# Currency strategies and their risk factors

**Auteur :** Akbel, Yasin
**Promoteur(s) :** Muller, Aline
**Faculté :** HEC-Ecole de gestion de l'ULg
**Diplôme :** Master en ingénieur de gestion, à finalité spécialisée en Financial Engineering
**Année académique :** 2015-2016
**URI/URL :** http://hdl.handle.net/2268.2/1411

# CURRENCY STRATEGIES AND THEIR RISK FACTORS

Jury:
Promoter:
Aline MULLER
Reader(s):
Tarik BAZGOUR
Federico PLATANIA

Dissertation by
**Yasin AKBEL**
For a Master's degree in Business Engineering with a specialization in Financial Engineering

Academic year 2015/2016

# Acknowledgements

*The writing of this master thesis would have not been imaginable without the previous advices, the encouragement and the patience of my family and friends. I particularly thank my friends in HEC-Liège for their support throughout my 5 years of study.*

*Before starting this master thesis, I would like to give a singular acknowledgement to several persons who helped me in the dissertation of this thesis:*

- *First, I thank my promoter, Mrs. Aline MULLER, for her valuable advices, her guidelines and also the fact she gave me the opportunity to carry out this thesis.*
- *I'm also grateful to my two readers, Mr. Federico PLATANIA and Mr. Tarik BAZGOUR for their availability throughout my research and also for their precious advices in order to improve my work.*
- *I am thankful to the jury for their attention and their work.*

*Finally, I want to thank all the persons who have, directly and indirectly, participated to the improvement and realization of this thesis.*

## List of abbreviations / Glossary

- FOREX, FX: Foreign Exchange
- OTC: Over-the-Counter
- BIS: Bank for International Settlements
- GBP: British Pound
- USD: US Dollar
- EUR: Euro
- JPY: Japanese Yen
- FED: Federal Reserve System
- ECB: European Central Bank
- BoJ: Bank of Japan
- BoE: Bank of England
- QE: Quantitative Easing
- PPP: Purchasing Power Parity
- LOP: Law of one Price
- HBS measurement: Harrod-Balassa Samuelson measurement
- GARCH modelling: Generalized Autoregressive conditional heteroscedasticity modelling
- ATM: At-the-money
- ITM: In-the-money
- OTM: Out-the-money
- ADF test: Augmented Dickey-Fuller test
- ACF: Autocorrelation function
- PACF: Partial Autocorrelation function
- ARMA model: Autoregressive-Moving Average model
- SACF: Sample Autocorrelation function
- OLS regressing: Ordinary Least Squares regression
- CME: Chicago Mercantile Exchange
- Q-Q plot: Quantile-Quantile plot
- ROI: Return on Investment
- VaR: Value at Risk

# Table of figures

# List of tables

# Table of contents

# 1. Introduction

After the Second World War, Bretton Woods System was created to ensure stable exchange rate between countries that was ravaged by war. The system was implemented to stabilize and standardize inflation in order to reconstruct the European countries (Eichengreen, 1992). Bretton woods system tied all major currencies against the U.S. dollar, which was itself backed up by gold. This system held correctly the world economy until 1967, when the first huge devaluation of exchange rate between the GDP/USD occurred. According to Bishop & Dixon (1992), the main reason for the collapse of Bretton Woods is due to payments imbalances among countries and to the sharply increasing foreign holdings of U.S. dollars. There was more U.S currency in circulation than gold to back it up; as a result, the dollar was overvalued, this led to speculative attacks against the dollar. On August 1971, the U.S. president, Richard Nixon, announced the suspension of the dollar's convertibility into gold; all major currencies, except French Franc, started to float (Garber, 1993). In 1973, after massive attempts to reinstate the system, the fixed exchanged rates' system collapsed and a period of primarily floating exchange rates began (Bishop & Dixon, 1992). As mentioned by Levinson (2005), the collapse of the fixed exchange rate system has added volatility on the currency market which led to a growth in currency trading.

The foreign exchange market, which is also known as the FX or FOREX, is the largest decentralized over-the-counter market for currencies trading (Levinson, 2005). The FOREX market is constituted by four different markets which work separately; (i) spot market is the place where currencies for immediate delivery are traded at the spot rate; (ii) futures market is the marketplace where standardized currency contracts are exchanged for a given date and a given strike price (iii) currency options market refers to contracts which give to the holder (buyer) the right to buy or sell foreign currencies or foreign-currency futures at a specified price and date; (iv) derivatives market trades instruments that are not traded on organized exchange market. i.e. Forward contracts, Foreign-exchange swaps, Forward rate agreement (Levinson, 2005). . On the FOREX, market participants, such as market makers, brokers and customers, are generally separated from each other and most of the transactions are made by phone or computer networks. The market is opened 24 hours a day, six days a week. The large commercial banks which are the market makers quote the buying (bid) and selling (ask) prices for each pair of currencies (Frankel, Galli, & Giovannini, 1996).

The Bank for International Settlements (2013), which is considered as the central bank of central banks, reports that in April 2013 that the daily average volume traded was worth \$5.3 trillion in comparison with \$4.0 trillion in April 2010. This report shows that the global growth does not directly profit to the real economy, the evolution is mostly imputed to financial institutions while FX transactions of non-financial customers decreased during this period. In terms of financial instruments, the majority of the turnover is composed of the FX swaps, followed by the spot rate and currency swaps. The main currencies traded are the U.S. dollar (USD), the euro (EUR) and the Japanese yen (JPY). This staggering number clearly shows that the foreign exchange market is one of the deepest and the most liquid in the world (Bank of England, 2009). By contrast with the liquidity of the market, FOREX stands for one of the most controversial trading places, as referring to the transparency. The level of regulation is very low due to the decentralized structure of the market, consequently there are no disclosure requirements in contrast to stock markets (Rime, 2001).

Another controversial aspect of the foreign exchange market is linked to its efficiency in the short run. As described by Fama (1965), if foreign exchange market are truly efficient, currencies exchange rate must change randomly after the release of new information. However, number of investors in foreign exchange market disagree with the fact that price is entirely determined by market fundamentals. Indeed, number of scientific authors who have tackled this phenomenon doubt on the random walk hypothesis in foreign exchange markets (Okunev & White, 2003). Okunev & White (2003) clarify the fact that London foreign dealers use different market analysis tool depending on the time horizon. Investors prefer to use technical rather than fundamental analysis tools to determine their short-term forecasting. Fundamental analysis is more used on a greater trading horizon, more than one week. They find two reasons explaining the inefficiency pattern in foreign exchange markets; (i) noise trading and (ii) central banks intervention. The first hypothesis is based on the fact that noise traders take their trading positions based upon previous directional fluctuation in the currency market, dominating the FOREX. This type of trading behaviour may conduct to an overreaction of the market, and thus pushing the asset prices beyond their true value. The other reason to hesitate about the efficiency in the foreign exchange markets is based on volatility created after a central bank intervention. As we may know, the first objective of central bank intervention is not to seek trading profits, but instead to reduce foreign exchange volatility and ensure that currencies reflect economical values. Unfortunately, central bank intervention produces non-random exchange rate movements, the market participants who are waiting this announcement are making profits based on technical trading tools (Okunev & White, 2003).

In this paper, I try to establish a procedure to invest in EURUSD currency pair during a period where there is monetary policy shifting in Europe and USA. As remarked by Redl (2015), this kind of transition period conducts to imperfect information circulation and misconnection between the currencies exchange rate level and market fundamentals. There are many reasons to explain the increase in volatility which started at the beginning of 2015 for the EURUSD currency pair. One of them is the different monetary policy followed by the Federal Reserve System (FED) and European Central Bank (ECB). At the beginning of 2015, FED has stopped its quantitative easing (QE) program and has also tightened its monetary policy by increasing the interest rate; meanwhile the ECB has started its QE program (Buttenwood, 2015). In this market situation, traditional strategy such as momentum failed to make profit. In this paper, I look at volatility as my friend and not my enemy and try to develop active management based on option strategy.

Before deciding to implement strategies, market participants first need to define what the drivers of the exchange market are, how it works. This paper is divided into 6 main parts. Section 2 describes the macro- and microeconomic fundamentals impacted the FOREX rate. Once the functioning of the market is understood, it is important to apprehend the volatility of the market, what are the effects which is inducing more or less volatility in the FX market. Section 2 gives also a short overview of aspects creating a volatile environment. After reviewing the literature concerning the key movement and volatility drivers of the FOREX, Section 3 and 4 present, respectively, the data collected used in the application of the strategy and the methodology procedure implemented in this Master thesis. Section 5 is dedicated to the presentation of the results obtained by the different computation. Finally, section 6 summarises the main points of this paper.

# 2. Literature Review

In order to put a good investment strategy in place, wise investors need to understand what are the key drivers impacting the market in which they want to invest, in order to anticipate asset movement. They also need to understand and assess volatility found in the market. As mentioned by Poon & Granger (2003), volatility is an important input in investment decisions and portfolio creation. After gathering various types of information regarding the drivers and volatility, market participants can try to implement investment strategy fitting their utility function.

This section is reviewing the academic literature concerning the drivers of the market and its volatility. The following section of this thesis is subdivided into three main points.

The first part is dedicated to the market factors impacting the change encountered in the foreign exchange market.

The second one describes the main aspects affecting the volatility of the market and how it can be calculated.

Finally, the last one highlights popular strategies used in the foreign exchange market.

## 2.1. What drives the foreign exchange market?

This section revisits the academic literature regarding the key drivers affecting foreign exchange market evolution. I have chosen to segregate this section into 2 parts. The first one focuses on macroeconomics fundamentals driving movements in exchange rates market. The second part emphasizes on the microstructure model affecting the foreign exchange market.

### 2.1.1. Macroeconomic fundamentals

Emerged during the 1970s, one of the main and the easiest approach explaining the price movement in the foreign exchange market is driven by the law of supply and demand, also known as the monetary approach. This model explains that the exchange rate is the relative price of two different currencies and is modelled by the relative supply and demand for those currencies. Nevertheless, currency supply and demand can be affected by many various types of macroeconomic fundamentals, such as interest rates, productivity differentials, economic growth, terms of trade, prices, government debt (Bailliu & King, 2005). These macroeconomic fundamentals are embedded in a list of indicators which have a major news effects on the foreign exchange rate, such as payroll employment, durable goods orders, trade balance, unemployment claims, retail sales, consumer confidence, industrial production, federal funds rate, GDP, for the main one. Some of these news announcements can have a positive or negative impact on the currency exchange rate. For instance, news showing a positive impact on the economy lead to an appreciation of the exchange rate (Andersen, Bollerslev, Diebold, & Vega, 2003). Therefore, it is essential to understand the reason which news release impact the foreign exchange and why. Many empirical research has been conducted to explain the market behaviour based on macroeconomic fundamentals. The following paragraphs clarify the main theory based on macroeconomic fundamentals.

One of the first theory explaining the evolution of exchange rate is based on purchasing power parity (PPP). PPP theory states that price levels in different regions of the world should be equal when expressed in a common currency. In order words, a unit of currency of one country should have the same purchasing power in a foreign country and therefore, the exchange rate is determined by the relative price level of the two countries (Sarno & Taylor, 2002). As an illustration, if goods and services from a country cost twice as much in the U.S., all other things being equal, 2 U.S. dollar will achieve the same purchasing power as one unit of the foreign currency, and consequently $2 will be the relative exchange rate. As a result, inhabitants of both countries will have the same purchasing power (Hopper, 1997). PPP model relies on the law of one price (LOP) theory stating that an identical product price should be the same in different market. In comparison to PPP theory, LOP only holds in the tradable sector, such as commodity markets. LOP theory is one of the key assumptions explaining how the productivity of a country might influence exchange rate evolution. (Alessandria & Kaboski, 2004)

Gorbachev et al. (2001) compare the productivity of the United States in the 1990s and the strength of the dollar during this period. In the 1990s, the United States experiences faster productivity in the traded sector than the Eurozone and Japan which has led to higher wages for the traded sector. This positive productivity difference of the US market has conducted to an increase in salary of employees of the traded sector. In reaction to this situation, employers of nontraded sector, who wanted to retain workers to go in the traded sector, offered higher incomes which has led to inflation in the domestic market. The foreign price level which remains steady and the domestic price increases have conducted to an appreciation of U.S. dollar against the yen and the euro. They confirm their theory by using the Harrod-Balassa-Samuelson (HBS) measure to identify the changes in the real exchange rate directly attributed to productivity gains in the traded sector. Their findings confirm the HBS effect which states that productivity growth will lead to a real rate appreciation only if it is concentrated in the traded sector, subject to foreign competition (Lothian & Taylor, 2008).

Another macroeconomic fundamentals factors which have an important impact on the relative currency exchange rates level is the evolution of the balance of payments of a country. Müller-Plantenberg (2010) investigates the impact of countries balance of payments on the evolution of international payment flows and therefore on nominal and real exchange rate movements. He establishes his thinking on the statement that currency supply and demand determine its exchange rate, and also the fact that international currency flows are driven by balance of payment transactions. He finds that balance of payments has an indirect impact on the supply and demand of a currency, through the change of the international payment flows. This model is showing that depending on a country exchange rate policy, fixed or flexible, and its capital flows policy, accommodating current account[1] imbalances or moving autonomously, have a huge impact on the behaviour of the exchange rate. Gaske (1992) shows graphically the linkage between the balance of payments flows and their underlying determinants with the foreign exchange market. He shows graphically the different impact of current-account flows and capital-account flows on the demand and supply of U.S dollar and therefore on the U.S. dollar exchange rates level. All other things being equal, a decrease (increase) in the demand of a currency leads to a decrease (increase) in its exchange rate. A decrease (increase) in the supply of a currency leads to an increase (decrease) in its exchange rate.

However, it exists restriction to the model explained above. All of the papers cited previously agree on one assumption; that adjustment coming from macroeconomic fundamental occurs on a long-run (one year or more). Bailliu & King (2005) explains that traditional models of exchange rate determination based on macroeconomic fundamental have moderated success in explaining long-run trends. Nonetheless, according to them, macroeconomic fundamental completely fails to predict exchange rates on short time horizons. This statement is confirmed by Taylor & Taylor

[1] Current account: sum of balance of trade (goods and services exports less imports), net income from abroad and net current transfers. (Investopedia)

(2004) who find that long-run PPP may hold in order to explain the exchange rate movements on a long time horizon, however, on short-run they find some disturbances and they cannot state that PPP can explain currency exchange rate movement on short time horizons. Another paper contesting short-run explanation is from Gorbachev et al. (2001) who express that productivity shock happens only on a long time horizon due to slow price and wage adjustments.

