumps affect the historic volatilities. We obtained the values for different frequencies, 1-minute, 5-minute and 15 minute frequencies.

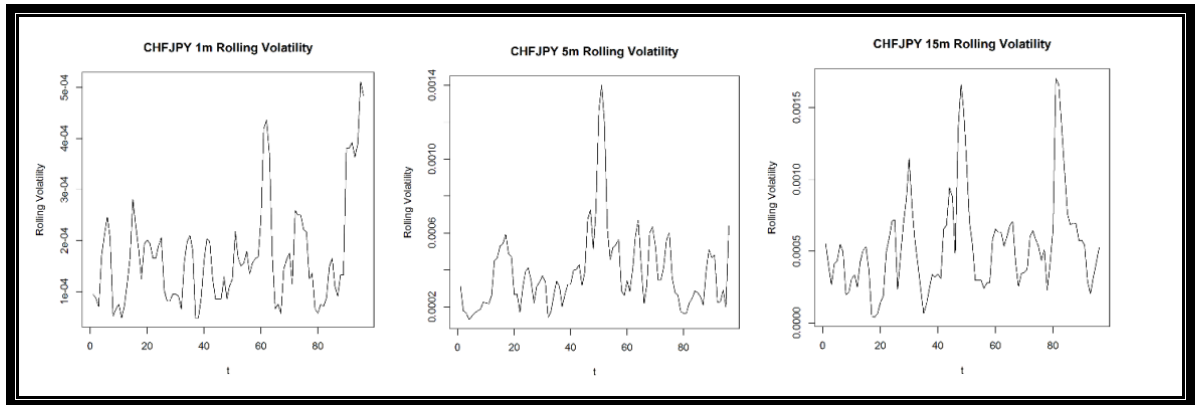
Table 5.13: Jumps effects on historical volatility (CHFJPY)

1-Minute	Volatility - CHFJPY
Historical volatility	0.1526596
Contribution of the positive jumps to volatility	0.5097592
Contribution of the negative jumps to volatility	0.4902408
5- Minute	Volatility - CHFJPY
Historical volatility	0.1527286
Contribution of the positive jumps to volatility	0.5115852
Contribution of the negative jumps to volatility	0.4884148
Frequency	
15- Minute	Volatility - CHFJPY
Historical volatility	0.1527285
Contribution of the positive jumps to volatility	0.5096721
Contribution of the negative jumps to volatility	0.4903279

Table 5.13 clearly shows that positive jumps have more effects on historic volatility. However, Table 6.25 indicates that the negative jumps have more effect on historic volatility¹³. It means that negative news have more effect than the positive ones in the market. As an example, we created the figure of rolling volatility of CHFJPY pair for last 100 values with different widths (5, 25, and 75 m).

¹³ See table 5.38

Figure 5.5: Rolling volatility (CHFJPY)



It can be summarized that the volatility is changing over time. There are the periods of low volatility and high volatility time. In the jump and co-jump detection parts we will see the effects of the changing volatility.

6.CONCLUSION

The first part of the dissertation concentrates on the conceptual framework and theory of the jumps and co-jumps. We present the quadratic variation and standard jump diffusion and jump detection models in which the price processes are separated as continuous and jump component. We have presented the ex post non-parametric metric of quadratic variation, realized variance and bipower variation which is robust to jump detection and also for estimating the continuous path variation. Our aim is to identify foreign exchange rate market jumps and co-jumps and to investigate how macroeconomic releases are related to these discontinuities. We use 1-min high frequency data on eleven exchange rates (CHFJPY, EURCHF, EURJPY, EURTRY, EURUSD, GBPCHE, GBPJPY, USDCHE, USDJPY, USDTRY and EURGBP) are investigated for six years from 2010 to 2016. We employ the Hausman type jump detection test proposed by Barndorff-Nielsen and Shephard (2006) this is based on the differences between realized variance and bipower variation and Ait-Sahalia and Jacod (2009) jump detection tests to detect intraday jumps for eleven exchange rate pairs and co-jumps for dollar, euro and corresponding cross pairs. Then we give attention to the co-jumps. Co-jumps results indicate that jumps are not independent between pairs.

Even though there is remarkable literature about jumps and co-jumps in financial markets, to our knowledge, no one has considered deeply their reactions to macroeconomic news announcements. The jump detection measure we use was proposed by Barndorff, Nielsen and Shephard (2009) and Ait-Sahalia-Jacod test (2010) remove any periodic patterns for robustness. More importantly, we apply the event study approach and news analysis to catch the news announcement effects within the 30 minutes after the announcement.

First, we find that jumps detection tests results are quite similar between BNS and AJ tests. The detected jumps are related to economic fundamentals, but jumps are only a small proportion of the sample news data. Jumps don't have long term memory. The effect is latent and disappears very quickly (mean reversion in the long term). Scheduled news announcements have significant effects on jumps. There are also speeches,

unscheduled news, but scheduled news is more influential because it is announced more frequently than speeches.

Secondly, scheduled news announcements related to employment, real activity monetary policy, current account have significant effects on jumps. ABD consumer confidence, Bloomberg global confidence, FOMC Rate Decision, ABD employment change, Business climate index, New home sales, ECB Announcement on interest rate, Current account balance, Labor costs, Trade balance, House price index, General government debt and GDP expectations show consistent effects on jumps and cojumps, which indicate the importance of the news about future expectations.

Thirdly, the null hypothesis that jumps are independent is rejected, as there are far more co-jumps than predicted by independence for all rate combinations. Some clustering of jumps and cojumps are also detected and can be related to the macroeconomic news announcements affecting the exchange rates.

Fourthly, Andersen et.al (2007) find that the predictability in volatility is mainly related to continuous diffusion and that jumps are not important. In contrast to the univariate case, predictability in average volatility across a group of assets can be linked to the occurrence of co-jumps. It is said that volatility rise subsequent to co-jump occurring. Another thing is that level of volatility doesn't influence the probability of co-jump occurring. However, the negative and positive jumps affect the volatility in different magnitudes.

Lastly, we choose one emerging market currency pairs and it is the first and comprehensive study includes an emerging market news and exchange rate data into the analysis. The results shows that emerging market countries is so sensitive and affect the low level of news besides the major market movements.

This dissertation clearly prove that jumps and co-jumps are the predictor of the discontinuities in foreign exchange rate markets. It is also proven that macroeconomic fundamentals have significant effect on jumps and co-jumps. There is a strong correlation between stock returns and jumps. This correlation is not only one signals that explain the comovements in that market. There are different metrics that affect the

comovements. The exact effect of the news can be realized in three stages. Pre-event, event and post-event time. We focussed on the event and post-event time in this dissertation and verify that post-event time have significant effect to match the jumps and co-jumps. The results of study can be used by finance practioners and researcher especially for behavioral finance cases. We find out the importance of jumps and co-jumps and their initial relation with the macroeconomic news announcements. Apart from this research we can extend our study to wavelet base new nonparametric tests by decomposing data into different time cycles and detect the arrival time of the jumps and co-jumps. We can apply this tests either in equity markets of bond markets too.



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Dissertations

Fan, R. (2016). Essays on Financial Econometrics: Co-jump detection and Density Forecasting, *Doctor of Philosophy in Accounting and Finance, Lancaster University Management School*.

Wang, J. (2015). Macroeconomic News Effects and Foreign Exchange Jumps, *Master of Science in Management (Finance, Goodman School of Business, Brock University*.

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APPENDIX



Appendix1: Descriptive statistic tables

Table 5.14: Statistical properties of Aith-Sahalia jumps detected from the test under the 95 % significance level from 2010 to 2016. (CHFJPY)

AJ-CHFJPY	1 Mins Frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	0.0001	0.0002	0.0004	0.0005	0.0005
Annualized SD	15.55	15.56	15.56	15.56	15.56
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1189	951	892	918	910
P (jump day) (%)	65.26	52.20	48.96	50.38	49.95
$E(\text{jumps} \text{jump day}) \%$	1.21	1.27	1.41	1.37	1.42
Number of Jumps	1433	1209	1257	1258	1289
P(jump) (%)	0.0006	0.002	0.005	0.010	0.02
$E(\text{jumpsize})$	3.283	2.1775	0.7822	0.6824	1.7313
# jump>0	698	586	626	605	656
P (jump>0) (%)	58.70	61.62	70.18	65.90	72.09
$SD(\text{jumpsize} \text{jump}>0)$	1.1273	0.00	0.00	0.00	1.2241
# jump<0	735	623	631	653	633
P (jump<0) (%) /P (jump>0) (%)	1.053	1.063	1.008	1.079	0.965
$SD(\text{jumpsize} \text{jump}<0)$	0.0009	0.1739	0.2352	0.1916	0.0499
% of negative jump	51.29	51.53	50.20	51.91	49.11
SD	1.32	1.44	1.41	1.41	1.39

Table 5.15: Statistical properties of Barndorff-Neielsen and Shephard jumps detected from the test under the 95 % significance level from 2010 to (CHFJPY)