### 2.1.2. Microstructure of FOREX

As explained earlier and confirmed by Frankel et al. (1996), macroeconomics fundamentals fail to explain short run exchange rates movements. The above mentioned challenges have pushed many authors to investigate other theories in order to explain short-term movements within the foreign exchange market. One of those models is the microstructure theory of the foreign-exchange market. The micro-based model explains movements of exchange rate described by short term determinants, such as the transmission of information among market agents, the behaviour of market participants, the influence of order flow, the diversity of participants' expectations, and the implications of such diversity for trading volume and exchange-rate volatility (Sarno & Taylor, 2001).

King et al. (2013) review the literature concerning the influence of order flows on short-term movements of currency exchange rates. They explain that in the foreign exchange market there is order imbalances coming from buying (or selling) pressure. This imbalances occur when the number of buyers (or sellers) of a currency are more important than the number of sellers (or buyers). This order flow imbalances influence exchange rates level; a buying pressure leads to an appreciation of the currency, on the contrary a selling pressure leads to a depreciation of the currency value. Bailliu & King (2005) add a nuance to this theory; they state that order flows are more informative when they carry information about macroeconomic fundamentals, however, less informative while order flows are a result of currencies inventory management by foreign exchange dealers in response to a liquidity shock. Therefore, information about macroeconomic fundamental influencing the order flows are more informative than inventory management conducted by foreign exchange dealers in response to liquidity shock.

King et al. (2013) also reveal that private information among market participants influences order flow and thus exchange rates level. They find that the interaction between informed agents (particularly financial customers) and uninformed agents (corporate customers) is a clear mechanism driving short-run exchange rate movements. This result comes from the fact that informed agents incorporate gradually the information they have into the price by taking positions within the market. The models explaining this mechanism is called the model of optimising agents. In this model, the presence of informed and uninformed traders results in an optimal trading strategy that creates a positive connection between the expectations of trading volume, and the time required for price to fully reflect information. The speed of adjustment of price increases, as a function of the number of informed agents active in the market (Melvin & Melvin, 2003). Moore & Payne (2011) also describe that better-informed participants trade more frequently and have a greater price impact. A distinction added by Menkhoff et al. (2012b) explain that uninformed agents respond less aggressively to changes in market conditions than informed agents and informed agents dominate the market concerning the response to liquidity. Liquidity of the foreign exchange market is a key component for its proper functioning. Bjonnes et al. (2005) highlight the importance of the liquidity found in the foreign exchange market. In their paper, they study the importance of non-financial customers (uninformed agents and end-customers) as providers of liquidity in the overnight market. As a response to the risky positions in the overnight market, market makers do not hold position during the night, they are only providers of liquidity during the trading day. According to the time of the day, liquidity imbalances occur which are driving short run changes of the exchange rates level.

Another aspect explaining the FOREX movements on short time horizon is described by Sarno & Taylor (2001). They explain that short-term prices movements may be impacted by Chartist analysis on exchange rate movement. They reveal that this popular model of Chartist analysis among FX dealers trade higher volume than nonfinancial companies. Another aspect which is collaborating the facts of Sarno & Taylor (2001) is that traders sharing the same information can interpret this information differently depending on their time horizon. For instance, FX dealers who want to search a short term profit will react quickly to the coming information, instead of corporate companies or central banks who consider a longer strategy. This perception of the market will affect both the volume of trade and market volatility, and as a result influence exchange rate movement on a short run (Melvin & Melvin, 2003). Bailliu & King (2005) add a subtlety to this theory by saying that depending on the type of actors dominating the market, short-term dynamics of exchange rate changes occur. For instance, they explain that disconnections between exchange rate and market fundamentals can happen during period dominated by Chartists or other speculative activities.

In conclusion, during the last forty years, many researchers have focused their studies in highlighting the functioning of the FOREX market in a floating regime. There are numerous approaches in order to explain the different drivers of the foreign exchange market. Macroeconomic-fundamentals and microstructure elements affect the exchange rate on a different time frame, and thus increase its volatility differently. Short term elements impacting the FOREX market add more volatility than macroeconomic fundamentals which take more than one year to be totally reflected in currency exchange rate level. A good investor needs to understand the complexity of this market and its impact on the asset volatility.

## 2.2. Volatility in the FOREX market

After the collapse of the Bretton Woods system in 1973, the foreign exchange market became considerably more volatile. The transition between the fixed exchange rate backed to the gold value and the pure floating system has impacted the degree of variation of the currency exchange market (Meese, 1990). The intensity of the fluctuations of the FOREX market can arise through many different forms. The first part of this section shows some forms of volatility which can appear in the FX market and the impact on the exchange rate. The second part describes the impact of the volatility on investors' decision-making. Finally, the last part focuses on how the dispersion of currency exchange rate can be modelled or forecasted.

### 2.2.1. Key drivers

First of all, the FOREX market pattern shows strong volatility clustering aspects in daily returns. In other words, large price movements are more likely to be followed by large price movements, and small price fluctuations are more likely to be followed by small price fluctuations (Melvin & Melvin, 2003). In their paper, Baillie & Bollerslev (1990) try to explain that volatility clustering does not necessarily imply the inefficiency of the FOREX market or the presence of arbitrage opportunity. They find that the news regarding FX market occur by clusters over time affecting the exchange rate price, and consequently increasing the volatility. But this news can either be contained within a region or widespread around trading regions. The first answer is given by Galagedera & Kitamura (2012) who enlighten that an increase in volatility can either affect only a specific region or impact other trading areas. The first aspect gives rise to the heat-wave effect where volatility of a trading zone is correlated with the next day's volatility in this zone. One argument showing that the volatility is contained in one region is given by Melvin & Melvin (2003) who demonstrate that market makers, trading in a specific region, adjust their positions in response to new information coming within this region. But this situation does not explain why volatility could persist across trading regions. In *effect of exchange rates return on volatility spill-over across trading regions*, Galagedera & Kitamura (2012) demonstrate that volatility spill-over is more likely to occur from the nearest region if the regions share same trading hours. According to Baillie & Bollerslev (1990), this volatility spill-over may be due to the U-shaped pattern of trading hours, where heavy trading happens at the opening and at the closing of each trading day. Another aspect explaining the volatility spill-over is linked to the fact that public information from one region might affect the economy or policy of another region.

So, how economic policy can affect exchange rate volatility? A first answer is given by Dimitris et al. (2015). In their paper, they examine the effect of the quantitative easing (QE) decisions taken by the European Central Bank (ECB), the Bank of Japan (BoJ) and the Bank of England (BoE) on the volatility transmissions through the EUR, JPY and GBP. After reviewing the scientific literature and listing all the decisions taken by Central Banks like the purchase of corporate and government bonds or real estate investments, they conduct their tests. Their findings are divided into three parts. First, they discover an increased volatility spill-over between EUR to JPY and EUR to GBP after ECB announcements, and between GBP to EUR linked to BoE announcements. Secondly, they find that ECB and BoE announcements have a greater impact on EUR and JPY currency volatility. Finally, they notice a smoothing effect on volatility of EUR and GBP depending on BoJ and ECB announcements, respectively. Nevertheless these findings need to be contrasted. Before a fundamental release like Central Banks announcements, the impact of noisy news or noise shocks are important drivers of the exchange rate (Redl, 2015). Redl (2015) remarks an overreaction of the market after a noise shock followed by a period of reversal. He finds that noise shocks are more important during periods of shifting monetary policy. During transition time, imperfect information is in circulation which is perceived differently by market participants. These agents base their decisions on a mix of news and noise. Consequently, agents expectations take time to be completely adjusted in the exchange rates level, and the final result depends on how the noise is perceived within the observable signal. If the perception of the coming news is large (small), the market reacts in anticipation of this signal and when the news occurs the market makes a small (large) adjustment. However, if the signal is just noise, the market will return to its early situation (Forni, Gambetti, Lippi, & Sala, 2014). Forni et al. (2014) clearly show that in the foreign exchange market a disconnection between currency exchange prices and fundamentals may occur. This disconnection can have lots of origins inside the foreign exchange market, the following paragraph will explain some of them.

The release of major news (cf. macroeconomic fundamentals) shows quick adjustment patterns of the exchange rate, followed by little movements (Andersen, Bollerslev, Diebold, & Vega, 2003). The volatility adjustment to news occurs gradually after the release. Andersen et al. (2003) explain, the importance of the impact depends on whether news release has a certain time (day and hour) or not. On the one hand, uncertain release times may conduct to less liquid market nearby the announcement realisation. This market situation is explained by the readiness of participants to take position in the market given that the participants does not know precisely the time when the information will be available. Thus, this situation conducts in smaller adjustments around the announcements, generating more progressive adjustments few hours after the news release. On the other hand, great preannouncements of news release lead to gradual adjustments in the market prior to the actual information release. Investors are anticipating the movement of the market, generated by the release, by taking position. Another aspect that needs to be taken into account is the correlation between different news release. Diverse news can bear the same information, and thus, the market will only react to the first information. For example, U.S. durable goods order will affect all currency pairs related to the dollar, in contrast to U.S. factory orders, released later, will not. Both of this news bear roughly the same information, as a consequence, volatility will be more important on the first information release instead of the last one. Until now, we assumed that the news effects are constant, however, this is not really the case. The adjustment response following a news release is asymmetric and characterised by a sign effect. Bad news arrival will have a greater impact on the foreign exchange market than good news (Andersen, Bollerslev, Diebold, & Vega, 2003).

Another aspect increasing the volatility of a currency is linked to a country’s economic structure. Indeed, Coudert et al. (2015) investigate the relationship between terms of trade in commodity-exporting countries and their real exchange rates. After conducting a test on 68 commodity exporting countries, they find a volatility spill-over between the commodities market and the exchange rates. In the short run, they even find a bigger correlation for oil exporting countries, such as Norway, Australia, Canada, between their real exchange rate and period of high volatility within commodity markets. This transmission of volatility and price adjustments can be explained by the law of one price on tradable goods. According to the law of one price theory, all tradable goods are subject to competitiveness and the price remains the same in terms of PPP within different countries. In this case, a decrease in the commodity price leads to a decline in terms of trade, and therefore to the depreciation of the real exchange rate (Mendoza, 1995). However some commodities, like gold, are perceived as a hedge in period of high volatility in the FOREX market. The price pattern of gold can expose the perception of the market by market participants. During period of high volatility in the exchange market, market agents use gold as a hedge. If the market is perceived as volatile, the price of gold is going up and if the exchange market is calming down, the price of gold decreases (Beckmann, Czudaj, & Pilbeam, 2015). Moreover, Beckmann et al. (2015) find that gold price increase occurs generally after a depreciation of the U.S. dollar.

### 2.2.2. Volatility estimation methods

After explaining some key drivers of the volatility in the foreign exchange market, it is important to understand; first, what is volatility for investors and then how it can be computed. According to Poon & Granger (2003), who have reviewed 93 papers dealing with volatility issues, they find that volatility forecasting is crucial for investors in their process of portfolio allocation. They explain that financial volatility is an important input in investment decisions and portfolio creation. As said earlier, financial volatility is used in investment decision-making, security valuation, risk management and also in the valuation of derivative securities such as currency options (Quek & Tung, 2011). Whilst daily and monthly financial asset returns has a random walk, return volatility is highly predictable. At first sight, volatility is seen as a parameter explaining the instability of a market. High volatility leads to high instability, and vice-versa (Andersen, Bollerslev, Diebold, & Labys, 2001). As a consequence, the intensity of the variation of currency exchange rate prices is a key component which needs to be modelled and forecasted carefully. Many different models are used depending on investors' view, backward or forward-looking. Three general methods are widespread in order to model or forecast the volatility; (i) historical volatility, (ii) implied volatility, (iii) finally the model-based volatility forecasting (Quek & Tung, 2011). In their paper, Poon & Granger (2003) show the differences between these different models.

Historical volatility is computed based on past-time series, it represents the average deviation from the average price of an asset. It shows the expected trading range of market. The most used methods to calculate the historical volatility is the standard deviation:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$$

Where:

- $\mu$ : mean return of the time series
- $x_i$ : price of asset at time $i$
- $N$ : total number of days.

Therefore, standard deviation measures the dispersion of a set of historical returns from its mean. The more spread apart the returns, the higher the deviation, and thus, the higher the volatility. Despite, standard deviation shows very good result in-sample parameter estimation. In ex-post squared returns, this method explains few of the variability encountered by the market. This issue is showing that standard deviation has a limited practical value. Standard deviation has a poor predictive power and it does not provide a good volatility forecast for daily squared returns (Andersen & Bollerslev, 1998). Andersen & Bollerslev (1998) find that this poor predictive power is due to inherent noise in the return generating processes. Furthermore, standard deviation assumes that returns are normally distributed. This pattern is not seen in the exchange market (Wang, Fawson, Barrett, & McDonald, 2001).

Implied volatility is a forward-looking and shows the expected future volatility perceived by the market. It is generally used in the valuation of options. Implied volatility is an indicator of the market expectation of volatility over the option maturity. The volatility embedded in option valuation increases as a function of strike price and maturity. It can be computed by deriving the Black-Scholes formula (Jorion, 1995).

$$c = [S\,N(d_1) - K\,N(d_2)]e^{rt}, \qquad d_1 = \frac{\ln\left({}^{S}/_{K}\right) + \left(r + {}^{\sigma^2}/_{2}\right)t}{\sigma\sqrt{t}}, \qquad d_2 = d_1 - \sigma\sqrt{t}$$

Where:

- $c$ : call price
- $S$ : spot exchange rate
- $t$ : time to maturity
- $K$ : option striking price
- $r$ : risk-free rate and finally
- $\sigma$ : standard deviation (that needs to be computed).

This approach has weaknesses described by Andersen et al. (2000). Knowing that implied volatility depends on the maturity and strike price, we have the effect of volatility smile which is as more as we are from the maturity and in-the-money or out-the-money, the volatility forecasted increases. Furthermore, researchers have found that the expected volatility perceived embedded in options prices usually exceeds the realised volatility (Bollerslev & Zhou, 2006). This disconnection between the perception and the realisation of the market is very important, in order to choose a good model to forecast volatility.

The last two methods are based on a strong assumption stating that exchange rate time series are normally distributed and, furthermore, the volatility is constant over time, this assumption does not hold during periods of volatility clustering (Baillie & Bollerslev, 1990), noise shocks (Redl, 2015), speculative attacks (Wang, Fawson, Barrett, & McDonald, 2001). Exchange rate distribution can show clustering, possible skewness, thick tails (leptokurtosis) and it is not necessarily constant overtime. Therefore, estimation methods of volatility that takes into account all these aspects are needed. One of these methods is Generalized AutoRegressive Conditional Heteroscedasticity (GARCH) modelling. GARCH model assumes that the volatility is heteroscedastic, that is to say this model assumes that volatility is not constant overtime. GARCH model captures volatility clustering and some leptokurtosis distribution found in the foreign exchange market (Wang, Fawson, Barrett, & McDonald, 2001). Whilst the normal GARCH(1,1) model can capture some degree of leptokurtosis, it fails to sufficiently capture it. In reaction to that, Bollerslev (1987) introduces a model where the GARCH is combined with a Student-t distribution in order to capture more kurtosis effect found in foreign exchange rate time series (Alexander & Lazar, 2006). For a GARCH(p,q):

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \mu_{t-i}^2 + \sum_{j=1}^{p} \gamma_j \sigma_{t-j}^2$$

Where:

- $p \geq 0$ : order of the GARCH terms
- $q \geq 0$ : order of the ARCH terms
- $\omega \geq 0$ constant parameter that needs to be modelled
- $\alpha \geq 0$ parameter of ARCH terms that needs to be modelled
- $\gamma \geq 0$ parameter of GARCH terms that needs to be modelled

## 2.3. Trading on currency market

After reviewing all the literature concerning the drivers of the currency exchange rate level and its volatility. This section describes and explains the profitability pattern of popular strategies which are found in the foreign exchange market.

### 2.3.1. Traditional strategies

The first strategy is the currency momentum. In finance, momentum effect is the empirical observed tendency for rising asset prices to rise further and falling prices to keep falling. Momentum investing strategy, also known as the Long/Short strategy, is seen when an investor is taking a long position in a currency, which has shown previously an upward trend relative to another currency and shorting a currency that has been in a downtrend relative to another. The idea behind momentum strategy is that once a trend is established, it is more likely that this trend will continue rather than showing a reversal. Okunev & White (2003) has conducted this strategy on the eight major currencies, USD, EUR, JPY, CAD, AUD, NZD, GBP and CHF. After identifying the most attractive and the least attractive currencies by using technical tools, such as the moving average, they initiate their long/short position by buying currency which has shown previous upward trend and selling currency which has shown downward trend. Once they initiate their strategy, after one month, all the positions were revaluated. In terms of transaction costs, they show that this strategy is not too expensive because it requires only three to four rebalancing a year. They find that long/short strategy focusing generally on medium time horizon (3 to 12 months) shows profit. This strategy mostly work when the market shows clear trend and is steady (Conrad

& Kaul, 1998). One example showing the importance of the economic stability on the success of currency momentum strategy has been analysed by Orlov. Orlov (2016) investigates the impact of the equity market stability and illiquidity on dollar-based momentum. He finds that the profitability of trends based strategy depends on the level of equity market illiquidity. Returns of long/short momentum strategy are lower (higher) when the equity market is showing high (low) illiquidity.

Another strategy used during many years by traders around the world is the carry trade. The idea behind a currency carry trade is based on borrowing money in a country showing low interest rate and using this fund to invest it in a country having higher interest rates. Investors are going long in high-yield currencies and short in low-yield currencies. If the exchange rate remains the same, the profit will be equal to the difference between the high and low interest rate when no transaction costs are taken into account. However, this is never the case, the risk with a carry trade strategy is the uncertainty found in the exchange rate market. Indeed, currency carry trade fails during periods of market turmoil. This poor returns during market turmoil is due to the fact that this strategy is very sensitive to third moment issue. During periods of high negative skew caused by target currencies to crash or on the contrary funding currencies to appreciate, carry trade strategies will show poor profits (Berge, Jorda, & Taylor, 2010). Furthermore, Menkhoff et al. (2012a) prove that carry trades return is a compensation for time-varying risk. Indeed, they find empirically that high interest rate currencies are negatively correlated with global FX volatility, and therefore they deliver low profits in market showing high volatility. On the contrary, low interest rate currencies provide a hedge during market turmoil by giving positive returns relative to high interest rate currencies.

### 2.3.2. Option-Based strategies

The collapse of the Bretton Woods system in 1973 has led to a more volatile foreign exchange rate market. In reaction to this situation, over the past decade, one of the perceptible changes in the market has been the growth of the derivatives market (Chang & Wong, 2003). In April 2013, foreign exchange derivatives accounted for nearly 62% of total turnover of the foreign exchange market (Bank for International Settlements, 2013). Financial derivatives in the foreign exchange market are mainly traded in the Over-the-Counter (OTC) market and divided in 4 parts; (i) the FX swaps (44% of total turnover), (ii) forwards (13%), (iii) currency option and futures options (5%) and finally (iv) currency swaps (1%) (Bank for International Settlements, 2013). One part of this financial tools is used by multinational company to hedge their currencies risk (Geczy, Minton, & Schrand, 1997). Nevertheless, the other part of this financial derivatives does not necessarily profit to the real economy. Financial institutions and traders use them to construct investment strategies in order to get profit. Many different strategies have been developed by using a mix of different financial derivatives, such as the bull-spread, butterfly spread, straddle, strangle, covered call. These strategies are designed based on the investors perception of the market.

#### *2.3.2.1. Strategy description*

Hull (2012) explains that if investors view is similar to other market participants view, it will be reflected in the price of different asset traded, such as options. For instance, suppose that a central bank has to make a big announcement but the outcome is not clearly known, this announcement will create volatility. In this case, a straddle strategy will be appropriate. However, if an investor view does not differ from other market participants, this view will be redirected in the options prices. Currency options will be more expensive to purchase. Therefore, initial investment will be higher, and a bigger move in the exchange rate level will be necessary to make profit. For a straddle or any investment strategy to be profitable, investors need to take a different view from the rest of the market and this view must be right. A description of Option-Based strategies can be found in the appendix 1.

#### *2.3.2.2. Previous studies*

Options trading offer more possibilities than direct investment in the underlying asset. There is many different possibilities, investors can buy or sell the option, make combination with other options or make combination with the underlying. Investors who want to implement strategies based on options need to understand what are the key factors which increase or decrease the value of an option. These factors are the underlying price, change in volatility and the time to maturity. Therefore experienced investors take into account these factors in their decision to implement a strategy rather than another one. First, the price expectation needs to be modelled in order to see in which direction the market will move whether it will rise, fall or remain steady. This modelling can be done by fundamental or technical analysis. The second important factor that needs to be taken into account is the perception of the future volatility. If an investor expects big price movements, the option has more chance to be exercised before expiration. However, market exhibiting previous high volatility will lead to higher price for the option and this higher price will affect option strategy return. Thus, it is crucial to forecast the underlying volatility and this forecast need to be different of the market perception which is reflected in the option pricing. The last important factor is time to expiry. Contrary to the underlying asset, option has a limited life. When investors put in place an option strategy, their price movement expectation must take place before expiry, after expiry the option no longer exists. As a result, the investors price expectation must not only move on the perceived future direction, but also before the option life expiry. The view of the time frame will define the maturity month. The option price also depends on the remaining maturity, all other things being equal, an option having with high time to expiry will be more expensive to purchase than an option with few remaining weeks or days. Therefore strategy implementation time and its cost are crucial to its success.

In conclusion, Option-Based strategy decision should not only be related to the underlying price movements but also to its volatility and the option's remaining life. As shown in figure 1, these three aspects are linked to each other. Price movements are related to market volatility and volatility expectation can affect the time frame determination. As an illustration, if a strategy is betting on high price movement, for a high volatility expectation option with short maturity can be considered. Although the option has a short maturity, the underlying price might move sufficiently to make an important profit.

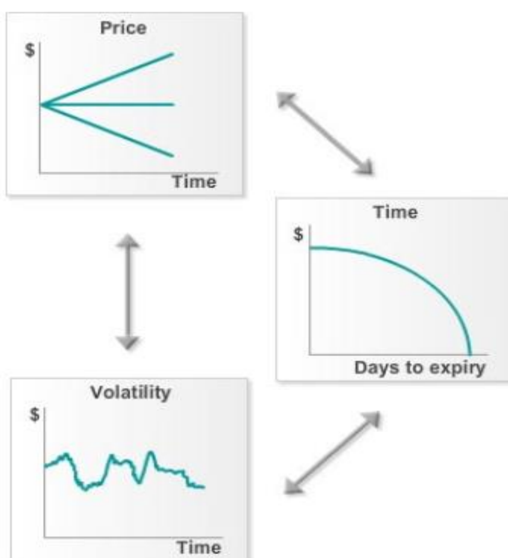



*Figure 1: Option pricing factors*

Lots of research has been carried out on option strategies and their profitability. This section is going to enumerate different studies conducted on Option-Based strategy returns.

The first study has been carried out by Merton et al. (1978). In their study, they show the benefit for an investor to use option strategies. Their aim is to show the return characteristics of two diverse option strategies; a fully covered writing strategy and a buying strategy which is a combination of options and riskless commercial paper purchase, and they also demonstrate the change of the risk-return pattern induced by option strategies. A fully covered strategy is based on buying a call option and owning the corresponding amount of the underlying instrument. The second strategy is based on investing 10% of the portfolio in call options and 90% in riskless commercial paper. They assumed a holding period of six months for both of their strategies from July 1963 until December 1975. In their sample, they use four different exercise prices which are 0.9, 1, 1.1, 1.2 times the underlying price. The results of their research are showing that the maximum return is obtained when the exercise price is higher but with a lower exercise price there is more chance that the option is exercised. They observe, for both strategies, that the lowest exercise price leads to less volatility and low return, on the contrary the highest exercise price provides the highest return and volatility. They conclude that the covered strategy outperforms the buying strategy when the market is stable. In contrast, buying strategy outperforms covered strategy when the market is very volatile (Merton, Scholes, & Gladstein, 1978). Nevertheless, Merton et al. (1978) do not explain if option strategies are outperforming stock market. Isakov & Morard (2001) tackle this question, the purpose of their research is to investigate if the covered call strategy provide higher returns than holding a long position in stocks. They implemented their strategy on the Swiss Market Index. The covered call strategy returns are calculated in two different ways. Whether the option is exercised or the option is not exercised. Their results show that covered calls have lower risk than investing directly on the stocks but their returns are quite equal. Isakov & Morard (2001) find that covered call strategy outperforms equally weighted portfolio and stock market indices.

Another study investigating the returns on calls, puts and straddles strategy has been conducted by Coval & Shumway (2001). They conducted this research on the S&P 500 from January 1990 until October 1995. They investigate the expected option returns in the context of asset-pricing theory. According to asset-pricing theory, option risks should be priced in the same way as other assets. Therefore, under strong assumption, expected option returns should vary linearly with option betas. However, they find that with a zero-beta strategy, such as the At-the-Money (ATM) straddle, their positions produce an average loss of roughly 3% per week. Their results suggest that there are more factors than market risk which is taken into account for the risk pricing included in option contracts. Since the zero-beta straddle returns are related to the market volatility, Coval & Shumway's results imply that the systematic stochastic volatility might be an important factor for asset pricing (Coval & Shumway, 2001).

Santa-Clara & Saretto (2009) has also conducted research on the risk and return of option strategies. In their paper, they use a wide range of strategies, such as naked, covered calls and puts, straddles, strangles and calendar spreads, with different exercise prices. They use three different exercise prices, ATM, 5% OTM and 10% OTM and focusing on one maturity of 45 days. They conduct the implementation of those strategies on the S&P 500 from January 1996 to April 2006. In their research paper, they only use American options. Their strategy is based on holding an option for one month and then sell it on the market. If an option is ITM, the option is sold and the profit is invested into a risk-free asset. Their results show that naked calls deliver positive returns but they show up with high volatility. All naked puts have negative average returns. Nevertheless, they observe that shorting a put has high average returns but these returns are generated by high volatility which can lead to a possibility of bearing huge losses on this position. Covered call position generate the equivalent positive returns as the underlying stocks but with lower risk. A long position in the underlying and a long position in the put, also known a protective put, leads to lower returns and risk that covered calls. Straddle and strangle close to maturity offer high average return but this comes with high volatility. Finally, calendar spreads have positive average returns but less than straddle and strangle. They find that, on the contrary of previous studies showing high returns to option strategies, returns obtained by investors which are subject to the margin call system and transaction costs are not as large as formerly documented (Santa-Clara & Saretto, 2009).

The general conclusion of all these papers is that covered calls and calls perform at least equally well as the underlying stocks. This deduction is not observed with put options. The returns of this strategy are lower than the underlying stocks or even negative. These papers do not show a categorical interpretation about straddle strategy returns. Concerning strangle and calendar spreads, only Santa-Clara & Saretto (2009) has concluded that these strategies lead to a positive return. In conclusion, we can see that some studies have been conducted on the profitability of option strategies on stock market. Nevertheless, this paper is going to verify if some of these statements also hold for the foreign exchange market. In the following chapter, I will try to give an answer in order to see whether Option-Based strategies outperform “traditional” strategies.

# 3. Data

Here, this section describes how the data has been collected and managed in order to use it in this paper. Furthermore, some data analysis has been conducted with the purpose of seeing if some patterns exist or not.

## 3.1. Data collection

In order to answer the research question it is important to collect and analyse data of foreign currency. Nevertheless, depending on the frequency of the data, period under observation, data collection can be done from a range of different data providers. This collection has been done in 2 parts.

The first one is related to EURUSD exchange rate, this collection has been done thanks to the database of Histdata.com and cover the period from the 1st March 2015 to the 31st December 2015. After discussion with different people, such as Mrs Muller[2], we all have agreed to use the most traded currency. This selection has not been done randomly, this choice was made in order to avoid market liquidity risk that can be encountered in FOREX market. As mentioned by the Bank for International Settlements (2013), this currency pair is the most liquid one. The period from the 1st March 2015 to the 31st December 2015 was chosen due to the special pattern observed. This period was a period of high volatility in the exchange market which was induced by many factors such as central bank intervention in Europe and United States, global economy incertitude, economic policy changes and many other economic aspects. The collection of this currency pair was carried out on the 14th February 2016. The data collected include 263 trading days.

The second part of data collection is related to the currency option. This data is needed for the construction of trading strategies based on options, such as the straddle. For this part of the data collection, I have encountered several data gathering issues. As explained in section 2.3, financial derivatives are mainly traded on the OTC market which makes difficult to collect representative data. Finally, I have found some data coming from Datastream thanks to the connection provided by HEC-Liège in some classes. All the options collected are European options which can only be exercised at maturity.