BNS-S-CHFJPY	1 Minutes Frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	0.0001	0.0002	0.0006	0.0004	0.0003
Annualized SD	15.55	15.56	15.56	15.56	15.56
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1169	1169	1169	1161	1189
P (jump day) (%)	64.16	64.16	64.16	63.72	65.26
$E(\text{jumps} \text{jump day})$ (%)	0.97	1.14	1.15	1.08	1.12
Number of Jumps	1136	1330	1350	1258	1336
P(jump) (%)	0.0004	0.0018	0.0055	0.0103	0.0218
$E(\text{jumps} \text{size})$	0.0233	4.007	3.8375	4.3823	4.0759
# jump>0	565	672	756	598	623
P (jump>0) (%)	49.74	50.53	56.00	47.54	46.63
$SD(\text{jumps} \text{size} \text{jump}>0)$	0.0004	0.056	0.0056	5.351	2.5224
# jump<0	571	658	594	660	713
P (jump<0) (%) /P (jump>0) (%)	1.011	0.979	0.786	1.104	1.144
$SD(\text{jumps} \text{size} \text{jump}<0)$	8.6108	8.6108	8.6108	0.0639	2.9093
% of negative jump	50.26	49.47	44.00	52.46	59.97
SD	1.48	1.37	1.35	1.41	1.36

Table 5.16: Statistical properties of Aith-Sahalia jumps detected from the test under the 95 % significance level from 2010 to 2016 (GBPCHF)

AJ-GBPCHF	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 min
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	0.0001	0.0001	0.0003	0.0004	0.0003
Annualized SD	0.0937	0.0937	0.0935	0.0935	0.0935
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1047	1002	996	1103	1034
P (jump day) (%)	57.46	54.99	54.67	60.54	56.75
$E(\text{jumps} \text{jump day})$ (%)	1.14	1.30	1.22	0.84	1.20
Number of Jumps	1198	1301	1216	930	1242
P(jump) (%)	0.0005	0.0018	0.0050	0.0076	0.0203
$E(\text{jumpsizes})$	3.4256	0.9399	0.8011	0.6592	1.4565
# jump>0	543	651	563	429	439
P (jump>0) (%)	0.453	0.500	0.463	0.461	0.353
$SD(\text{jumpsizes} \text{jump}>0)$	0.0357	0.0073	0.0002	0.0063	0.9699
# jump<0	655	650	653	501	803
P (jump<0) (%) /P (jump>0) (%)	0.0253	0.0884	0.2664	1.0233	128.07 02
$SD(\text{jumpsizes} \text{jump}<0)$	1.8993	0.0005	0.0006	0.0001	0.0006
% of negative jump	54.67	49.96	53.70	53.87	64.65
SD	1.44	1.39	1.43	1.63	1.36

Table 5.17: Statistical properties of Barndorff-Neielsen and Shephard jumps detected from the test under the 95 % significance level from 2010 to 2016 (GBPCHF)

BNS-S-GBPCHF	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	0.0001	0.0001	0.0003	0.0004	0.0003
Annualized SD	0.0937	0.0937	0.0935	0.0935	0.0935
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1062	1172	997	1167	1112
P (jump day) (%)	58.29	64.32	54.72	64.05	61.03
$E(\text{jumps} \text{jump day})$ (%)	1.13	1.11	1.22	1.07	1.09
Number of Jumps	1198	1301	1216	1254	1216
P(jump) (%)	0.00046	0.00177	0.00496	0.01023	0.01985
$E(\text{jumps} \text{size})$	4.0767	4.007	3.8375	4.3823	4.0759
# jump>0	470	562	711	750	633
P (jump>0) (%)	0.0182	0.0764	0.2901	0.612	0.2492
$SD(\text{jumps} \text{size} \text{jump}>0)$	30.2844	0.0081	0.0049	0.0088	2.7059
# jump<0	728	739	505	504	583
P (jump<0) (%) /P (jump>0) (%)	0.0281	0.1005	0.206	0.4113	92.9293
$SD(\text{jumps} \text{size} \text{jump}<0)$	0.2965	0.0426	0	0.0002	0.0017
% of negative jump	60.77	56.80	41.53	40.19	47.94
SD	1.41	1.37	1.41	1.38	1.43

Table 5.18: Statistical properties of Aith-Sahalia jumps detected from the test under the 95 % significance level from 2010 to 2016 (GBPJPY)

AJ-GBPJPY	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	0.0001	0.0002	0.0004	0.0005	0.0003
Annualized SD	22.23	22.30	22.30	22.30	22.29
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1047	1011	953	943	969
P (jump day) (%)	57.46	55.49	52.31	51.76	53.18
$E(\text{jumps} \text{jump day})$ (%)	1.49	1.32	1.33	1.32	1.40
Number of Jumps	1565	1332	1269	1242	1354
P(jump) (%)	0.000605	0.001812	0.005178	0.010135	0.022098
$E(\text{jumps} \text{size})$	3.4128	0.9564	0.8135	0.675	1.4644
# jump>0	632	783	572	592	645
P (jump>0) (%)	0.0244	0.1065	0.2334	0.4831	0.2119
$SD(\text{jumps} \text{size} \text{jump}>0)$	0.0753	0.0025	0.0043	0.0018	0.8857
# jump<0	933	549	697	650	709
P (jump<0) (%) /P (jump>0) (%)	0.0361	0.0746	0.2844	0.5304	114.1707
$SD(\text{jumps} \text{size} \text{jump}<0)$	0.0013	0.0003	0.0002	0.0002	0.0002
% of negative jump	59.62	41.22	54.93	52.33	52.36
SD	1.24	1.35	1.40	1.42	1.36

Table 5.19: Statistical properties of Barndorff-Neielsen and Shephard jumps detected from the test under the 95 % significance level from 2010 to 2016 (GBPJPY)

BNS-S-GBPJPY	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	0.0001	0.0002	0.0004	0.0005	0.0003
Annualized SD	22.29	22.30	22.30	22.30	22.29
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1050	1081	1158	1159	1073
P (jump day) (%)	57.63	59.33	63.56	63.61	58.89
$E(\text{jumps} \text{jump day})$ (%)	1.49	1.23	1.10	1.07	1.15
Number of Jumps	1565	1332	1269	1242	1236
P(jump) (%)	0.000605	0.001812	0.005178	0.010135	0.020172
$E(\text{jumps} \text{size})$	2.6377	4.0399	3.9712	4.5376	3.7966
# jump>0	640	642	765	739	670
P (jump>0) (%)	0.0247	0.0873	0.3121	0.603	0.2568
$SD(\text{jumps} \text{size} \text{jump}>0)$	0.0037	0.0066	0.0076	0.011	2.503
# jump<0	925	690	504	503	566
P (jump<0) (%) /P (jump>0) (%)	0.0357	0.0938	0.2056	0.4105	91.0896
$SD(\text{jumps} \text{size} \text{jump}<0)$	0.0002	0.0074	0.0001	-0.0001	0.0001
% of negative jump	59.11	51.80	39.72	40.50	45.79
SD	1.24	1.37	1.37	1.39	1.42

Table 5.20: Statistical properties of Aith-Sahalia jumps detected from the test under the 95 % significance level from 2010 to 2016. (USDCHF)

AJ-USDCHF	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	0.0001	0.0002	0.0003	0.0004	0.0002
Annualized SD	0.0591	0.0598	0.0598	0.0598	0.0596
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1041	1002	986	974	1001
P (jump day) (%)	57.14	54.99	54.12	53.46	54.94
$E(\text{jumps} \text{jump day})$ (%)	1.11	1.36	1.30	1.34	1.27
Number of Jumps	1155	1358	1277	1302	1273
P(jump) (%)	0.000446	0.001847	0.005210	0.010625	0.020776
$E(\text{jumps} \text{size})$	3.5736	0.9492	0.7184	0.6433	1.4711
# jump>0	571	617	0	704	473
P (jump>0) (%)	0.0226	0.0839	0	0.0574	0.041
$SD(\text{jumps} \text{size} \text{jump}>0)$	0.0255	0.0095	0	0.0148	1.0113
# jump<0	584	741	1277	598	800
P (jump<0) (%) /P (jump>0) (%)	0.0023	0.1008	0.521	0.488	122.8879
$SD(\text{jumps} \text{size} \text{jump}<0)$	0.0017	0.0003	0.0002	0.0001	0
% of negative jump	50.56	54.57	100.00	45.93	62.84
SD	1.47	1.35	0.00	1.38	1.35

Table 5.21: Statistical properties of Barndorff-Neielsen and Shephard jumps detected from the test under the 95 % significance level from 2010 to 2016. (USDCHE)

BNS-S-USDCHE	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	0.0001	0.0002	0.0003	0.0004	0.0002
Annualized SD	0.0591	0.0598	0.0598	0.0598	0.0596
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1049	1015	1064	986	1021
P (jump day) (%)	57.57	55.71	58.40	54.12	56.04
$E(\text{jumps} \text{jump day})$ (%)	1.10	1.34	1.20	1.32	1.40
Number of Jumps	1155	1358	1277	1302	1429
P(jump) (%)	0.000446	0.001847	0.005210	0.010625	0.023322
$E(\text{jumps} \text{size})$	3.078	4.0795	4.1017	4.6956	3.9887
# jump>0	573	716	576	797	826
P (jump>0) (%)	0.0226	0.1847	0.235	0.6504	0.2732
$SD(\text{jumps} \text{size} \text{jump}>0)$	0.0058	0.0107	0.0032	0.0129	2.6273
# jump<0	582	642	701	505	603
P (jump<0) (%) /P (jump>0) (%)	0.023	0	0.286	0.4121	92.6267
$SD(\text{jumps} \text{size} \text{jump}<0)$	0.0003	0.0003	0.0079	0.0001	0.0001
% of negative jump	50.39	47.28	54.89	38.79	42.20
SD	1.47	1.35	1.39	1.35	1.31

Table 5.22: Statistical properties of Aith-Sahalia jumps detected from the test under the 95 % significance level from 2010 to 2016. (USDJPY)

AJ-USDJPY	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	0.0002	0.0002	0.0003	0.0004	0.0002
Annualized SD	15.01	15.07	15.07	15.07	15.05
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	994	1005	1001	1081	1023
P (jump day) (%)	54.56	55.16	54.94	59.33	56.15
$E(\text{jumps} \text{jump day})$ (%)	1.26	1.15	1.00	1.23	1.17
Number of Jumps	1253	1158	1001	1332	1193
P(jump) (%)	0.000484	0.001575	0.004084	0.010870	0.019471
$E(\text{jumps} \text{size})$	3.7458	2.1873	2.0068	4.0399	2.995
# jump>0	724	553	641	642	640
P (jump>0) (%)	0.0292	0.0755	0.2615	0.0873	0.1134
$SD(\text{jumps} \text{size} \text{jump}>0)$	0.0004	0.0005	0.0032	0.0066	2.0376
# jump<0	529	605	360	690	553
P (jump<0) (%) /P (jump>0) (%)	0.0214	0.0823	0.1469	0.0938	83.033
$SD(\text{jumps} \text{size} \text{jump}<0)$	0.001	0.0001	0.0001	0.0074	0.0033
% of negative jump	42.22	52.25	35.96	51.80	46.35
SD	1.40	1.47	1.52	1.37	1.44

Table 5.23: Statistical properties of Barndorff-Neielsen and Shephard jumps detected from the test under the 95 % significance level from 2010 to 2016. (USDJPY)

BNS-S-USDJPY	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	0.00004	0.0002	0.0003	0.0004	0.0002
Annualized SD	15.006	15.071	15.071	15.071	15.055
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1063	1256	1028	1011	1090
P (jump day) (%)	58.34	68.94	56.42	55.49	59.82
$E(\text{jumps} \text{jump day})$ (%)	1.10	1.13	1.03	1.32	1.14
Number of Jumps	1168	1413	1057	1332	1241
P(jump) (%)	0.000451	0.001922	0.004313	0.010870	0.020254
$E(\text{jumps} \text{size})$	3.1996	4.175	4.7986	0.9564	3.2824
# jump>0	693	811	764	783	763
P (jump>0) (%)	0.028	0.1103	0.3117	0.1065	0.1391
$SD(\text{jumps} \text{size} \text{jump}>0)$	0.0007	0.0093	0.0024	0.0025	2.2226
# jump<0	475	602	293	549	478
P (jump<0) (%) /P (jump>0) (%)	0.0192	0.0819	0.1195	0.0746	71.7718
$SD(\text{jumps} \text{size} \text{jump}<0)$	0.0008	0.0043	0.0025	0.0003	0.032
% of negative jump	40.67	42.60	27.72	41.22	38.52
SD	1.44	1.32	1.38	1.35	1.38

Table 5.24: Statistical properties of Aith-Sahalia jumps detected from the test under the 95 % significance level from 2010 to 2016. (USDTRY)

AJ-USDTRY	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	0.0001	0.0002	0.0003	0.0004	0.0003
Annualized SD	0.5189	0.5166	0.5166	0.5166	0.5166
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1212	1001	1015	1002	1006
P (jump day) (%)	66.52	54.94	55.71	54.99	55.21
$E(\text{jumps} \text{jump day})$ (%)	1.20	1.38	1.24	1.36	1.35
Number of Jumps	1458	1383	1263	1358	1356
P(jump) (%)	0.000563	0.001881	0.005153	0.011082	0.022131
$E(\text{jumps} \text{size})$	3.635	2.1238	3.4398	0.9492	2.5369
# jump>0	806	734	651	617	702
P (jump>0) (%)	0.0437	0.1139	0.303	0.0839	0.1361
$SD(\text{jumps} \text{size} \text{jump}>0)$	0.0007	0.0007	0.0005	0.0095	1.6976
# jump<0	652	649	612	741	654
P (jump<0) (%) /P (jump>0) (%)	0.0353	0.1007	0.2849	0.1008	96.3181
$SD(\text{jumps} \text{size} \text{jump}<0)$	0.0006	0.0001	412373	0.0003	0.0016
% of negative jump	44.72	46.93	48.46	54.57	48.23
SD	1.30	1.34	1.41	1.35	1.36

Table 5.25: Statistical properties of Barndorff-Neielsen and Shephard jumps detected from the test under the 95 % significance level from 2010 to 2016. (USDTRY)

BNS-S-USDTRY	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	0.0001	0.0002	0.0003	0.0004	0.0003
Annualized SD	0.5189	0.5166	0.5166	0.5166	0.5171
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1070	1252	1047	1015	1096
P (jump day) (%)	58.73	68.72	57.46	55.71	60.15
$E(\text{jumps} \text{jump day})$ (%)	1.36	1.17	1.20	1.24	1.25
Number of Jumps	1450	1466	1258	1263	1368
P(jump) (%)	0.000560	0.001994	0.005133	0.010307	0.022327
$E(\text{jumps} \text{size})$	3.5099	3.3499	3.4926	3.4398	3.448
# jump>0	794	686	755	651	722
P (jump>0) (%)	0.043	0.1064	0.3081	0.303	0.1901
$SD(\text{jumps} \text{size} \text{jump}>0)$	0.0006	0.0003	0.0004	0.0005	2.3037
# jump<0	656	780	503	612	646
P (jump<0) (%) /P (jump>0) (%)	0.0355	0.121	0.2052	0.2849	47.2222
$SD(\text{jumps} \text{size} \text{jump}<0)$	0.0006	0.0041	0.0014	412373	0.0007
% of negative jump	45.24	53.21	39.98	48.46	47.22
SD	1.31	1.30	1.38	1.41	1.35

Table 5.26: Statistical properties of Aith-Sahalia jumps detected from the test under the 95 % significance level from 2010 to 2016. (EURCHF)

AJ-EURCHF	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	0.0001	0.0001	0.0002	0.0003	0.0002
Annualized SD	0.102	0.1021	0.1021	0.1021	0.1021
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1071	1003	993	1167	1058
P (jump day) (%)	58.78	55.05	54.50	64.05	58.07
$E(\text{jumps} \text{jump day})$ (%)	1.38	1.35	1.21	1.07	1.25
Number of Jumps	1477	1355	1204	1254	1323
P(jump) (%)	0.000571	0.001843	0.004913	0.010233	0.021592
$E(\text{jumps} \text{size})$	3.3163	1.0488	0.8042	4.3823	2.3879
# jump>0	701	643	597	750	673
P (jump>0) (%)	0.0283	0.0875	0.2436	0.612	0.2428
$SD(\text{jumps} \text{size} \text{jump}>0)$	0.0002	0.0075	0.0105	0.0088	1.5168
# jump<0	776	712	607	504	650
P (jump<0) (%) /P (jump>0) (%)	0.0313	0.0968	0.2477	0.4113	103.6284
$SD(\text{jumps} \text{size} \text{jump}<0)$	0.0013	0.0003	0.0002	0.0002	0.0005
% of negative jump	52.54	52.55	50.42	40.19	49.13
SD	1.30	1.36	1.44	1.38	1.37

Table 5.27: Statistical properties of Barndorff-Neielsen and Shephard jumps detected from the test under the 95 % significance level from 2010 to 2016. (EURCHF)

BNS-S-EURCHF	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	0.0001	0.0001	0.0002	0.0003	0.0002
Annualized SD	0.102	0.1021	0.1021	0.1021	0.1021
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1032	1014	1008	1172	1056
P (jump day) (%)	56.64	55.65	55.32	64.32	57.96
$E(\text{jumps} \text{jump day})$ (%)	1.08	1.34	1.19	1.11	1.18
Number of Jumps	1117	1355	1204	1301	1244
P(jump) (%)	0.000432	0.001843	0.004913	0.010617	0.020303
$E(\text{jumps} \text{size})$	2.7185	3.3207	3.5934	4.007	3.4099
# jump>0	542	743	678	562	631
P (jump>0) (%)	0.0209	0.1011	0.2766	0.0764	0.1187
$SD(\text{jumps} \text{size} \text{jump}>0)$	0.0024	0.0029	0.0028	0.0081	2.3272
# jump<0	575	612	526	739	613
P (jump<0) (%) /P (jump>0) (%)	0.0222	0.0824	0.2146	0.1005	94.2352
$SD(\text{jumps} \text{size} \text{jump}<0)$	0.0003	0.003	0.0001	0.0426	0.0001
% of negative jump	51.48	45.17	43.69	56.80	49.28
SD	1.50	1.35	1.43	1.37	1.42

Table 5.28: Statistical properties of Aith-Sahalia jumps detected from the test under the 95 % significance level from 2010 to 2016. (EURGBP)

AJ-EURGBP	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	0.0001	0.0001	0.0003	0.0004	0.0002
Annualized SD	0.0502	0.0501	0.0501	0.0501	0.0501
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1006	1001	997	983	996
P (jump day) (%)	55.21	54.94	54.72	53.95	54.67
$E(\text{jumps} \text{jump day})$ (%)	1.25	1.14	1.22	1.33	1.16
Number of Jumps	1260	1143	1216	1307	1158
P(jump) (%)	0.000487	0.001555	0.004961	0.010666	0.018899
$E(\text{jumps})$	3.709	2.127	3.8375	3.9435	3.4043
# jump>0	683	516	711	704	653
P (jump>0) (%)	0.0271	0.0702	0.2901	0.5745	0.2405
$SD(\text{jumps} \text{jump}>0)$	0.0063	0.0075	0.0049	0.0048	2.2371
# jump<0	577	627	505	603	505
P (jump<0) (%) /P (jump>0) (%)	0.0229	0.0853	0.206	0.4921	77.2762
$SD(\text{jumps} \text{jump}<0)$	0.0009	0.0001	0	0.0006	0.0046
% of negative jump	45.79	54.86	41.53	46.14	43.61
SD	1.40	1.47	1.41	1.38	1.46