[2] Aline Muller has a Ph.D. in International Finance. She is also a professor of Finance at HEC-Management School of The University of Liège.

The data related to the options include basic information such as the strike price, expiration date, and cost. Concerning the specification of the options, currency options used in this paper are European option with a contract size of 10.000 Euros. That means for the purchase of one contract, you have an exposure of 10 000 Euros. These options are quoted in terms of U.S. dollars per unit of the underlying currency, the premium is paid and received in U.S. dollars. The contract point value is equal to $100 (i.e. 0.01 * 10 000). The premium quotation is expressed in point value. As an illustration if a premium is quoted at 3.45, the cost of this contract is $345 (3.45 * $100). Each contract is expiring the Saturday following the third Friday of the expiration month (NASDAQ, n.d.).

### 3.2. Data management

The purpose of this section is to obtain a representative sample of EURUSD currency for the chosen period. Accordingly, I first filtered my currency data in order to observe missing data for the chosen trading period. Thanks to the high liquidity and the specification of the FOREX market which is a worldwide decentralised market, I did not find any missing data for my EURUSD quotation.

Concerning the currency option data base, the data provided from Datastream was displayed per strike price and maturity. After collecting the data for different maturity and strike price, I proceed a matching between the FX market and option market data in order to see if there is no missing data between both databases. During the data cleaning, I observe that the FX market open one day before the option market. To be consistent between both databases, I removed the Sunday trading day from the FOREX database.

## 3.3. Data analysis

Before starting any strategy implementation, it is important to analyse EURUSD data's behaviour. The goal of this section is to understand the behaviour of the EURUSD exchange rate returns which is represented by Figure 2 below:

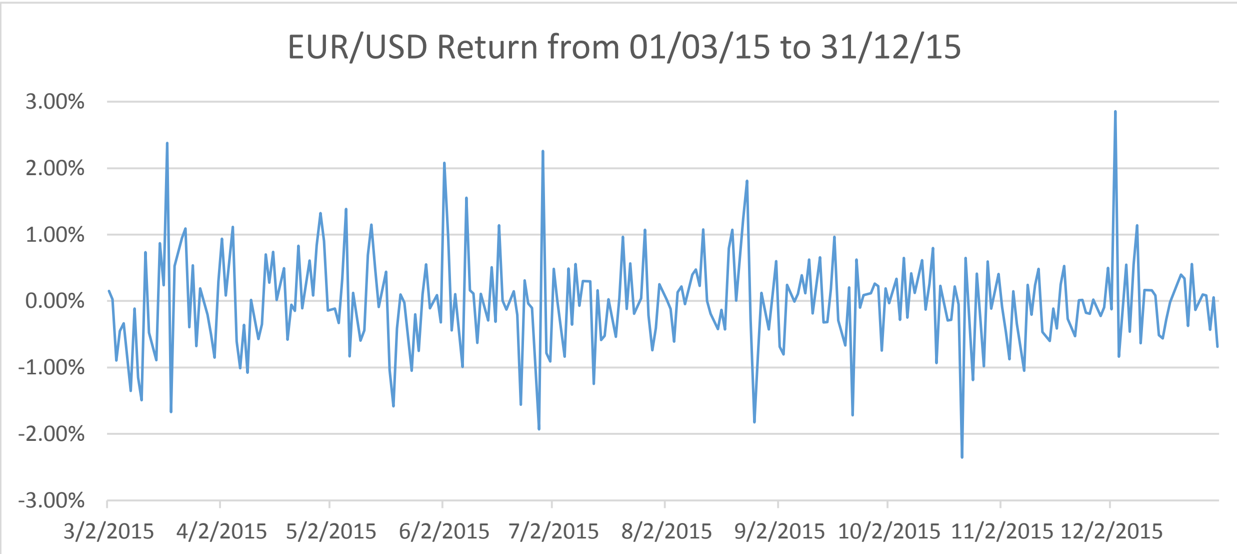



*Figure 2: EURUSD Return from 01/03/15 to 31/12/15*

At the first sight, we can immediately see that there is no clear upward or downward trend. The EURUSD returns from 01/03/15 to 31/12/15 is going sideways within a highly volatile period. Before going further, we need to check these assumptions with statistical tests. The following points are going to show some statistical tools that I have used in order to confirm or disapprove my previous statements.

Appendix 12 presents basic data calculation, such as return, mean, standard deviation, variance, median, min, max, skewness and kurtosis of each period. We can see that our data has a negative skewness of -0.1337496 and an excess of kurtosis of -0.732611. These values mean that we have more chance to have a positive return but less chance to have extreme values than normal distribution.

### 3.3.1. Trend analysis

Knowing that some strategies are based on trends, therefore, before starting any computation or strategy implementation, the first thing I do, is to analyse the presence of a trend in EURUSD time series. Figure 2 displayed in the previous section clearly shows that there is not a clear trend pattern. In order to be sure with this assumption, I have used a regression analysis to confirm the presence of a trend or not. The aim of computing regression analysis is to check the presence of relationship between the dependent variable, EURUSD returns and the independent variable, time. In order words, I want to see if my returns are increasing or decreasing with respect to the variable time, that is to say if there is a presence of an upward or downward tendency. The regression analysis is modelled such as:

$$R_t = \alpha + \beta * t + \varepsilon_t$$

Where:

- $R_t$ : Return a time $t$ (dependent variable)
- $t$ : time variable (independent variable)
- $\alpha$: intercept when $t$ = 0
- $\beta$: slope = rate of increase/decrease of $R_t$
- $\varepsilon_t$: "noise" term reflecting other factors that influence the return, can also be considered as the variance

In order to run this regression, the variable time is assigned with numerical values. As an illustration, I have assigned the first date in the sample a value of 1, the second date a value of 2, and so forth. This regression analysis is going to estimate the parameters $\alpha$ and $\beta$. These values are going to be confirmed with statistical tests like the p-value. To be sure that the value found is significant, I have used a p-value with 5% level of significance.

### 3.3.2. Stationarity

After performing a regression analysis to detect a trend, it is now important to observe the statistical properties of significant variable, such as a constant mean. The verification of this assumption is done by a stationarity analysis. If the mean of the observed time series is stationary over time, it indicates that the mean is constant over time (Elliot, Rothenberg, & Stock, 1996). This pre-calculation is imperative, because it determines which mean calculation model is going to be used.

#### *3.3.2.1. Augmented Dickey Fuller test*

This stationarity analysis is conducted by an Augmented Dickey Fuller (ADF) test. An ADF test assesses the presence of a unit root in a times series based on the model hereafter:

$$y_t = c + \delta t + \phi y_{t-1} + \beta_1 \Delta y_{t-1} + \cdots + \beta_p \Delta y_{t-p} + \varepsilon_{t'}$$

Where:

- $\Delta$ : differencing operator ➔ $\Delta y_t = y_t - y_{t-1}$
- $p$ : number of lagged difference terms
- $\varepsilon_{t'}$ : mean zero innovation process.

For this test, I am going to assess the null hypothesis of the presence of unit root:

$$H_0 : \phi = 1$$

For a time series showing no trend and drift, $\delta = 0$ and $c = 0$, respectively (Mathworks, n.d.). If the test has a unit root, the time series is stationary. It will indicate that the properties of this time series depend on the time at which they are observed.

##### *3.3.2.2. Autocorrelation and Partial Autocorrelation*

In order to confirm my findings from the ADF test, I am going to check the robustness of these results with an Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF).

I am going to use the plot of these functions in order to see the dependence between time series and the variable time. In order to do that I am going to plot the ACF and PACF thanks to the "autocorr()" and "parcorr()" function in Matlab.

The equation for an ACF is:

$$R_{(s,t)} = \frac{E[(X_t - \mu_t)(X_s - \mu_s)]}{\sigma_t \sigma_s}$$

Where:

- $X_t, X_s$ : value of the return for time $t$ and $s$, respectively
- $\mu_t, \mu_s$ : mean of the return for time $t$ and $s$, respectively
- $\sigma_t, \sigma_s$ : variance of the return for time $t$ and $s$, respectively
- $R_{(s,t)}$ : Autocorrelation Function value lies between $[-1, 1]$

I am going to use a 5% significance level and compare the ACF and PACF plot against the critical upper and lower limits of:

$$\pm 1.96/\sqrt{n}$$

Where:

- $n$: is the length of the observed time series (Tsay, 2005).

# 4. Methodology

The section 4 describes the methodology applied during this paper. The methodology of this paper is divided into 4 different parts. As explained in the literature review, in order to implement Option-Based strategy 3 key factors need to be defined; the future price expectation, the volatility expectation and finally the time to maturity. As it is commonly known, for option pricing, these 3 factors are closely linked to each other. This section is going to explain how I have defined these 3 important elements which are crucial in my strategy decision. After that, an explanation of the different strategy implementation will be given.

## 4.1. Underlying price forecasting

The success of any investing strategy relies mostly on the future underlying price movements. The forecasting of the EURUSD price movement is a key factor that needs to be taken into consideration in order to reduce the number of suitable strategy. There are many ways to forecast the future price of an asset, some investors rely on fundamental analysis and other on technical rules (Hopper, 1997). Some methods are relying on mathematical models, such as the Autoregressive – Moving Average model (ARMA).

### 4.1.1. Time series analysis

The goal of this analysis is to provide a mathematical model that adequately describes the behaviour of the EURUSD exchange rate which is represented like this:

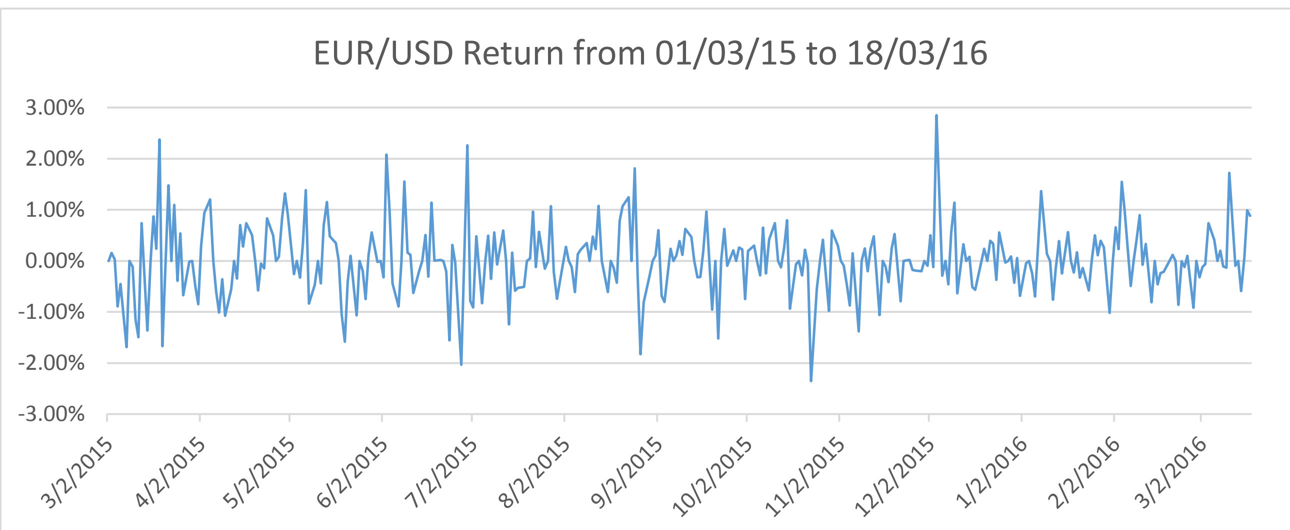



*Figure 3: Historical EURUSD Return pattern*

Since it has been recognised that financial returns aren't completely random processes (Okunev & White, 2003), I am going to use time series analysis in order to model the daily EURUSD exchange rate returns.

In order to do that, I am going to use an additive model:

$$X_t = m_t + S_t + Y_t$$

Where:

$X_t$ : Exchange rate return time series

$m_t$ : Trend component

$S_t$ : Seasonal component

$Y_t$ : Random part

In this equation, the deterministic part, $m_t$ and $S_t$, need to be extracted, before modelling the random part $Y_t$. If this random part $Y_t$ is not independent and identically distributed (iid), it can be modelled and analysed and can give us a forecast of the future value of the EURUSD returns.

#### 4.1.1.1. Treatment of the trend

First, we want to know, if the returns are following a trend or not. Firstly, I am going to draw a scatter plot in order to know if graphically we can see a dependency between $X_t$ and t. However in this section, I am going to remove the deterministic component corresponding to the trend. There are two different methods that enable to detect and remove the trend. The first one is the parametric method with an OLS regression and the second one is a non-parametric method, moving average estimation. In this paper, I am going to use the parametric method with the OLS regression. After performing this task, I am going to remove this trend thanks to the "detrend( )" function in Matlab.

#### 4.1.1.2. Treatment of the seasonality

After removing the trend, I am going to remove the other deterministic part the seasonality. The seasonality is a cycle of period $x$. In order to identify this cycle of seasonality, I will use two different methods. The first one is to look graphically to the detrended data graph and observe if there is a cycle occurring on the observed period. The second one is to plot the Sample autocorrelation function (SACF) in Matlab. The SACF graph is going to show if there is any correlation between data of different lag t.

#### 4.1.1.3. Treatment of the stochastic part

After withdrawing the trend and the seasonality of the time series, I am going to treat the real random part $Y_t$ and try to model it with an ARMA model. Before any computation, the first objective is to check whether the remaining time series is a white noise. If it is the case, therefore the analysis would be complete because it would not be able to model the returns any further.

##### *4.1.1.3.1. Independence test*

Theoretically, a time series $X_t$ is a white noise when it is a sequence of iid random variables with a finite mean and variance. In practice, it is easy to come to this conclusion by checking all the ACF and see if they are close to 0. If this is the case, our returns at time t and t + y will show independency and it will not be possible to model our returns. In order to check this assumption, I am going to use a Partial autocorrelation function.

For the partial autocorrelation function, I will not go further into the analysis because the result from the PACF will be the same as found in the section 3.4.2.2. However, in order to check the robustness of this finding I am going to use the Ljung-Box test. With this test I am going to check jointly if several autocorrelations of EURUSD returns are zero. In other words, that returns are not correlated to the past:

$$H_0: \rho_0 = \rho_1 = \cdots = \rho_m = 0$$

$$H_1: \rho_i \neq 0 \; for\; some\; i \in \{1, \dots, m\}$$

$$Q(m) = n(n+2)\sum_{k=1}^{m} \frac{\widehat{\rho_k}^2}{n-k}$$

Where:

$H_0$: Null hypothesis stating that returns are independently distributed

$H_1$: Alternative hypothesis stating that returns are not independently distributed.

$n$: Sample size

$\widehat{\rho_k}$: Sample autocorrelation at lag k

$m$: Number of lag tested

Under the null hypothesis, the statistic $Q$ should follow a Chi-squared distribution with $m$ degrees of freedom. The capital asset pricing model suggests that, in efficient markets, futures prices cannot be predicted and therefore the returns should not be correlated (Fama, 1965). The Ljung-Box test offer a way to check the efficient market assumption. All the computations are done in Matlab and can be found in appendix 3.

### 4.1.2. Exchange rate forecasting thanks to futures contracts

In the case where my data are independent, it will not be able to model the data thanks to an ARMA model. In order to deal with this issue, I will also use a Market-Based approach to forecast the exchange rate change. As it is commonly known, investors trading on foreign exchange assets can use various types of financial instruments (Bank for International Settlements, 2013). One of them is futures contract. Some investors use prices in futures contracts as a way of forecasting the future spot price of an asset. In this paper, I follow the same logical thinking. I have downloaded the settlement price of EURUSD futures contracts. These data have been downloaded from Datastream and are CME Euro FX Futures maturing in March 2016. I have chosen the date of March 2016 because my option used in my trading strategies are also maturing in March 2016. Thanks to this settlement price, I have a way to forecast the exchange rate maturing until the 14$^{h}$ March 2016 where my futures contracts are expiring.

## 4.2. Volatility forecasting

The second aspect of the success of an Option-Based strategy is relative to the forecasted volatility. A good volatility forecasting can tell us the right moment to enter a position. If we perceive an increase in volatility, it will be interesting to enter into a position betting on a volatility increase, such as the straddle. Another aspect of volatility calculation is linked to the option pricing, in order to increase the success of option strategy, it will also be appropriate to look at the present volatility. Low volatility will lead to low option premium payment. Therefore it is very important to link the current volatility and the forecasted the EURUSD volatility in order to choose the most suitable strategy. The calculation of historical volatility is very easy to compute, standard deviation is a good indicator of past volatility. However, the forecasting of future volatility is a little bit more difficult to compute. There are many approaches to do that.

The first approach which is the most intuitive one, is the use of historical volatility and assume that the EURUSD will have the same behaviour in the future as it has been seen in the past. More concretely, if I consider a position maturing in 3 months, I will use as volatility forecasting a 3 months historical volatility. This method assumes that the volatility will remain constant over time and it is showing a homoscedastic pattern. As explained by Andersen & Bollerslev (1998), in case where the underlying is showing a clear non-constant volatility pattern, standard deviation has a poor predictive power and it does not provide a good volatility forecast for daily squared returns.

$$\sigma_t = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} = \sigma_{t+3\,months}$$

Another approach is by assuming the future volatility might be different from the observed volatility in the past. Investors might think that after a period of low volatility in the market, EURUSD exchange rate might show an increase in its volatility due to different extern factors. This second approach assumes that the volatility will have a different behaviour than the past that is to say the volatility is heteroscedastic. As explained in the literature review, the most common method used to forecast foreign exchange volatility is the GARCH(1,1) (Alexander & Lazar, 2006).

Before deciding a method to forecast my volatility, I am going to check if my exchange rate returns are following a normal distribution or not. This test is going to confirm the choice of the right method to forecast the volatility. If my returns are clearly not showing a Gaussian distribution, I am going to use a GARCH modelling because GARCH takes into account volatility clustering, possible skewness, thick tails (leptokurtosis). This volatility forecasting will be computed each trading days until the maturity of the option used. This forecasted volatility is going to help in the decision of investing or not at time t and also which strategy to implement. The calculation has been made on Matlab (appendix 5).

### *4.2.1.Normality tests*

In order to be sure with the choice of a GARCH model, in this section I aSmirnovm going to describe the different test I have used in order to see if my returns are following a Gaussian distribution or not. For checking the normality assumption, I am going to use 2 different approaches the Quantile-Quantile plot (Q-Q plot) and the Kolmogorov-. The Q-Q plot will offer a graphical way to see if EURUSD returns are following a normal distribution or not. In order to check the robustness of this value, I am going to use a Kolmogorov-Smirnov test (appendix 4).

## 4.3. Investing decision with the remaining time to maturity

After performing the estimation of the future exchange rate level and future expected volatility, the next important task is to determine the investment strategy to choose at time t. Before deciding the choice of the most suitable strategy, I have looked to three different indicators. The first one is linked to the observed ex-ante volatility in the market. After that, the observation of the volatility expectation (ex-post) in the future. Finally, the forecasted exchange rate which indicates the direction in which the market is expected to go.

### 4.3.1. Observation of the ex-ante volatility

As explained by Hull (2012), investors views need to be different from other market participants, otherwise these views are reflected in the price of different financial assets, such as options. As explained in the section 2.3.2.1. Strategy decision, if a central bank has to make a big announcement, this announcement will create volatility. In this case, a straddle strategy will be appropriate. However, if investors' view does not differ from other market participants, his view is redirected in the options prices. Therefore, the initial investment required is higher, and a bigger move in the exchange rate is necessary in order to make profit. For this reason, the day where big announcement in the market is released, I make the choice not to put a strategy in place due to the increase in option prices.

### 4.3.2. Observations of the forecasted volatility

The observations of the forecasted volatility tendency are imperative in the choice of a suitable investing strategy which suits the best the expected market condition. For instance, if I perceive an increase in the future volatility, I will use strategy which takes profit from this situation, such as the straddle. Conversely, if I perceive that the forecasted volatility decrease, I will prefer a strategy betting on stability in the market, such as the butterfly-spread. Nevertheless, knowing that the forecasting power of the volatility decrease as far as we are from the maturity, we need to take this aspect into account. For this reason the observations of this volatility need to be done carefully, consequently I will also look to the forecasted volatility of previous trading days in order to see a tendency in the forecasted volatility, contraction or expansion of the volatility cluster.

### 4.3.3. Observations of the forecasted exchange rate level

The choice of the strategy based on the volatility will also be combined with the forecasted exchange rate level, in order to take the most suitable strategy. Forecasted exchange rate will give me the expected direction in which the market is going. This will help me in order to choose alternative investment strategy, for instance if I perceive that the market ethesexpected volatility is high and the future exchange rate is expected to increase, I will choose the strap strategy because it takes into account these 2 factors.

#### 4.3.4. Determination of the strategy

These 3 factors above combined, which are the ex-ante volatility, ex-post volatility and the forecasted price, will determine which strategy to choose or not with the remaining time to maturity. In order to define the most suitable strategy, I have divided my approach into 3 separate actions.

First, I determine if an investment for the day is appropriate. In order to determine that firstly when it is Sunday in Europe, the foreign exchange market starts to trade in Asia-Pacific area, during these days the currency option market is not yet opened and therefore it is impossible for me to enter into a position. After that, I check if there is a federal holiday in the USA, if it is the case the CME does not open and I do not have a way to forecast the future exchange rate level, for this reason these days I also decide not to enter into a position because I have not all the information required to decide. Lastly, if I see a huge price movement during the day I want to implement a strategy, I also decide not to enter into a position. As described by Hull (2012), market situation is reflected in option pricing and in the case of huge movement, the price of option increases and therefore the breakeven of my strategy is also higher.

Secondly, as explained in the section above, 4.3.3., I determine if the forecast from my futures contract price is higher or lower than my current spot price. This comparison helps in order to choose the most suitable strategy.

Finally, after deciding in which direction the market is going, I check my forecasted volatility found by the GARCH models in order to determine if the forecasted volatility of different trading days shows contraction or an expansion of the volatility.

After performing this strategy choice, I wait that the options expire and calculate the profitability of my position. This will be explained in more details in the following section.

### 4.4. Strategy implementation

Before starting any profitability observation, I first will conduct the implementation of the strategy on a coding language. After gathering all the data, strategy implementation will be done on Matlab. Matlab choose is quite obvious as a coding tool in order to manage different databases. Matlab provides a very easy and useful programming tools to reconnect databases between each other in order to make different calculation that cannot be done with Excel.

#### 4.4.1. Strategy investing on volatility

The first strategies coded in Matlab will be strategy betting on volatile market during the observed period. These strategies focusing on volatility are the straddle, strip and strap. In order to implement this strategy, I have used the previous work of Hull (2012).

For a straddle, I will code all the different scenarios possible on Matlab (Appendix 6). This code is generating 5 different outputs. The first output is showing the strike price at which I will enter the position at time t. Then it shows the initial cost of the strategy, which is equal for a straddle the sum of the call and put purchased. After that, I will compute the Upper- and Lower- breakeven of my strategy. Finally, I will calculate the total profit obtained at maturity when the options are exercised or not.

So, as to enter a position at time t, I will match my first database containing the exchange rate for the chosen period and my second database with the options prices. In order to do that, I will check at time t, my exchange rate level and I will compare it with the option having the closest strike price. After having the strike price of my option, I will take its quoting price at time t with the purpose of computing my strategy cost and profit. As an illustration, if the EURUSD is quoting at 1.1182 the 3rd March 2015, I check my option database and the closest strike price is 112[3] and I take the price of the call and put options quoted the 3rd March 2015, which is equal to 1.815 and 1.925, respectively. After having this precious information, I could make different calculation to obtain the profitability of my strategy.

Concerning the strip and strap, I have followed the same procedure but concerning the initial investment I have used an additional put and call for my strip and strap, respectively. The

[3] Option strike price are quoted in pip (one hundred times the exchange rate level)

breakeven was also modified in order to represent the profit level of my different strategy. The code of these two strategies can be found in the appendices 7 and 8.

### 4.4.2. Strategy investing on stationarity

To implement this strategy, I use the same technique as the straddle in order to choose the different option strike prices. The construction of my strategy was based on the sale of one ATM option which was determined as the same technique used for the straddle. Concerning the ITM and OTM options, I decided to choose equal distance from the ATM option. To put it differently, if for the construction of my strategy I need to sell 2 call option ATM with a strike of 112. At the same time I buy one ITM option with a strike of 110 and an OTM option with a call of 114, both of them have equal distance of the ATM strike. In this example, the distance in terms of point value is equal to 2.

The difficult part of this investment strategy is the parametrisation of the spread of the Butterfly-spread because lots of possibilities are conceivable associated to the distance of the spread. In order to do that in my Matlab code (appendix 9), I will implement a variable "Spread_length" in which I can decide to put the distance of my spread. The variable "Spread_length" is iterated with different values lying between 1 and 10, which is equal in terms of point value to 0.5 and 5, respectively. This modification is taken into account for my different profitability, breakeven calculation. In order to choose the most suitable spread, I will conduct a back-testing of my Butterfly-spread strategy on three different periods and choose the spread showing the highest profitability.

### 4.4.3. Strategy investing on trend

Concerning strategy investing on trend, I will separate my calculation in two. The first one is focusing on strategies using currency options and the second one is focusing on strategy investing directly in the underlying, here, the EURUSD exchange rate.

#### *4.4.3.1. Bull/Bear spread*

For my bull spread, I will use the same parametrisation method of the butterfly spread. The length of my spread is also lying between 1 and 10. After the parametrisation of the bull spread, I will decide to choose the spread of my strategy showing the highest profitability among the different period. The Matlab code can be found in appendices 10 and 11.

#### *4.4.3.2. Momentum*

The momentum strategy is the easiest strategy to code. It is taking position in the underlying at time t and at the end of the period, taking the reverse position in order to compare the result with the previous strategies.

# 5. Empirical Findings and Analysis

This section will show the different results I have obtained for my different calculation. This section is divided into 2 main parts. The first part is showing the result of my different statistical test conducted on my EURUSD return database. The second part is focusing on the implementation of my different strategies and the profit obtained from the different position.

## 5.1. Data analysis

### 5.1.1. Trend analysis result

The trend analysis of the data has been computed separately for all the observed period from the 1st March 2015 to 31st December 2015 thanks to Excel Analysis toolPak. All the output provided by Excel from this regression analysis can be observed in the appendix 13. In the table above, I have only gathered the important information.

| | ***Coefficients*** | ***Erreur-type*** | ***Statistique t*** | ***Probabilité*** |
|---|---|---|---|---|
| *Constante* | -6,06877E-05 | 0,000866707 | -0,070020943 | ***0,944230609*** |
| *Period (t)* | -8,19515E-08 | 5,69168E-06 | -0,014398457 | ***0,988523091*** |

*Table 1: Regression analysis result*

According to the figure in Table 1, we can observe that for the different time period the coefficient of variable time ($\beta$) is not statistically significant. The p-value is higher 0.05, even close to 1, which indicates that the coefficient found from the regression is not significant, the variable time, t, does not explain the data behaviour.

Statistically, the null hypothesis which is:

$$H_0 : \beta_1 = 0$$

cannot be rejected at the 5% level of significance. This leads that there is not enough indication showing that there is a trend in the data. Even if the independent time variable ($\beta$) was statistically significant, we can see on Table 1 that these values are closed to 0 (-8.19515E-08) and it also indicates that even the trend was confirmed, the slope will be very low and not significant to take it into account.

Therefore our model can be represented by:

$$R_t = \alpha + \varepsilon_t$$

Where:

- $R_t$ : Return a time $t$ (dependent variable)
- $\alpha$: intercept when $t$ = 0
- $\varepsilon_t$: "noise" term reflecting other factors that influence the return, can also be considered as the variance

Now we need to understand the noise part of our model, we need to see if it is constant over time or not. This test will be conducted in the next section.

### 5.1.2. Stationarity result

#### *5.1.2.1. Augmented Dickey Fuller test*

Table 2, hereafter, represents the results obtained from the adftest() function on Matlab with the default settings ($\alpha$ = 0.05, $l$ = 0, model = AR, standard t-statistic):

| | **01/03/15-31/12/15** | |
|---|---|---|
| | H | p-value |
| *ADF Test* | 1 | 0,001 |

*Table 2: ADF Test result*

According to this figure, we can see that the ADF test returns 1 for the period under investigation. This value means that the null hypothesis of presence of a unit root is rejected and consequently, the returns data is stationary. These values are significant with the default significance level of 5%.

#### *5.1.2.2. Autocorrelation and Partial Autocorrelation function*

To check the robustness of me previous findings, I also decided to plot the ACF and the PACF of the different periods. The different plot can be found in appendix 14.

In appendix 3, I have plotted the ACF and PACF of the observed period. The 2 different plots are clearly showing that obviously every data are perfectly correlated with itself but there is not a significant correlation between data at time t and the lagging data.