Table 5.29: Statistical properties of Barndorff-Neielsen and Shephard jumps detected from the test under the 95 % significance level from 2010 to 2016. (EURGBP)

BNS-S-EURGBP	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	0.0001	0.0001	0.0003	0.0004	0.0002
Annualized SD	0.0502	0.0501	0.0501	0.0501	0.0501
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1050	1086	1045	1055	1059
P (jump day) (%)	57.63	59.60	57.35	57.90	58.12
$E(\text{jumps} \text{jump day})$ (%)	1.32	1.22	1.18	1.19	1.23
Number of Jumps	1381	1326	1233	1252	1298
P(jump) (%)	0.000534	0.001803	0.005031	0.010217	0.021184
$E(\text{jumps} \text{size})$	2.8432	3.4258	3.6271	3.858	3.4386
# jump>0	723	715	618	646	676
P (jump>0) (%)	0.0287	0.0972	0.2522	0.5272	0.2263
$SD(\text{jumps} \text{size} \text{jump}>0)$	0.0007	0.0006	0.0034	0.0036	2.2714
# jump<0	658	611	615	606	622
P (jump<0) (%) /P (jump>0) (%)	0.0261	0.0831	0.2509	0.4945	99.361
$SD(\text{jumps} \text{size} \text{jump}<0)$	0.0008	0.0001	0.0002	0.0002	0.0026
% of negative jump	47.65	46.08	49.88	48.40	47.92
SD	1.34	1.37	1.42	1.41	1.39

Table 5.30: Statistical properties of Aith-Sahalia jumps detected from the test under the 95 % significance level from 2010 to 2016. (EURJPY)

AJ-EURJPY	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	0.0005	0.0008	0.0003	0.0004	0.0005
Annualized SD	1.3549	1.5866	1.5896	1.5236	1.5136
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	892	1103	1015	1002	1003
P (jump day) (%)	48.96	60.54	55.71	54.99	55.05
$E(\text{jumps} \text{jump day})$ (%)	1.41	1.14	1.09	0.98	1.12
Number of Jumps	1257	1254	1103	986	1121
P(jump) (%)	0.000486	0.001706	0.004500	0.008046	0.018295
$E(\text{jumps} \text{size})$	0.7822	0.6592	1.1369	1.2951	0.9684
# jump>0	596	630	485	490	493
P (jump>0) (%)	0.6492	0.6184	0.6592	0.7184	0.3444
$SD(\text{jumps} \text{size} \text{jump}>0)$	0.0007	0.0006	0.0034	0.0036	0.4412
# jump<0	661	624	618	496	628
P (jump<0) (%) /P (jump>0) (%)	0.5129	1.0233	0	0	127.3327
$SD(\text{jumps} \text{size} \text{jump}<0)$	0.2352	0.0211	0.0352	0.00321	0.0211
% of negative jump	52.59	49.76	56.03	50.30	56.02
SD	1.41	1.41	1.49	1.59	1.48

Table 5.31: Statistical properties of Barndorff-Neielsen and Shephard jumps detected from the test under the 95 % significance level from 2010 to 2016. (EURJPY)

BNS-S-EURJPY	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	0.0005	0.0008	0.0003	0.0004	0.0005
Annualized SD	1.3549	1.5866	1.5896	1.5236	1.5896
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1121	1068	1013	1025	1057
P (jump day) (%)	61.53	58.62	55.60	56.26	58.01
$E(\text{jumps} \text{jump day})$	1.10	1.32	1.11	1.14	1.19
Number of Jumps	1229	1415	1129	1173	1260
P(jump) (%)	0.000475	0.001924	0.004607	0.009572	0.020564
$E(\text{jumps} \text{size})$	3.5099	3.3499	3.4926	3.4398	3.448
# jump>0	573	635	726	561	623
P (jump>0) (%)	0.0355	0.121	0.2052	0.2849	0.1617
$SD(\text{jumps} \text{size} \text{jump}>0)$	0.0006	0.0041	0.0014	412373	2.3238
# jump<0	656	780	503	612	637
P (jump<0) (%) /P (jump>0) (%)	0.043	0.1064	0.3081	0.303	117.0956
$SD(\text{jumps} \text{size} \text{jump}<0)$	0.0006	0.0003	0.0004	0.0005	0.0014
% of negative jump	53.38	55.12	44.55	52.17	50.56
SD	1.42	1.32	1.48	1.46	1.41

Table 5.32: Statistical properties of Aith-Sahalia jumps detected from the test under the 95 % significance level from 2010 to 2016. (EURTRY)

AJ-EURTRY	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	2.7851	2.5342	2.328	2.4475	2.5237
Annualized SD	5.4236	5.8752	5.5733	5.5537	5.6064
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1081	1172	1161	1167	1145
P (jump day) (%)	59.33	64.32	63.72	64.05	62.84
$E(\text{jumps} \text{jump day})$ (%)	1.23	1.11	1.08	1.07	1.12
Number of Jumps	1332	1301	1258	1254	1286
P(jump) (%)	0.000515	0.001769	0.005133	0.010233	0.020988
$E(\text{jumps} \text{size})$	4.0399	4.007	3.9769	4.3823	4.1015
# jump>0	642	562	1255	750	802
P (jump>0) (%)	0.0873	0.0764	1.0241	0.612	0.45
$SD(\text{jumps} \text{size} \text{jump}>0)$	0.0066	0.0081	0.0 056	0.0088	2.5821
# jump<0	690	739	3	504	484
P (jump<0) (%) /P (jump>0) (%)	0.0938	0.1005	0.0024	0.4113	77.193
$SD(\text{jumps} \text{size} \text{jump}<0)$	0.0074	0.0426	0.0639	0.0002	1.0369
% of negative jump	51.80	56.80	0.24	40.19	37.64
SD	1.37	1.37	0.14	1.38	1.35

Table 5.33: Statistical properties of Barndorff-Neielsen and Shephard jumps detected from the test under the 95 % significance level from 2010 to 2016. (EURTRY)

BNS-S-EURTRY	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	2.7851	2.5342	2.328	2.4475	2.5237
Annualized SD	5.4236	5.8752	5.5733	5.5537	5.6064
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1047	1014	1212	1025	1074
P (jump day) (%)	57.46	55.65	66.52	56.26	58.95
$E(\text{jumps} \text{jump day})$	1.20	1.34	1.20	1.00	1.14
Number of Jumps	1258	1355	1452	1028	1219
P(jump) (%)	0.000486	0.001843	0.005924	0.008389	0.019895
$E(\text{jumps} \text{size})$	3.4926	3.3207	3.635	1.0282	2.8691
# jump>0	755	743	806	296	576
P (jump>0) (%)	0.3081	0.1011	0.0437	0.0335	1.3128
$SD(\text{jumps} \text{size} \text{jump}>0)$	0.0004	0.0029	0.0007	0.00021	1.1004
# jump<0	503	612	652	732	643
P (jump<0) (%) /P (jump>0) (%)	0.2052	0.0824	0.0353	0.8294	0.745
$SD(\text{jumps} \text{size} \text{jump}<0)$	0.0014	0.003	0.0006	293	0.0024
% of negative jump	39.98	45.17	44.90	71.21	52.75
SD	1.38	1.35	1.31	1.41	1.43

Table 5.34: Statistical properties of Aith-Sahalia jumps detected from the test under the 95 % significance level from 2010 to 2016. (EURUSD)

AJ-EURUSD	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	7.6844	7.6422	7.6874	7.6443	7.6646
Annualized SD	11.5643	11.5687	11.5598	11.5561	11.5622
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1159	1011	1172	943	1071
P (jump day) (%)	63.61	55.49	64.32	51.76	58.78
E (jumps jump day) (%)	1.07	1.32	1.11	1.32	1.19
Number of Jumps	1242	1332	1301	1242	1279
P(jump) (%)	0.000480	0.001812	0.005308	0.010135	0.020874
$E(\text{jumpsizes})$	4.5376	0.9564	4.007	0.675	2.544
# jump>0	739	783	562	592	669
P (jump>0) (%)	0.603	0.1065	0.0764	0.4831	0.3173
$SD(\text{jumpsizes} \text{jump}>0)$	0.011	0.0025	0.0081	0.0018	1.5746
# jump<0	503	549	739	650	610
P (jump<0) (%) /P (jump>0) (%)	0.4105	0.0746	0.1005	0.5304	47.6935
$SD(\text{jumpsizes} \text{jump}<0)$	-0.0001	0.0003	0.0426	0.0002	0.0007
% of negative jump	40.50	41.22	56.80	52.33	47.69
SD	1.39	1.35	1.37	1.42	1.40

Table 5.35: Statistical properties of Barndorff-Neielsen and Shephard jumps detected from the test under the 95 % significance level from 2010 to 2016. (EURUSD)

BNS-S-EURUSD	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
Number of Observation	2,587,655.00	735,264	245,088	122,544	61,272
$E(\text{abs}(\text{return}))$	7.6844	7.6422	7.6874	7.6443	7.6646
Annualized SD	11.5643	11.5687	11.5598	11.5561	11.5622
Number of sample days	1822	1822	1822	1822	1822
Number of Jumps days	1189	997	1161	1189	1134
P (jump day) (%)	65.26	54.72	63.72	65.26	62.24
$E(\text{jumps} \text{jump day})$	1.21	1.22	1.08	1.21	1.18
Number of Jumps	1433	1216	1258	1433	1336
P(jump) (%)	0.000554	0.001654	0.005133	0.011694	0.021804
$E(\text{jumps} \text{size})$	3.283	3.8375	3.9769	3.283	3.5951
# jump>0	659	711	662	686	493
P (jump>0) (%)	0.0003	0.2901	1.0241	0.0003	0.3287
$SD(\text{jumps} \text{size} \text{jump}>0)$	1.1273	0.0049	5.351	1.1273	2.3097
# jump<0	774	505	596	747	843
P (jump<0) (%) /P (jump>0) (%)	0.055	0.206	0.0024	0.055	117.6553
$SD(\text{jumps} \text{size} \text{jump}<0)$	0.0009	0	0.0639	0.0009	1.0364
% of negative jump	54.01	41.53	47.38	52.13	63.10
SD	1.32	1.41	1.41	1.32	1.32

Appendix 2: Largest jumps matched with news

Table 5.36: Largest jumps matched with news

<i>MERGE CHFJPY WITH NEWS</i>							
Time	Country	News	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins frequency
01.06.10 10:00	United States	ABD Consumer Confidence	2.677583	1.808263	1.022943	0.5358015	0.823621
02.10.10 14:00	United States	Bloomberg Global Confidence	NaN	1.689658	1.34498	1.239979	1.908919
01.04.11 14:20	United States	ABD Employment Change	NaN	0.4862441	0.955195	0.6233285	1.733799
01.07.11 07:00	China	Business Climate Index	0	2.442956	0.5685295	0.5316973	1.820767
02.08.11 10:00	United States	New Home Sales	0	1.59133	0.9629749	0.800329	5.077511
01.12.11 11:00	Eurozone	ECB Announcement Interest Rate	NaN	1.381138	1.299344	0.9949653	3.355934
04.04.13 08:35	United States	CPI Ex Food and Energy	0	1.354607	0.878621	0.6402647	1.931517
12.07.16 09:45	France	Current Account Balance	0	1.981512	0.6905749	0.8715381	1.413067
12.09.16 09:00	Germany	Labor Costs SA QoQ	0	2.694689	0.7469912	0.5505121	2.741538
05.12.16 14:30	United States	Trade Balance	NaN	2.674344	0.8301228	1.086301	5.939251
01/17/11 14:25	United States	FOMC Rate Decision	NaN	2.617873	1.576505	0.8876158	4.936264
01/29/16 07:38	Japan	BOJ Basic Balance Rate	NaN	0.955202	0.6709429	0.7379923	2.574998
05/25/11 08:35	United States	Initial Job Claims		2.128805	1.332891	1.356992	2.295772
07/27/10	Italy	Chamber Votes		4.046138	1.320276	1.144623	4.447026

16:00		Confidence on Deficit Cuts					
12/13/16 11:30	United Kingdom	House Price Index YoY	NaN	1.493831	1.286894	1.501672	2.848709
12/15/16 11:30	Italy	General Government Debt	0	2.964723	1.681903	1.128281	3.957624
20/01/15 10:00	China	Bloomberg GDP Monthly Estimate YoY	NaN	0.2424834	0.7395015	0.6521066	0.216174
MERGE EURUCHF WITH NEWS							
Time	Country	News	1 Minutes Frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
01.06.10 10:00	United States	ABD Consumer Confidence	0.632405	0.005942	0.744331	0.1557106	0.3577964
02.10.10 14:00	United States	Bloomberg Global Confidence	0.891568	1.240773	1.893371	0.23966	0.1850452
01.04.11 14:20	United States	ABD Employment Change	1.393607	0.4139196	1.908731	0.0727915	1.006539
01.07.11 07:00	China	Business Climate Index	0.354817	0.0076933	1.052548	1.10969	0.3957099
02.08.11 10:00	United States	New Home Sales	0.315577	1.140027	0.6688684	0.6887274	0.1378783
01.12.11 11:00	Eurozone	ECB Announcement Interest Rate	0.964051	0.7619185	0.8878731	0.8513959	2.419744
04.04.13 08:35	United States	CPI Ex Food and Energy	0.232815	3.366511	3.385785	0.969689	1.786926
12.07.16 09:45	France	Current Account Balance	1.02768	0.8020738	1.21229	0.8465937	0.5529328
12.09.16 09:00	Germany	Labor Costs SA QoQ	2.01471	0.3159773	0.8802566	0.3338352	1.588172
05.12.16 14:30	United States	Trade Balance	1.094689	3.141009	0.3551635	0.1333704	1.094689
01/17/11 14:25	United States	FOMC Rate Decision	0.531507	0.9104603	0.3176433	0.806296	0.0327121
01/29/16	Japan	BOJ Basic Balance	1.963759	0.4420359	1.69314	3.67733	0.2846371

07:38		Rate					
05/25/11 08:35	United States	Initial Job Claims	0.132368	0.7366009	1.361477	0.3367218	1.308521
07/27/10 16:00	Italy	Chamber Votes Confidence on Deficit Cuts	0.964835	0.2660378	0.1652634	0.2255138	0.3686878
12/13/16 11:30	United Kingdom	House Price Index YoY	0.116775	0.5893646	0.5316566	1.719844	0.3653325
12/15/16 11:30	Italy	General Government Debt	1.606214	1.655951	1.606214	0.3488216	0.6064087
20/01/15 10:00	China	Bloomberg GDP Monthly Estimate YoY	0.889836	0.9872684	1.1665382	0.7822494	0.780733
MERGE EURJPY WITH NEWS							
Time	Country	News	1 Minutes Frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
01.06.10 10:00	United States	ABD Consumer Confidence	1.113071	0.947948	0.8075807	0.4977662	0.2368028
02.10.10 14:00	United States	Bloomberg Global Confidence	0	1.072317	0.6808325	0.546855	0.3198409
01.04.11 14:20	United States	ABD Employment Change	NaN	1.900611	0.5029607	0.3712547	0.141688
01.07.11 07:00	China	Business Climate Index	0	1.080112	0.4773785	0.3343579	0
02.08.11 10:00	United States	New Home Sales	NaN	0.9743975	0.5456769	0.4697015	0.292047
01.12.11 11:00	Eurozone	ECB Announcement Interest Rate	0	1.090614	0.8415482	0.3312164	0.1831954
04.04.13 08:35	United States	CPI Ex Food and Energy	0	0.8140177	0.4816223	0.2566762	0.2005645
12.07.16 09:45	France	Current Account Balance	NaN	1.191422	0.33103	0.2786898	0.2012242
12.09.16 09:00	Germany	Labor Costs SA QoQ	0	1.291223	0.5490371	0.2996072	0.2980112
05.12.16	United	Trade Balance	NaN	1.573817	0.8632273	0.5253144	1.155016

14:30	States						
01/17/11 14:25	United States	FOMC Rate Decision	0	1.209838	0.6625083	0.5373366	0.2982549
01/29/16 07:38	Japan	BOJ Basic Balance Rate	0	0.5513732	0.2837499	0.2457712	0.1586813
05/25/11 08:35	United States	Initial Job Claims	0	1.482305	0.6028146	0.4881937	0.211721
07/27/10 16:00	Italy	Chamber Votes Confidence on Deficit Cuts	0	1.798742	0.7175443	0.3422058	0.2848542
12/13/16 11:30	United Kingdom	House Price Index YoY	NaN	1.378787	0.5729726	0.2617555	0.1754545
12/15/16 11:30	Italy	General Government Debt	0	0.9591918	0.6505612	0.4158493	0.206812
20/01/15 10:00	China	Bloomberg GDP Monthly Estimate YoY	0	1.2072948	0.5981903	0.3876595	0.272761
MERGE EURTRY WITH NEWS							
Time	Country	News	1 Minutes Frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
01.06.10 10:00	United States	ABD Consumer Confidence	0.248101	0.3524401	0.2464933	0.3380177	0.433485
02.10.10 14:00	United States	Bloomberg Global Confidence	1.237088	0.7569492	0.9449107	1.218638	0.613457
01.04.11 14:20	United States	ABD Employment Change	0.24688	0.3113504	0.2142025	0.4102144	0.0961012
01.07.11 07:00	China	Business Climate Index	1.108098	0.8206144	0.255078	0.8055347	0.7597388
02.08.11 10:00	United States	New Home Sales	1.288808	2.116666	0.6823401	1.153886	0.3368461
01.12.11 11:00	Eurozone	ECB Announcement Interest Rate	0.223499	0.2217626	1.183176	1.199905	0.878881
04.04.13 08:35	United States	CPI Ex Food and Energy	0.495023	3.021884	1.752643	0.0264569	0.8881998
12.07.16	France	Current Account	0.87831	1.454131	0.477085	0.8689777	5.302542

09:45		Balance					
12.09.16 09:00	Germany	Labor Costs SA QoQ	0.052409	2.620026	1.183143	0.6412325	1.020939
05.12.16 14:30	United States	Trade Balance	0.5592	0.8090505	0.4440329	0.2174984	0.5592002
01/17/11 14:25	United States	FOMC Rate Decision	0.452995	0.5903235	2.131172	1.137337	0.8392225
01/29/16 07:38	Japan	BOJ Basic Balance Rate	0.998381	1.036709	0.065537	0.3997965	0.9134242
05/25/11 08:35	United States	Initial Job Claims	0.195306	1.707424	0.6477883	0.4705741	1.11295
07/27/10 16:00	Italy	Chamber Votes Confidence on Deficit Cuts	0.24688	1.108098	1.288808	0.223499	0.495023
12/13/16 11:30	United Kingdom	House Price Index YoY	0.95163	3.529082	0.5102289	2.491334	3.648937
12/15/16 11:30	Italy	General Government Debt	0.742155	1.504822	0.742155	1.18347	1.237603
20/01/15 10:00	China	Bloomberg GDP Monthly Estimate YoY	0.394977	0.2168588	0.2940182	0.2481009	0.35244
MERGE EURUSD WITH NEWS							
Time	Country	News	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
01.06.10 10:00	United States	ABD Consumer Confidence	0.534603	0.5300978	2.218841	0.3857545	0.854854
02.10.10 14:00	United States	Bloomberg Global Confidence	0.482391	0.8733484	0.1381038	0.0331457	0.2327889
01.04.11 14:20	United States	ABD Employment Change	1.267094	0.228312	0.26268	0.3487291	1.429528
01.07.11 04:00	China	Business Climate Index	1.363586	0.9343289	1.052548	1.10969	0.3957099
02.08.11 10:00	United States	New Home Sales	0.315577	1.140027	0.6688684	0.6887274	0.1378783
01.12.11	Eurozon	ECB Announcement	0.964051	0.7619185	0.8878731	0.8513959	2.419744