These findings are confirming what we have previously found with the ADF test which is that our data are stationary over time

## 5.2. EURUSD exchange rate forecasting

### 5.2.1. Time series analysis

Here, I am going to present the result found from my time series analysis. As explained earlier, I have used an additive model. In this model, I have removed the deterministic part, the trend and the seasonality, and try to develop a model for the stochastic part:

$$X_t = m_t + S_t + Y_t$$

#### *5.2.1.1. Treatment of the trend*

Before starting any computation, I have plotted a scatter plot, in order to see graphically if there is a dependency between my Exchange rate return, $X_t$, and the variable time, $t$ on the observed period going from the 1st March 2015 to the 31th December 2015.

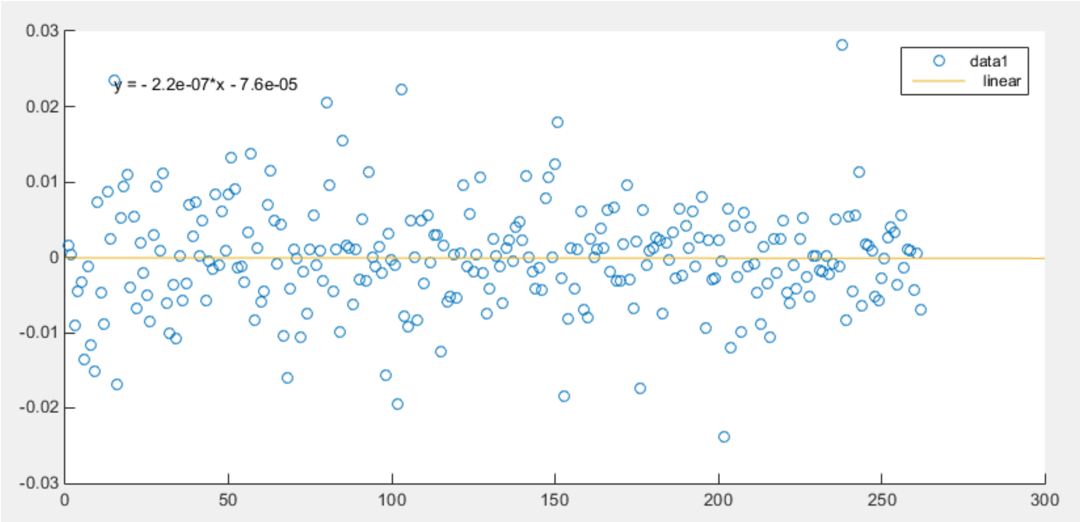



*Figure 4: Scatter plot of the EURUSD returns*

As shown on Figure 4 plotted on Matlab, we clearly see that trend variable is very low. The OLS regression confirms the visual finding because the slope of our trend is equal to -2.2*10^-7. We can say that our variable has no dependency with the variable time. The result obtained here are quite similar has the one found in the section 5.1. Trend analysis result. However, in this section I am going to go further in the analysis and remove this small trend from the raw data returns. In order to do that, I used the "detrend( )" function in Matlab.

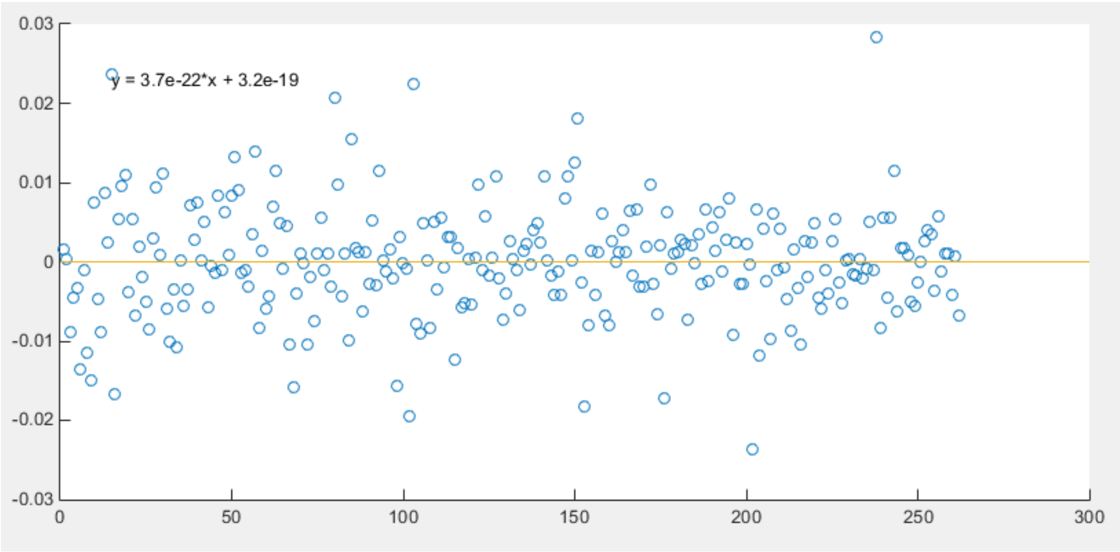



*Figure 5: Scatter plot of the detrended EURUSD returns*

Here, on Figure 5, we can see that the detrended graph is very similar with the trend and therefore conclude that the deterministic part, trend, has a very low impact on the model.

### *5.2.1.2. Treatment of the seasonality*

After removing the trend, in this section I try to determine the presence of seasonality on the detrended data. In order to see the presence of an economic cycle, I have used the SACF function in Matlab.

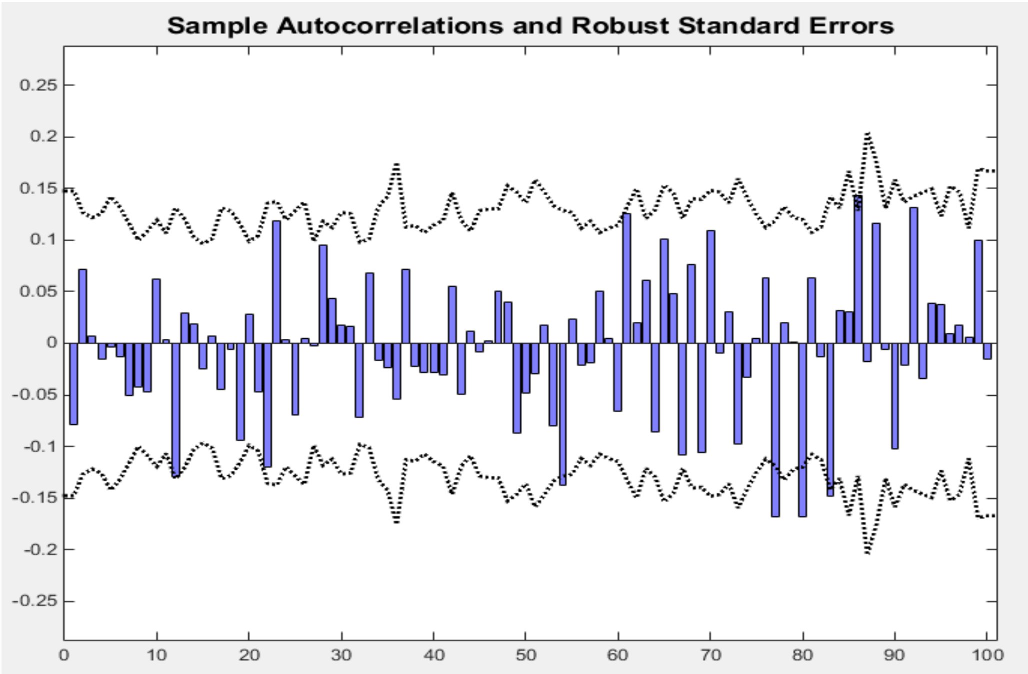



*Figure 6: EURUSD returns - SACF graph of the plotted in Matlab*

My SACF graph, Figure 6, is clearly showing that there is no correlation between data of different lags. Thanks to this graph, we can say that our EURUSD returns are not following a cyclical pattern. They fluctuate randomly.

After knowing that our removing the trend and knowing that our data is not following a cyclical pattern. We can say that our data does not depend anymore on the trend and the seasonality.

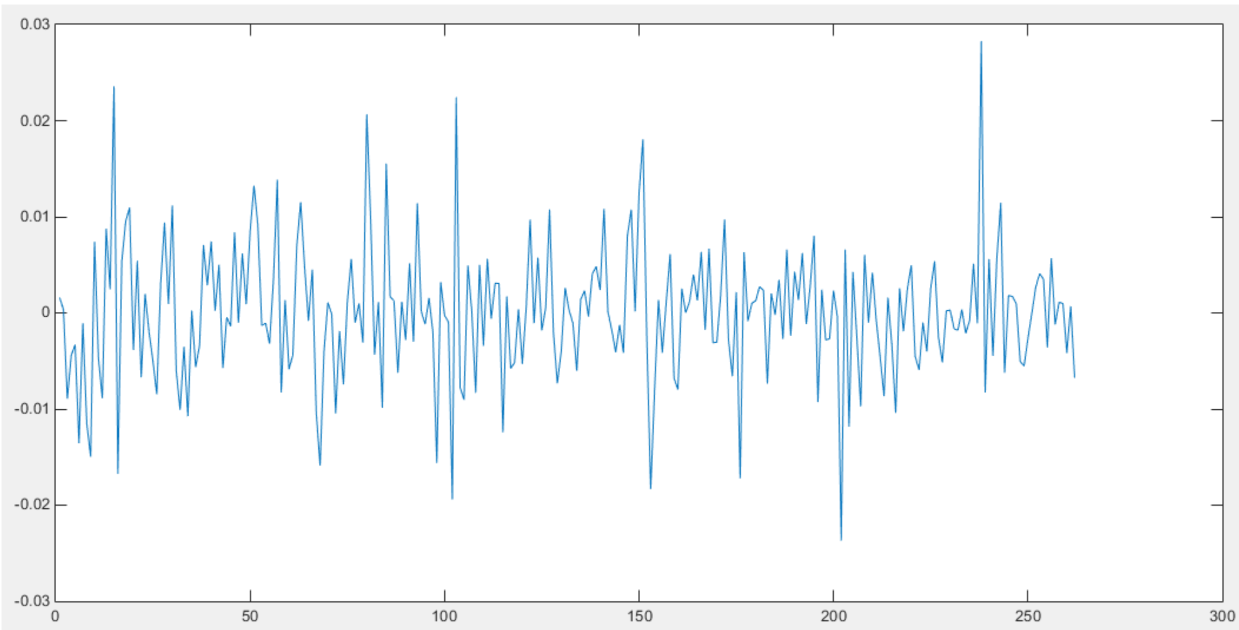



*Figure 7: EURUSD returns without the trend and the seasonality*

Figure 7, above, represents our new data set without the trend and the seasonality. Until now the model became:

$$X_t = -2.2 * 10^{-7} * t - 7.6 * 10^{-5} + Y_t$$

The residuals that need to be modelled is represented as:

$$Y_t = X_t + 2.2 * 10^{-7} * t + 7.6 * 10^{-5}$$

#### 5.2.1.3. Treatment of the stochastic part

After removing the trend and the seasonality, I check if my residuals is a white noise. If it is the case, it would not be able to model the residual of the returns. In order to verify this statement, I am going to check the correlation between my data and its distribution.

###### 5.2.1.3.1. Independence test

The PACF plotted in the section 5.1.2.2 (appendix 14) clearly show that most of the lag l autocorrelations are not rejected, because they do not exceed the limit of the acceptance region (± 1.96/√N). The time dependency is totally removed so we cannot reject the null hypothesis stating that our residuals behave like a sequence of iid random variables. In order to confirm the graphical interpretation of this result, I have also made a Ljung-Box test. The following table shows the result of the Ljung-Box test on the residuals.

| *Lag* | Q | p-value |
|---|---|---|
| *1* | 1,84783615 | 0,17403527 |
| *2* | 2,02363206 | 0,36355815 |
| *3* | 2,40841877 | 0,49206939 |
| *4* | 2,41060028 | 0,66071247 |
| *5* | 2,8283664 | 0,72642608 |
| *6* | 2,8307117 | 0,82977468 |
| *7* | 2,83200023 | 0,90009643 |
| *8* | 3,30706923 | 0,9136366 |
| *9* | 3,46772308 | 0,94283997 |
| *10* | 5,10703307 | 0,88391429 |

*Table 3: Ljung-Box test result*

The result of this test is showing that all the p-values are higher than $\alpha$ (significance level of 5%), therefore we should not reject the null hypothesis. Thus we can conclude that the ACF are not significantly different from zero. This result suggests that our returns are not serially correlated.

In conclusion, the PACF and the Ljung-Box test is showing that the detrended and deseasonlized returns are independent. Therefore it would not be possible to model the residuals with an ARMA model. This result is confirming what it has been found previously in section 5.2 "Stationarity analysis" where we saw that the raw exchange rate returns have a stationary pattern. As a result, a time series analysis will not be possible in order to forecast the future exchange rate return. Therefore, another way of forecasting EURUSD exchange rate should be considered. In response to that, I have decided to choose the Market-based approach to forecast the future spot rate thanks to the information observed in futures contract. In order to do that, I have gathered data from Datastream. The data gathered is Chicago Mercantile Exchange (CME) forex futures contract on

EURUSD from the 1st January 2016 to the 14th March 2016. This data can be found in appendix 15.

## 5.3. Volatility forecasting

Before any decision of methods of volatility forecasting, I have checked the normality assumption in order to be sure of my model used.

### 5.3.1. Normality test

The QQ-plot of the residuals (appendix 15) clearly shows that the residuals are not close from a normal distribution, we can clearly see that the extremity of the QQ-plot are far away from the normal distribution. Indeed, after drawing the histogram of the residuals (appendix 16) and compare it to a normal distribution, graphically we can see that the shape of the distribution is high and it has bigger tail on the left and a thinner tail on the right.

In order to confirm my graphical observation, I have also conducted a Kolmogorov-Smirnov test.

| Stat | p-value | H |
|---|---|---|
| **0,4867** | 3,4428e-55 | 1 |

*Table 4: Kolmogorov-Smirnov test result*

This test suggests that we can reject the null hypothesis stating that our residuals follow a normal distribution. Moreover, this result is statistically significant, given the very low p-value.

In conclusion, all the tests are giving the same result that the EURUSD returns are not following a Gaussian distribution.