11:00	e	Interest Rate					
04.04.13 08:35	United States	CPI Ex Food and Energy	0.232815	3.366511	3.385785	0.969689	1.786926
12.07.16 09:45	France	Current Account Balance	1.02768	0.8020738	1.21229	0.8465937	0.5529328
12.09.16 09:00	Germany	Labor Costs SA QoQ	2.01471	0.3159773	0.8802566	0.3338352	1.588172
05.12.16 14:30	United States	Trade Balance	1.094689	3.141009	0.3551635	0.1333704	1.094689
01/17/11 14:25	United States	FOMC Rate Decision	0.531507	0.9104603	0.3176433	0.806296	0.0327121
01/29/16 07:38	Japan	BOJ Basic Balance Rate	1.963759	0.4420359	1.69314	3.67733	0.2846371
05/25/11 08:35	United States	Initial Job Claims	0.132368	0.7366009	1.361477	0.3367218	1.308521
07/27/10 16:00	Italy	Chamber Votes Confidence on Deficit Cuts	0.964835	0.2660378	0.6627792	0.2255138	0.3686878
12/13/16 11:30	United Kingdom	House Price Index YoY	0.116775	0.5893646	0.5316566	1.719844	0.3653325
12/15/16 11:30	Italy	General Government Debt	1.606214	1.655951	1.606214	0.3488216	0.6064087
20/01/15 10:00	China	Bloomberg GDP Monthly Estimate YoY	0.91323	1.0433784	1.0772075	0.8009661	0.84122
MERGE EURGBP WITH NEWS							
Time	Country	News	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
01.06.10 10:00	United States	ABD Consumer Confidence	4.481091	1.447614	0.317247	0.2194816	0.28884
02.10.10 14:00	United States	Bloomberg Global Confidence	0	0.5171242	0.2777124	0.2039603	0.1461753
01.04.11 14:20	United States	ABD Employment Change	NaN	0.6836075	0.5450141	0.2989256	0.1814299
01.07.11	China	Business Climate	0	0.8051679	0.3251232	0.2258226	0

07:00		Index					
02.08.11 10:00	United States	New Home Sales	NaN	1.471465	0.6775461	0.3829199	0.2512924
01.12.11 11:00	Eurozone	ECB Announcement Interest Rate	0	1.386355	0.8957686	0.4277052	0.1801601
04.04.13 08:35	United States	CPI Ex Food and Energy	0	0.842733	0.3328012	0.3248661	0.246871
12.07.16 09:45	France	Current Account Balance	NaN	0.9253202	0.784905	0.3767777	0.1637321
12.09.16 09:00	Germany	Labor Costs SA QoQ	0	1.033479	0.7263814	0.4780707	0.3015584
05.12.16 14:30	United States	Trade Balance	NaN	0.8595207	0.3273857	0.2637544	0.2250991
01/17/11 14:25	United States	FOMC Rate Decision	0	1.306785	0.7323222	0.3755049	0.3102806
01/29/16 07:38	Japan	BOJ Basic Balance Rate	0	1.190027	0.7461996	0.5588106	0.2826944
05/25/11 08:35	United States	Initial Job Claims	0	1.121126	0.4587055	0.329803	0.2531219
07/27/10 16:00	Italy	Chamber Votes Confidence on Deficit Cuts	0	1.765638	0.8286105	0.4629925	0.2220443
12/13/16 11:30	United Kingdom	House Price Index YoY	NaN	1.128712	0.5822086	0.3009976	0.2266656
12/15/16 11:30	Italy	General Government Debt	0	0.7473674	0.6489107	0.3866756	0.2306338
20/01/15 10:00	China	Bloomberg GDP Monthly Estimate YoY	0	1.0770026	0.5754276	0.3510668	0.219412
MERGE USDCHE WITH NEWS							
Time	Country	News	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
01.06.10 10:00	United States	ABD Consumer Confidence	0.589793	0.5915187	0.4414635	0.4254734	0.2135139
02.10.10	United	Bloomberg Global Confidence	0	0.8505536	0.5026469	0.2380626	0.2631958

14:00	States						
01.04.11 14:20	United States	ABD Employment Change	NaN	0.5852114	0.6813772	0.3691216	0.3080816
01.07.11 04:00	China	Business Climate Index	0	0.6069204	0.3508933	0.3846779	0
02.08.11 10:00	United States	New Home Sales	NaN	1.380978	0.5403354	0.3827607	0.1689028
01.12.11 11:00	Eurozone	ECB Announcement Interest Rate	0	1.340526	0.6064839	0.5010179	0.1639197
04.04.13 08:35	United States	CPI Ex Food and Energy	0	0.4313515	0.4545822	0.3048581	0.1952992
12.07.16 09:45	France	Current Account Balance	NaN	1.515519	0.4948714	0.2216324	0.1428249
12.09.16 09:00	Germany	Labor Costs SA QoQ	0	1.49355	0.8280149	0.3107331	0.2649941
05.12.16 14:30	United States	Trade Balance	NaN	1.285778	0.4983337	0.372663	0.5746575
01/17/11 14:25	United States	FOMC Rate Decision	0	1.570946	0.697302	0.4186344	0.2025203
01/29/16 07:38	Japan	BOJ Basic Balance Rate	0	1.318095	0.5442556	0.3331339	0.2305522
05/25/11 08:35	United States	Initial Job Claims	0	0.9471668	0.5458675	0.4441512	0.1955072
07/27/10 18:00	Italy	Chamber Votes Confidence on Deficit Cuts	0	0.8147188	0.5593999	0.2448379	0.1385312
12/13/16 11:30	United Kingdom	House Price Index YoY	NaN	1.864404	0.8165192	0.4375526	0.1973109
12/15/16 11:30	Italy	General Government Debt	0	0.5084241	0.5034408	0.3820838	0.204541
20/01/15 10:00	China	Bloomberg GDP Monthly Estimate YoY	0	1.0691038	0.5666117	0.3607122	0.216522
MERGE GBPJPY WITH NEWS							
Time	Country	News	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency

01.06.10 10:00	United States	ABD Consumer Confidence	0.115864	0.659293	0.804615	0.3469988	0.2977998
02.10.10 14:00	United States	Bloomberg Global Confidence	0	1.226798	0.4627143	0.3072788	0.2683954
01.04.11 14:20	United States	ABD Employment Change	NaN	0.5868664	0.6878315	0.356399	0.1806944
01.07.11 07:00	China	Business Climate Index	0	0.7669563	0.3957143	0.3474079	0
02.08.11 10:00	United States	New Home Sales	NaN	1.169059	0.7443996	0.3514597	0.2054164
01.12.11 11:00	Eurozone	ECB Announcement Interest Rate	0	1.375112	0.8155033	0.4547871	0.2402102
04.04.13 08:35	United States	CPI Ex Food and Energy	0	0.626612	0.3955141	0.2337964	0.1784352
12.07.16 09:45	France	Current Account Balance	NaN	1.22311	0.6151846	0.3425897	0.19585
12.09.16 09:00	Germany	Labor Costs SA QoQ	0	0.2864698	0.5288324	1.630944	1.113721
05.12.16 14:30	United States	Trade Balance	0	0.5696246	0.5999084	0.3239311	0.239247
01/17/11 14:25	United States	FOMC Rate Decision	0	0.8938619	0.776691	0.4240309	0.32463
01/29/16 07:38	Japan	BOJ Basic Balance Rate	0	0.7172132	0.7284114	0.3742607	0.361591
05/25/11 08:35	United States	Initial Job Claims	NaN	0.962156	0.5553011	0.3191098	0.207245
07/27/10 16:00	Italy	Chamber Votes Confidence on Deficit Cuts	0	0.8703914	0.6912038	0.2938091	0
12/13/16 11:30	United Kingdom	House Price Index YoY	NaN	0.997912	0.4215553	0.3529091	0.91818
12/15/16 11:30	Italy	General Government Debt	NaN	0.4565409	0.6925639	0.5273478	0.282071
20/01/15 10:00	China	Bloomberg GDP Monthly Estimate YoY	NaN	0.7738557	0.97344	0.7080695	0.301233
MERGE USDTRY WITH NEWS							

Time	Country	News	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
01.06.10 10:00	United States	ABD Consumer Confidence	0	0.3360535	0.2611807	0.07656	41661.07
02.10.10 14:00	United States	Bloomberg Global Confidence	0	0.3662937	1.2870824	0.5293192	0.349246
01.04.11 14:20	United States	ABD Employment Change	0	1.047134	0.7095957	0.5289168	0.2791025
01.07.11 07:00	China	Business Climate Index	NaN	1.054141	0.4094552	0.2807814	NaN
02.08.11 10:00	United States	New Home Sales	NaN	2.091088	0.5937615	0.4066014	0.2233688
01.12.11 11:00	Eurozone	ECB Announcement Interest Rate	NaN	1.614178	0.7806683	0.5794842	0.2540234
04.04.13 08:35	United States	CPI Ex Food and Energy	0	0.5338818	0.4217498	0.3128293	0.1815154
12.07.16 09:45	France	Current Account Balance	NaN	1.302592	0.5192686	0.24345	0.1660869
12.09.16 09:00	Germany	Labor Costs SA QoQ	0	0.8445402	0.3968231	0.3000086	0.3063803
05.12.16 14:30	United States	Trade Balance	NaN	1.903374	0.539537	0.2613124	0.5028593
01/17/11 14:25	United States	FOMC Rate Decision	NaN	0.9856224	0.5594889	0.3039608	0.1940311
01/29/16 07:38	Japan	BOJ Basic Balance Rate	0	1.467547	0.5980132	0.5227028	0.2981753
05/25/11 08:35	United States	Initial Job Claims	0	1.07386	0.4744266	0.2813298	0.2027769
07/27/10 16:00	Italy	Chamber Votes Confidence on Deficit Cuts	0	1.2400702	0.5202878	0.3538592	0.226275
12/13/16 11:30	United Kingdom	House Price Index YoY	0	0.434954	0.3535186	0.2760026	0.178929
12/15/16 11:30	Italy	General Government Debt	0	1.064008	0.6757146	0.4620979	0.2198213
20/01/15	China	Bloomberg GDP		0.702594	1.5232948	1.0436546	0.72986

10:00		Monthly Estimate YoY					
MERGE USDJPY WITH NEWS							
Time	Country	News	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
01.06.10 10:00	United States	ABD Consumer Confidence	0.10485	0.5968675	0.6421076	0.3614299	0.2832553
02.10.10 14:00	United States	Bloomberg Global Confidence	0	0.80224	0.6380514	0.2830023	0.240756
01.04.11 14:20	United States	ABD Employment Change	NaN	1.25609	0.7519191	0.2557739	0.2842288
01.07.11 04:00	China	Business Climate Index	0	0.4214701	0.3106177	0.2122833	0
02.08.11 10:00	United States	New Home Sales	NaN	1.01124	0.5096994	0.3199915	0.208146
01.12.11 11:00	Eurozone	ECB Announcement Interest Rate	0	1.544931	0.6579035	0.3701715	0.1584806
04.04.13 08:35	United States	CPI Ex Food and Energy	0	0.6287236	0.398435	0.2223278	0.1508007
12.07.16 09:45	France	Current Account Balance	NaN	1.138424	0.6245858	0.3583573	0.1672901
12.09.16 09:00	Germany	Labor Costs SA QoQ	0	0.9061456	0.3668901	0.2093075	0.2299282
05.12.16 14:30	United States	Trade Balance	NaN	1.536235	0.7428006	0.4823222	0.9373503
01/17/11 14:25	United States	FOMC Rate Decision	0	0.582694	0.5886908	0.2846369	0.266359
01/29/16 07:38	Japan	BOJ Basic Balance Rate	0	1.095924	0.3335174	0.3960948	0.2167726
05/25/11 08:35	United States	Initial Job Claims	0	1.590708	0.696802	0.3791066	0.2433128
07/27/10 16:00	Italy	Chamber Votes Confidence on Deficit Cuts	0	0.9694887	0.4271361	0.3438791	0.233272
12/13/16 11:30	United Kingdom	House Price Index YoY	NaN	1.199324	0.4130199	0.6537581	0.1906521

12/15/16 11:30	Italy	General Government Debt	0	1.693581	1.853243	0.489651	0.2451936
20/01/15 10:00	China	Bloomberg GDP Monthly Estimate YoY	0	1.0608804	0.6222137	0.3513809	0.253487
MERGE GBPCHF WITH NEWS							
Time	Country	News	1 Minutes frequency	5 Mins Frequency	15 Mins Frequency	30 mins Frequency	60 mins Frequency
01.06.10 10:00	United States	ABD Consumer Confidence	0.668035	0.9449793	0.5821608	0.3262238	0.2493985
02.10.10 14:00	United States	Bloomberg Global Confidence	0	0.5009884	0.2733435	0.1944016	0.1390646
01.04.11 14:20	United States	ABD Employment Change	NaN	0.8471014	0.7089553	0.2297215	0.1528966
01.07.11 04:00	China	Business Climate Index	0	0.4343213	0.2894447	0.1955916	0
02.08.11 10:00	United States	New Home Sales	NaN	1.67138	0.7758765	0.5314592	0.1590333
01.12.11 11:00	Eurozone	ECB Announcement Interest Rate	0	0.6473476	0.5256289	0.340649	0.1635592
04.04.13 08:35	United States	CPI Ex Food and Energy	0	0.6778346	0.4678457	0.3659911	0.2846353
12.07.16 09:45	France	Current Account Balance	NaN	1.044866	0.6626982	0.4923278	0.1697749
12.09.16 09:00	Germany	Labor Costs SA QoQ	0	1.100795	0.6134076	0.4148856	0.2017797
05.12.16 14:30	United States	Trade Balance	NaN	1.716249	0.4582363	0.3525547	0.3606081
01/17/11 14:25	United States	FOMC Rate Decision	0	1.770236	1.108722	0.4916125	0.2131027
01/29/16 07:38	Japan	BOJ Basic Balance Rate	0	0.9826409	0.7080472	0.5346875	0.2496104
05/25/11 08:35	United States	Initial Job Claims	0	1.322415	0.6136982	0.4291049	0.1740007
07/27/10 16:00	Italy	Chamber Votes Confidence on	0	1.586547	0.579282	0.2895575	0.2636148

		Deficit Cuts					
12/13/16 11:30	United Kingdom	House Price Index YoY	NaN	0.9026144	0.368947	0.2341749	0.1805327
12/15/16 11:30	Italy	General Government Debt	0	0.620504	1.157239	0.3256268	0.1968014
20/01/15 10:00	China	Bloomberg GDP Monthly Estimate YoY	0	1.219037	0.9372473	0.3146131	0.181009



Table 5.37: Macroeconomic News

Country	Macroeconomic News
United States	ADP Employment Change
United States	Avg Hourly Earning MOM Prod
United States	Avg Weekly Hours Production
United States	Business Inventories
United States	Change in Nonfarm Payrolls
United States	Chicago Purchasing Manager
United States	Construction Spending MoM
United States	Consumer Confidence Index
United States	FOMC Rate Decision
United States	Empire Manufacturing
United States	Factory Orders
United States	Existing Home Sales
United States	GDP Annualized QoQ - Advance
United States	GDP Annualized QoQ -Preliminary
United States	Housing Starts
United States	IBD/TIPP Economic Optimism
United States	Import Price Index MoM
United States	Industrial Production MoM
United States	Initial Jobless Claims
United States	ISM Manufacturing
United States	ISM Milwaukee
United States	ISM Non-Manf. Composite
United States	Net Long-term TIC Flows
United States	Minutes of FOMC Meeting
United States	NAHB Housing Market Index
United States	New Home Sales
United States	Nonfarm Productivity - Final
United States	Nonfarm Productivity -Preliminary
United States	PCE Core MoM
United States	Pending Home Sales MoM
United States	Personal Consumption -Preliminary
United States	Personal Spending
United States	Philadelphia Fed Business Outlook
United States	PPI Ex Food and Energy MoM
United States	PPI MoM
United States	Retail Sales Ex Auto MoM
United States	Trade Balance
United States	Unemployment Rate
United States	Univ. of Michigan Confidence -Preliminary

United States	Wholesale Inventories MoM
United Kingdom	Bank of England Bank Rate
United Kingdom	CPI Core YoY
United Kingdom	CPI MoM
United Kingdom	GDP QoQ - Advance
United Kingdom	Industrial Production MoM
United Kingdom	Nationwide House PX MoM
United Kingdom	Retail Price Index
United Kingdom	Retail Sales Ex Auto YoY
United Kingdom	RPI Ex Mort Int.Payments (YoY)
United Kingdom	RPI MoM
United Kingdom	Total Business Investment QoQ-Preliminary
United Kingdom	Visible Trade Balance GBP/Mn
Spain	CPI EU Harmonised YoY - Final
Spain	CPI MoM
Spain	Retail Sales WDA YoY
Spain	Unemployment Rate
Japan	GDP Nominal SA QoQ -Preliminary
Japan	Housing Starts YoY
Japan	Retail Trade YoY
Italy	Business Confidence
Italy	GDP WDA QoQ - Final
Italy	GDP WDA QoQ - Preliminary
Italy	Industrial Production WDA YoY
Italy	Retail Sales MoM
Italy	Total investments
Italy	Trade Balance Total
Italy	Unemployment Rate Quarterly
Germany	Construction Investment QoQ
Germany	Exports QoQ
Germany	Factory Orders WDA YoY -Preliminary
Germany	GDP SA QoQ - Preliminary
Germany	IFO Business Climate