### 5.3.2. Volatility forecasting result

As demonstrated by the different tests from the section above, EURUSD returns are clearly not following a Gaussian distribution. The data analysis (section 3.3) has shown the presence of a skewed and leptokurtic distribution, thus this paper is following the same specification for the GARCH modelling as followed by Bollerslev (1987). The specification of the model is a GARCH(1,1) with a t-distribution. The computation of the GARCH has been conducted for all the trading days in the investing period under investigation, that is to say from the 1st January 2016 until the 18th March 2016 where the call and put options expire. The parameter estimation for the 67 trading days can be found in appendix 18. Thanks to these parameters, I have forecasted the volatility for each trading day until the 18th March 2016. The number of days forecasted decreases as we approach the option maturity day. As an illustration, for the first day, t, I have forecasted the volatility for 67 trading days, for t + 1, 66, and so forth. The result of this volatility forecasting can be found in appendix 19 where 67 charts illustrate graphically the forecasted volatility obtained thanks to the GARCH modelling.

These charts show that the forecasted variance (solid red line) converges asymptotically to the unconditional innovation variance (dotted red line). Thus, the longer the time frame we forecast the volatility, the less information is given by the GARCH model. In other words, as long as we are far from maturity, these graphs do not give solid value but instead show a tendency about the future volatility.

We can see graphically that within some period, future volatility clustering increase and within other volatility remain constant over time. The obtained data show an increase in the intensity of the volatility from period t, t + 11, t + 35, t + 41 to t + 3, t + 19, t + 37, t + 44, respectively. We can also see that during some period, the volatility forecasting is constant over time and is equal to the unconditional volatility (period: t + 7 ➔ t + 10; t + 32 ➔ t + 34). Most of the forecasted volatility increases relative to the variable time, nevertheless within some period we can see that the forecasted volatility decreases as function of the time. After crosschecking these observations with news release which occurred in the market, the forecasted volatility has a decreasing pattern after an important announcement has been done by the ECB and FED. These findings confirm what has been previously observed by Andersen & al. (2003) who were stating that the release of a major news shows quick adjustment pattern of the exchange rate followed by little adjustment. The little adjustment of the volatility after the news release is reflected in the GARCH models for the following days after the major announcement. This little adjustment has a particular pattern which is a decrease in the forecasted exchange rate volatility obtained with the GARCH modelling (i.e. t + 29 ➔ t + 31; t + 60 ➔ t + 63).

## 5.4. Strategy decision

This section is going to show the different reflection I performed in order to choose the most suitable strategy which takes best into account the current information found in the market.

### 5.4.1. Preselection

The investment period on EURUSD currency in which strategies are implemented focuses on two and a half month period from the 1st January 2016 until the 18th March 2016. Before looking to any exchange rate or volatility forecast, it may be useful to review the historical behaviour of the EURUSD pair over the period going from the 1st March 2015 to the 31st December 2015. The result obtained by the augmented dickey fuller test as well as the linear regression, in section 5.1. Data analysis and 5.2.1. Time series analysis shows the absence of a trend on the EURUSD currency pair. Clearly, these tests indicate that there is no correlation between the EURUSD returns and the variable time, therefore investment strategy which considers the presence of a trend in its profitability success can be dropped. As a result, strategies such as momentum, bull spread, bear spread are not considered as good strategy for the investment period from the 1st January 2016 to the 18th March 2016 and are rejected.

Another strategy that can also be rejected without any calculation is the carry trade strategy. As proved by Menkhoff et al. (2012a), carry trade strategy delivers low profits in market showing high volatility which is currently the case for the EURUSD currency pair on the period under investigation. Another non-negligible aspect is the low interest-spread between the FED (0.25%-0.5%) and the ECB (0.0%), even if we are investing on a real long time horizon this low interest-spread does not offer profitable investment strategy.

### 5.4.2. Strategy implementation

After removing strategy which do not comply with past data analysis, I have implemented the methodology that I have developed in section 4.3.4. The choice between strategy investing on volatility or stability has been done thanks to comparison of each GARCH forecasting result with previous days. The tightening or the increase of the forecasted volatility a time t in comparison with previous GARCH forecast offers a way to determine the changes in the expected volatility. This comparison offers a volatility tendency that is taken into account in the choice of the appropriate strategy. As an illustration, if a tightening of the volatility is observed the choice of strategy anticipating a stable market is the most applicable, and therefore butterfly-spread will be the most suitable strategy. On the contrary, if an increase of the forecasted volatility is observed the choice of strategy which takes into account the volatility will be the most appropriate, such as the Strip or Strap. The choice between these two last strategies, Strip and Strap, are determined by the expected exchange level, if an increase in the underlying price is anticipated by the market-based approach, Strap strategy will be considered. On the opposite, if a decrease in the underlying price is anticipated, Strip strategy will be considered. The Table 5, below, summarises all the strategies put in place for each trading days. In the last column of the table, I have computed the Return on Investment (ROI) of each strategy implemented in order to have a way of comparison between the efficiency of the different investments.

$$ROI = \frac{(Gain\ from\ the\ investment - Cost\ of\ the\ investment)}{Cost\ of\ the\ investment}$$

Where $(Gain\ from\ the\ investment - Cost\ of\ the\ investment) = Profit$

| | Date | Spot rate | Futures contract settlement price | Strategy | Initial Investment | | Profit | | Return on Investment |
|---|---|---|---|---|---|---|---|---|---|
| *t* | 01/01/2016 | 1,08841 | Holiday | No investment | $ | - | $ | - | *0,00%* |
| *t+1* | 03/01/2016 | 1,08539915 | Sunday | No investment | $ | - | $ | - | *0,00%* |
| *t+2* | 04/01/2016 | 1,08275497 | 1,0852 | Strap | $ | 597,50 | $ | 338,46 | *56,65%* |
| *t+3* | 05/01/2016 | 1,07519937 | 1,0765 | Strap | $ | 599,50 | $ | 536,46 | *89,48%* |
| *t+4* | 06/01/2016 | 1,07789981 | 1,0805 | Strap | $ | 589,00 | $ | 446,96 | *75,88%* |
| *t+5* | 07/01/2016 | 1,0925976 | 1,0954 | Strap | $ | 611,00 | $ | 124,96 | *20,45%* |
| *t+6* | 08/01/2016 | 1,08676 | 1,0939 | Butterfly | $ | 70,50 | $ | -70,50 | *-100,00%* |
| *t+7* | 10/01/2016 | 1,09410381 | Sunday | No investment | $ | - | $ | - | *0,00%* |
| *t+8* | 11/01/2016 | 1,08579993 | 1,0874 | Butterfly | $ | 76,00 | $ | -76,00 | *-100,00%* |
| *t+9* | 12/01/2016 | 1,08439875 | 1,08725 | Butterfly | $ | 77,50 | $ | -77,50 | *-100,00%* |
| *t+10* | 13/01/2016 | 1,08860123 | 1,08955 | Strap | $ | 553,00 | $ | 282,96 | *51,17%* |
| *t+11* | 14/01/2016 | 1,08589423 | 1,0872 | Strap | $ | 563,50 | $ | 372,46 | *66,10%* |
| *t+12* | 15/01/2016 | 1,08962 | 1,0942 | Strap | $ | 585,00 | $ | 250,96 | *42,90%* |
| *t+13* | 17/01/2016 | 1,09200108 | Sunday | No investment | $ | - | $ | - | *0,00%* |
| *t+14* | 18/01/2016 | 1,08950257 | Holiday | No investment | $ | - | $ | - | *0,00%* |
| *t+15* | 19/01/2016 | 1,09129798 | 1,09365 | Strap | $ | 543,50 | $ | 292,46 | *53,81%* |
| *t+16* | 20/01/2016 | 1,08770132 | 1,09055 | Strap | $ | 536,00 | $ | 299,96 | *55,96%* |
| *t+17* | 21/01/2016 | 1,08620095 | 1,08995 | Strap | $ | 550,50 | $ | 385,46 | *70,02%* |
| *t+18* | 22/01/2016 | 1,0848 | 1,08065 | Strip | $ | 528,00 | $ | -60,02 | *-11,37%* |
| *t+19* | 24/01/2016 | 1,07990193 | Sunday | No investment | $ | - | $ | - | *0,00%* |
| *t+20* | 25/01/2016 | 1,08530498 | 1,0862 | Strip | $ | 487,50 | $ | -19,52 | *-4,00%* |
| *t+21* | 26/01/2016 | 1,08649588 | 1,0866 | Strap | $ | 493,50 | $ | 442,46 | *89,66%* |
| *t+22* | 27/01/2016 | 1,09079802 | 1,09075 | Strap | $ | 481,50 | $ | 354,46 | *73,62%* |
| *t+23* | 28/01/2016 | 1,09369707 | 1,09535 | Strap | $ | 479,00 | $ | 256,96 | *53,64%* |
| *t+24* | 29/01/2016 | 1,09007 | 1,0845 | Strip | $ | 510,00 | $ | -92,02 | *-18,04%* |
| *t+25* | 31/01/2016 | 1,08259082 | Sunday | No investment | $ | - | $ | - | *0,00%* |
| *t+26* | 01/02/2016 | 1,08972824 | 1,0902 | Strap | $ | 468,50 | $ | 367,46 | *78,43%* |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| *t+27* | 02/02/2016 | 1,09220386 | 1,0928 | Strap | $ | 473,50 | $ | 362,46 | *76,55%* |
| *t+28* | 03/02/2016 | 1,10910237 | 1,1122 | Strap | $ | 523,00 | $ | -87,04 | *-16,64%* |
| *t+29* | 04/02/2016 | 1,11999643 | 1,1216 | Strap | $ | 517,00 | $ | -281,04 | *-54,36%* |
| *t+30* | 05/02/2016 | 1,1165 | 1,11705 | Strap | $ | 497,50 | $ | -161,54 | *-32,47%* |
| *t+31* | 07/02/2016 | 1,1145041 | Sunday | No investment | $ | - | $ | - | *0,00%* |
| *t+32* | 08/02/2016 | 1,11898124 | 1,12045 | Butterfly | $ | 82,50 | $ | 99,52 | *120,63%* |
| *t+33* | 09/02/2016 | 1,12899947 | 1,13035 | Butterfly | $ | 84,50 | $ | 197,52 | *233,75%* |
| *t+34* | 10/02/2016 | 1,12809527 | 1,13025 | Butterfly | $ | 81,00 | $ | 201,02 | *248,17%* |
| *t+35* | 11/02/2016 | 1,13179791 | 1,1329 | Strap | $ | 565,50 | $ | -529,54 | *-93,64%* |
| *t+36* | 12/02/2016 | 1,1294 | 1,12635 | Strap | $ | 495,50 | $ | -459,54 | *-92,74%* |
| *t+37* | 14/02/2016 | 1,12259901 | Sunday | No investment | $ | - | $ | - | *0,00%* |
| *t+38* | 15/02/2016 | 1,11740577 | Holiday | No investment | $ | - | $ | - | *0,00%* |
| *t+39* | 16/02/2016 | 1,11470294 | 1,1144 | Strap | $ | 479,50 | $ | -143,54 | *-29,94%* |
| *t+40* | 17/02/2016 | 1,11229753 | 1,11445 | Strap | $ | 481,00 | $ | -45,04 | *-9,36%* |
| *t+41* | 18/02/2016 | 1,11109877 | 1,1104 | Strap | $ | 453,00 | $ | -17,04 | *-3,76%* |
| *t+42* | 19/02/2016 | 1,1116 | 1,11335 | Strap | $ | 466,00 | $ | -30,04 | *-6,45%* |
| *t+43* | 21/02/2016 | 1,1123966 | Sunday | No investment | $ | - | $ | - | *0,00%* |
| *t+44* | 22/02/2016 | 1,10280335 | 1,10355 | Strap | $ | 428,50 | $ | 107,46 | *25,08%* |
| *t+45* | 23/02/2016 | 1,10270607 | 1,10245 | Strap | $ | 406,00 | $ | 129,96 | *32,01%* |
| *t+46* | 24/02/2016 | 1,10139441 | 1,10195 | Strap | $ | 437,50 | $ | 198,46 | *45,36%* |
| *t+47* | 25/02/2016 | 1,10249937 | 1,103 | Strap | $ | 419,50 | $ | 216,46 | *51,60%* |
| *t+48* | 26/02/2016 | 1,10132 | 1,0939 | Strap | $ | 385,50 | $ | 250,46 | *64,97%* |
| *t+49* | 28/02/2016 | 1,09239471 | Sunday | No investment | $ | - | $ | - | *0,00%* |
| *t+50* | 29/02/2016 | 1,08889759 | 1,08935 | Strip | $ | 410,50 | $ | 7,48 | *1,82%* |
| *t+51* | 01/03/2016 | 1,08759487 | 1,0877 | Strip | $ | 391,50 | $ | 26,48 | *6,76%* |
| *t+52* | 02/03/2016 | 1,08689737 | 1,0873 | Strip | $ | 348,00 | $ | 119,98 | *34,48%* |
| *t+53* | 03/03/2016 | 1,09489453 | 1,09645 | Strap | $ | 368,00 | $ | 367,96 | *99,99%* |
| *t+54* | 04/03/2016 | 1,09385 | 1,10115 | Strap | $ | 386,50 | $ | 349,46 | *90,42%* |
| *t+55* | 06/03/2016 | 1,09939647 | Sunday | No investment | $ | - | $ | - | *0,00%* |
| *t+56* | 07/03/2016 | 1,10160065 | 1,1014 | Strap | $ | 365,50 | $ | 270,46 | *74,00%* |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| *t+57* | 08/03/2016 | 1,10040057 | 1,10135 | Strap | $ 345,50 | $ 290,46 | *84,07%* |
| *t+58* | 09/03/2016 | 1,09890103 | 1,09995 | Strap | $ 354,50 | $ 281,46 | *79,40%* |
| *t+59* | 10/03/2016 | 1,11784303 | 1,1178 | No investment | $ - | $ - | *0,00%* |
| *t+60* | 11/03/2016 | 1,11067 | 1,1145 | Strap | $ 246,00 | $ 189,96 | *77,22%* |
| *t+61* | 13/03/2016 | 1,11679435 | Sunday | No investment | $ - | $ - | *0,00%* |
| *t+62* | 14/03/2016 | 1,11019826 | 1,1108 | Strap | $ 181,00 | $ 254,96 | *140,86%* |
| *t+63* | 15/03/2016 | 1,11090124 | 0 | No Investment | $ - | $ - | *0,00%* |
| *t+64* | 16/03/2016 | 1,12169993 | 0 | No Investment | $ - | $ - | *0,00%* |
| *t+65* | 17/03/2016 | 1,12189376 | 0 | No Investment | $ - | $ - | *0,00%* |
| *t+66* | 18/03/2016 | 1,13179791 | 0 | No Investment | $ - | $ - | *0,00%* |
| | | | | ***Total*** | ***$ 20 074,00*** | ***$ 6 524,43*** | ***32,50%*** |

*Table 5: Investment summary*

On Table 5, we can see that the ROI is lying between -100.00% and 248.17%. The minimum of 100.00% is normal because all the strategies implemented have a maximum lost limited to the initial investment which explains this value.