Germany	Imports QoQ
Germany	Industrial Production SA MoM -Preliminary
Germany	PPI MoM
Germany	Private Consumption QoQ
Germany	Retail Sales MoM
Germany	Unemployment Rate
Germany	ZEW Survey Current Situation
Germany	ZEW Survey Expectations
France	Consumer Spending (MoM)
France	Own-Company Production Outlook
France	PPI MoM
Eurozone	Business Climate Indicator
Eurozone	CPI Core YoY - Final
Eurozone	CPI Estimate YoY
Eurozone	ECB Announces Interest Rates
Eurozone	GDP SA QoQ - Final
Eurozone	Govt Expend QoQ - Preliminary
Eurozone	Gross Fix Cap QoQ - Final
Eurozone	Gross Fix Cap QoQ -Preliminary
Eurozone	Household Cons QoQ -Preliminary
Eurozone	Industrial New Orders SA MoM
Eurozone	Industrial Production SA MoM
Eurozone	Labour Costs YoY
Eurozone	PMI Manufacturing -Preliminary
Eurozone	Retail Sales MoM
Eurozone	Trade Balance SA
Eurozone	ZEW Survey Expectations
Turkey	Benchmark Repurchase Rate
Turkey	Capacity Utilization
Turkey	Central Gov't Budget Balance
Turkey	Consumer Confidence Index
Turkey	CPI Core Index YoY
Turkey	Effective Exchange Rate
Turkey	Foreign Tourist Arrivals YoY
Turkey	Foreigners Net Bond Invest
Turkey	Foreigners Net Stock Invest
Turkey	GDP SA/WDA QoQ
Turkey	GDP WDA YoY
Turkey	GDP YoY
Turkey	Home Sales
Turkey	Home Sales (YoY)
Turkey	House Price Index MoM

Turkey	Industrial Production YoY
Turkey	Markit/ISO Turkey PMI Mfg
Turkey	Overnight Borrowing Rate
Turkey	Overnight Lending Rate
Turkey	Real Sector Confidence NSA
Turkey	Real Sector Confidence SA
Switzerland	Credit Suisse Survey Expectations
Switzerland	Domestic Sight Deposits CHF
Switzerland	Employment Level
Switzerland	Employment Level (YoY)
Switzerland	Exports Real MoM
Switzerland	Foreign Currency Reserves
Switzerland	Imports Real MoM
Switzerland	Industrial Production (QoQ)
Switzerland	KOF Leading Indicator
Switzerland	Money Supply M3 YoY
Switzerland	PMI Manufacturing
Switzerland	Producer & Import Prices MoM
Switzerland	Producer & Import Prices YoY
Switzerland	Real Estate Index Family Homes
Switzerland	Retail Sales Real YoY
Switzerland	SECO 2012-2014 Economic Forecasts for Switzerland (Table)
Switzerland	SECO Consumer Confidence
Switzerland	SNB 3-Month Libor Target Rate
Switzerland	SNB 3-Month Libor Upper Target Range
Switzerland	SNB Sight Deposit Interest Rate
Switzerland	Total Sight Deposits CHF
Switzerland	UBS Consumption Indicator
Switzerland	UBS Real Estate Bubble Index
Switzerland	Unemployment Rate SA
China	Aggregate Financing CNY
China	Bloomberg GDP Monthly Estimate YoY
China	Business Climate Index
China	Exports YoY CNY
China	Fixed Assets Ex Rural YTD YoY
China	Foreign Direct Investment YoY
China	Foreign Direct Investment YoY CNY
China	Foreign Reserves
China	GDP YTD YoY
China	Imports YoY
China	Imports YoY CNY
China	Industrial Production YTD YoY

China	Industrial Profits YoY
China	Industrial Profits YTD YoY
China	Leading Index
China	Manufacturing PMI
China	Money Supply M0 YoY
China	Money Supply M1 YoY
China	Money Supply M2 YoY
China	New Yuan Loans CNY
China	Non-manufacturing PMI
China	Producer Price Index YTD YoY
China	Purchasing Price Index (YoY)
China	Reserve Requirement (Major Ban
China	Retail Sales YTD YoY
China	Swift Global Payments CNY
China	Trade Balance CNY

Table 5.38: Jumps effects on historical volatility

Frequency	Volatility - CHFJPY
1-Minute	
Historical volatility	0.1526596
Contribution of the positive return to volatility	0.5097592
Contribution of the negative return to volatility	0.4902408
Frequency	Volatility - CHFJPY
5- Minute	
Historical volatility	0.1527286
Contribution of the positive return to volatility	0.5115852
Contribution of the negative return to volatility	0.4884148
Frequency	Volatility - CHFJPY
15- Minute	
Historical volatility	0.1527285
Contribution of the positive return to volatility	0.5096721
Contribution of the negative return to volatility	0.4903279
Frequency	Volatility - EURCHF
1-Minute	
Historical volatility	0.08392786
Contribution of the positive return to volatility	0.007891785
Contribution of the negative return to volatility	0.9921082
Frequency	Volatility - EURCHF
5- Minute	
Historical volatility	0.08392786
Contribution of the positive return to volatility	0.007891785
Contribution of the negative return to volatility	0.9921082
Frequency	Volatility - EURCHF
15- Minute	
Historical volatility	0.08391687
Contribution of the positive return to volatility	0.005919771
Contribution of the negative return to volatility	0.9940802
Frequency	Volatility -EURGBP
1-Minute	

Historical volatility	0.06286822
Contribution of the positive return to volatility	0.09850497
Contribution of the negative return to volatility	0.901495
Frequency	Volatility - EURGBP
5- Minute	
Historical volatility	0.06259186
Contribution of the positive return to volatility	0.09989191
Contribution of the negative return to volatility	0.9001081
Frequency	Volatility - EURGBP
15- Minute	
Historical volatility	0.06259212
Contribution of the positive return to volatility	0.09736719
Contribution of the negative return to volatility	0.9026328
Frequency	Volatility -EURJPY
1-Minute	
Historical volatility	0.1118647
Contribution of the positive return to volatility	0.3948045
Contribution of the negative return to volatility	0.6051955
Frequency	Volatility - EURJPY
5- Minute	
Historical volatility	0.1118421
Contribution of the positive return to volatility	0.3957836
Contribution of the negative return to volatility	0.6042164
Frequency	Volatility - EURJPY
15- Minute	
Historical volatility	0.111842
Contribution of the positive return to volatility	0.3929732
Contribution of the negative return to volatility	0.6070268
Frequency	Volatility - EURTRY
1-Minute	
Historical volatility	0.1525408
Contribution of the positive return to volatility	0.9718117
Contribution of the negative return to	0.02818831

volatility	
Frequency	Volatility - EURTRY
5- Minute	
Historical volatility	0.1513294
Contribution of the positive return to volatility	0.9793499
Contribution of the negative return to volatility	0.02065012
Frequency	Volatility - EURTRY
15- Minute	
Historical volatility	0.1513279
Contribution of the positive return to volatility	0.9794827
Contribution of the negative return to volatility	0.02051729
Frequency	Volatility -EURUSD
1-Minute	
Historical volatility	0.09136049
Contribution of the positive return to volatility	0.09382457
Contribution of the negative return to volatility	0.9061754
Frequency	Volatility - EURUSD
5- Minute	
Historical volatility	0.09126967
Contribution of the positive return to volatility	0.09585422
Contribution of the negative return to volatility	0.9041458
Frequency	Volatility - EURUSD
15- Minute	
Historical volatility	0.09127082
Contribution of the positive return to volatility	0.09475624
Contribution of the negative return to volatility	0.9052438
Frequency	Volatility -GBPCHF
1-Minute	
Historical volatility	0.06497978
Contribution of the positive return to volatility	0.1011009
Contribution of the negative return to volatility	0.8988991
Frequency	Volatility - GBPCHF
5- Minute	
Historical volatility	0.0647916

Contribution of the positive return to volatility	0.09691506
Contribution of the negative return to volatility	0.9030849
Frequency	Volatility - GBPCHE
15- Minute	
Historical volatility	0.0647914
Contribution of the positive return to volatility	0.0987781
Contribution of the negative return to volatility	0.9012219
Frequency	Volatility -GBPJPY
1-Minute	
Historical volatility	0.146178
Contribution of the positive return to volatility	0.5545485
Contribution of the negative return to volatility	0.4454515
Frequency	Volatility - GBPJPY
5- Minute	
Historical volatility	0.1462252
Contribution of the positive return to volatility	0.5555899
Contribution of the negative return to volatility	0.4444101
Frequency	Volatility - GBPJPY
15- Minute	
Historical volatility	0.1462251
Contribution of the positive return to volatility	0.5555824
Contribution of the negative return to volatility	0.4444176
Frequency	Volatility - USDCHE
1-Minute	
Historical volatility	0.06173561
Contribution of the positive return to volatility	0.3792466
Contribution of the negative return to volatility	0.6207534
Frequency	Volatility - USDCHE
5- Minute	
Historical volatility	0.06250947
Contribution of the positive return to volatility	0.3765144
Contribution of the negative return to volatility	0.6234856

Frequency	Volatility - USDCHF
15- Minute	
Historical volatility	0.06251041
Contribution of the positive return to volatility	0.3767034
Contribution of the negative return to volatility	0.6232966
Frequency	Volatility - USDJPY
1-Minute	
Historical volatility	0.1535607
Contribution of the positive return to volatility	0.494735
Contribution of the negative return to volatility	0.505265
Frequency	Volatility - USDJPY
5- Minute	
Historical volatility	0.1545301
Contribution of the positive return to volatility	0.5075793
Contribution of the negative return to volatility	0.4924207
Frequency	Volatility - USDTRY
15- Minute	
Historical volatility	0.1545303
Contribution of the positive return to volatility	0.5075502
Contribution of the negative return to volatility	0.4924498
Frequency	Volatility - USDTRY
1-Minute	
Historical volatility	0.2252296
Contribution of the positive return to volatility	0.9993548
Contribution of the negative return to volatility	0.0006451981
Frequency	Volatility - USDTRY
5- Minute	
Historical volatility	0.2261588
Contribution of the positive return to volatility	0.9991919
Contribution of the negative return to volatility	0.0008080986