Before going to any deep result observations, I have computed basic probability (table 6). Looking at the mean profitability on the overall period, we see that on average on the 67 trading days we have a profit of $97.38 per day. The overall profit obtained when all the options are exercised at maturity of $6524.43, with a minimum profit obtained from the strategy implemented at day t + 35 (11/02/2016) of $-529.54 and a maximum obtained from the strategy implemented the 5th January 2016 of $536.46. The skewness of the profit earned from different strategies implemented is negative which indicates that we have more chances to have positive return rather than negative one.

| Standard deviation | 203,57 |
|---|---|
| Mean | 97,38 |
| Skewness | -0,33 |
| Excess kurtosis | 0,65 |

*Table 6: Basic probability calculation of strategy profitability*

Concerning the strategy implementation, as we can see there are many days where no investment has been made. This is due to the fact that during some days foreign exchange market is open on the contrary of currency option market and CME. On the possible 67 trading days, I had the opportunity to invest only during 49 days in which I could implement my strategy. On this 49 days, I have decided not to invest the 10th March 2016 (t + 59), due to the surprise announcement of ECB on its monetary policy. This announcement has conducted to an increase in the call option prices and therefore, in the initial investment required in order to enter a position. For this reason I have decided not to invest during this day due to the increase in the initial cost. After this selection, on the 67 trading days, I have only invested on 48 days. Table 7, below, resumes the number of days where my strategy has a positive or negative return and the overall profit for each situation.

| | Number of trading days | Number of days in percentage | Initial Investment | Profit | Average profit per day | *Return on Investment* |
|---|---|---|---|---|---|---|
| *Day with positive profit* | 33 | 0,6875 | $ 13 846,50 | $ 8 674,37 | 262,86 | *62,65%* |
| *Day with negative profit* | 15 | 0,3125 | $ 6 227,50 | $ -2 149,94 | -143,33 | *-34,52%* |
| ***Total*** | ***48*** | ***1*** | ***$ 20 74,00*** | ***$ 6 524,43*** | ***135,93*** | ***32,50%*** |

*Table 7: Number of positive and negative returns obtained from the different strategy implementation*

We can observe (Table 7) that on this 48 days, 33 days have a positive profit and 15 a negative one. We can see that roughly 70% of the strategies implemented have a positive profit. On average the strategies with a positive profit make a gain of $262.86 per day in comparison to strategies bringing a negative profit which is lower in absolute terms, $143.33. The ROI measurement shows that per unit of dollar invested strategies with positive profit create more wealth ($0.63) than it is destroyed by strategies having negative profit ($-0.35). In conclusion, we can say that on the overall strategies with positive profit have a greater impact than strategies having negative profit.

| *Strategy* | Number of trading days | Number of days in percentage | Initial Investment | Profit | Average profit per strategy | Return on Investment |
|---|---|---|---|---|---|---|
| *Strap* | 36 | 0,75 | $ 16 926,50 | $6 268,00 | 174,11 | *37,03%* |
| *Strip* | 6 | 0,125 | $ 2 675,50 | $ -17,63 | -2,94 | *-0,66%* |
| *Butterfly* | 6 | 0,125 | $ 472,00 | $ 274,06 | 45,68 | *58,06%* |
| ***Total*** | ***48*** | ***1*** | $ 20 074,00 | $6 524,43 | ***135,93*** | ***32,50%*** |

*Table 8: Comparison of strategies implemented*

The Table 8 classifies the strategies taken by contributions to the profit. We see that Strap strategy contributes the most to the overall profitability, on average this strategy has contributed the most to the profit per day ($174.11) in comparison with the Strip ($-2.94) and Butterfly strategy ($45.68). Although we can see that the contribution to the overall profitability is higher for the Strap strategies. However Butterfly-spread has a higher ROI. This means that per unit of dollar invested Butterfly-spread strategies have created a wealth of $0.58 while Strap strategies have created only $0.37. In conclusion, per strategy implemented, Butterfly-spread strategy has created more wealth per unit of dollar invested than the other strategies.

#### 5.4.2.1. Computation Value-at-Risk (VaR)

I have also decided to compute the VaR on the overall investing period. The VaR is a statistical measure of possible losses, a percentile of the distribution of outcomes. The VaR is the amount of loss that a portfolio will experience over a period of time with a predefined probability under normal market conditions. I have followed the same procedure in order to determine if I continue to pursue this methodology, the possible loss I can experience. For this reason, I have computed the Gaussian and the Cornish-Fisher VaR However, I put more intention to the Cornish-Fisher VaR because it is more conservative way to calculate the VaR and it takes into account higher moments, such as the skewness and the kurtosis. The one day Cornish-Fisher of $-215.13 with a confidence level of 95% means that on the overall period, there was a 5% chance that the strategy implemented can lose more than $215.13. This value also means that if the market remains has the same condition and I implement the same methodology, I have 5% that my methodology will experience a loss higher than $215.13.

| Daily | Confidence Level | | 95% |
|---|---|---|---|
| | Reversed Normal distribution | | VaR |
| Gaussian VaR | 1,645 | - | 237,47 |
| Cornish-F VaR | 1,541 | - | 215,13 |

| Daily | Confidence Level | | 99% |
|---|---|---|---|
| | Reversed Normal distribution | | VaR |
| Gaussian VaR | 2,326 | - | 376,20 |
| Cornish-F VaR | 2,276 | - | 379,25 |

*Table 9: VaR computation result*

## 5.5. Limitations of the study and possible improvements

In this section, I enumerate the characteristics of my methodology that impact or influence the interpretation of the results obtained. To achieve satisfactory results in this master thesis, I have encountered several constraints that I present in this section. Actually, these constraints conduct me to think that there is a way of improvement that can be conducted in future version of options based investment on FOREX market. First, this section gives the issues I have faced during this paper. Then, it gives possible ways of improvement for future researches.

### 5.5.1. Limitations of the study

The first issue that I have encountered while doing this paper is the lack of available data on different financial markets. This difficulty has conducted to a matching problem of the different financial market information. As explained earlier in this paper, the FOREX market starts to trade on Monday on Asia-Pacific region, for the US market when the Asia-Pacific Market is opening, the local time is Sunday 5:00 pm and all the US market places are still closed. Therefore, there are some days when the foreign exchange market is open and the US market, where financial derivatives market is closed. Thus, there is not possibility to enter into a position whether due to the fact that the currency options market is closed or the CME is closed (holiday, Sunday) and, consequently, there is no way to forecast the expected exchange rate level thanks to the Market-Based approach. This led to the reduction of possible days where strategy could be implemented.

The second problem is quite similar with the first one and it is relative to the expiration date of my Euro FX futures contracts and currency option contracts. As a reminder, I have used Euro FX futures contracts maturing the 14th March 2016 in order to forecast the expected exchange rate level. Each settlement price provided by the CME offered me a way to obtain the exchange rate level price on 14 March 2016. However, the forecasts need to be done until the 18th March 2016 when the call and put options are expiring. Thus, the need of a better way to forecast the EURUSD exchange rate was necessary from a practical standpoint, such as an ARMA model but in practice this model was not applicable on the EURUSD exchange rate level due to the data independency of the different lag.

The third limitation is associated with the small number of strategies implemented (48 investment strategies). All strategies have been implemented one by one starting from the 1st January 2016 until the 14th March 2016. Knowing that my strategies are based on the profit obtained when the options are exercised at maturity, I needed to wait each time the maturity in order to see if my strategies are profitable or not. The application of the same strategies on another period will be possible only for a period when options are maturing the 17th June 2016 because the Euro FX futures contracts are quarterly contracts and they are used in order to observe the expected direction of the exchange rate level. The sample size is really too low to state clearly that this methodology is working in any market conditions. In order to really confirm the success of my methodology, it will be interesting to replicate the same methodology and wait the answer for the 17th June 2016.

### 5.5.2. Possible improvements

The main issue spotted in the previous section is related to the forecasting of the EURUSD exchange rate level in a market where high volatility is present. The Market-Based approach gives a direction but it also has some drawbacks, some days the CME is closed due to the US Federal holiday. Furthermore, it does not necessarily match the day when options expire, this kind of model can give a forecast to a day close to the option maturity day but not certainly the same. Thus, it could be interesting to develop a more accurate forecasting model which takes into account the current market specifications in order to forecast correctly the exchange rate level.

The second limitation is related to the small result sample which does not permit to clearly state if the methodology applied in this paper is working in other future periods, currencies and market conditions. Therefore, it will be interesting to replicate this methodology on a different time frame and currency pairs when all the required information is available.

# 6. Conclusion

This paper interrogates if active management based on option strategies provides great profit in a market experiencing high volatility and no clear trend. Extending theoretical framework on Option-Based strategy, the aim of the research conducted is to propose a model taking profit from the particular pattern found in a monetary policy shifting between ECB and FED. In order to be able to answer this question, a first understanding of the key factors impacting the price of an option has been required. These factors are the underlying price, the forecasted volatility and finally the maturity. The purpose of this master thesis was to understand these factors and their impact on the choice of the most suitable strategy.

The methodology that was implemented takes into account these 3 factors. First, the price was forecasted in order to indicate the direction in which the exchange rate will move in. The forecasting of the price has tried to be modelled with an ARMA model but due to the special pattern of the historical exchange rate level, this model failed to propose a way to forecast the expected exchange rate level. As a result, a Market-Based approach has been conducted to forecast the exchange rate level thanks to the settlement price found in the Euro FX futures contracts commercialized by the CME.

After having defined the expected exchange rate level, the second step of the methodology consisted to model the changes in the anticipated volatility. As it is commonly known, volatility can have a significant impact on the success of an Option-Based strategy, within a high volatile market, investors have more chances that the option will be ITM and exercised. Accordingly, in order to determine the most suitable strategy, a GARCH(1,1) model with t-distribution is proposed. This GARCH modelling offered for each trading day a forecast of the volatility on the option remaining days. To choose the best strategy, a comparison of the model a time t has been done with previous days forecast, the reason of this comparison was to observe expansion or contraction tendency in the forecasted volatility. The aim of this comparison was to determine if the forecasted volatility tendency increase or decrease and thanks to that determine if a strategy betting on volatility or stability will be the most appropriate.

After all the information gathered concerning the exchange rate level and volatility forecasting, the last parameter was to determine if with the remaining days the chosen strategy should be implemented or not.

The objective of this paper was to examine carefully and link these 3 factors in the construct a strategy taking the most profit of them. The result obtained from this methodology shows that on the 48 trading days where strategy has been implemented, 33 days (68.75%) has brought a positive profit. The days where strategy implemented bring positive profit has on average higher contribution to the overall profit per day ($262.86) than days bringing a negative one ($-143.33). In terms of Return on Investment (ROI), the results are showing that Butterfly-spread strategies bring more wealth per unit of dollar invested than Strap strategies, even if Strap strategies have the highest contribution to the overall profit.

However, these values need to be examined carefully, due to the lack of time and availability of currency options and FOREX futures contracts. The observed sample is not large enough to clearly state that this type of active management will work in any market condition. Further studies need to be conducted with the same methodology on a different future time frame to determine if this methodology is supported or not.

# Appendixes

## Table of Appendixes

***Strategy description***

## Appendix 1: Strategy description

If investors feels the market will follow an upward trend, they can implement a bull-spread strategy in order to get profit by controlling the downside risk. This strategy can be shaped by buying one in-the-money (hereafter ITM) European call option on an asset with a certain strike price ($K_1$) and at the same time by selling one out-the-money (hereafter OTM) European call option on the same asset with a higher strike price ($K_2$), with both the same expiration date. As a call option value declines with the strike price, this strategy requires an initial investment because the value of the call sold ($C_2$) is less than the value of the option bought ($C_1$). At maturity, 3 scenarios occurs;

1. $S_T \leq K_1$. Both calls are out of the money: Options are not exercised. Profit is less than 0. The investors lose is initial investment (In. Inv.) which is equal to the price of the call bought minus the price of the call sold. $In.Inv. = C_1 - C_2$
2. $K_1 < S_T < K_2$.The bought call is in the money, the other call is out the money: Only the option in the money is exercised: Profit = $S_T - K_1 - In.Inv.$
3. $S_T \geq K_2$. Both options are in the money. Profit = $S_T - K_1 - (S_T - K_2) - In.Inv.$ = $K_2 - K_1 - In.Inv.$

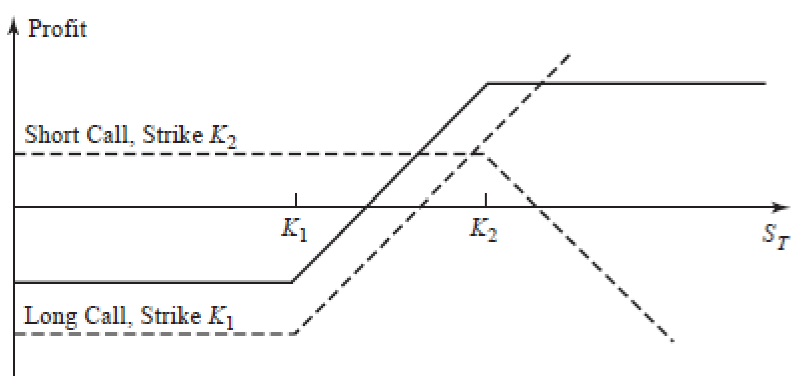



*Figure 8: Graphical representation of bull spread strategy using call options*

Figure 1 shows the different outcome. The profit from the strategy is indicated by the solid line. This strategy can be also created by put options. (Hull, 2012)

If investors feel the price will remain the same order in the near future, they will implement a butterfly spread by using a mixture of call options with different strike price and same maturity. This strategy is constructed by purchasing one ITM European call with a low strike price ($K_1$), purchasing one OTM European call with a high strike price ($K_3$), and selling at the same time two at-the money (hereafter ATM) European call with a strike price ($K_2 = 0.5(K_1 + K_3)$), halfway between $K_1$ and $K_3$, close to the current asset price. As shown is Figure 2, this strategy is profitable if the asset price does not move significantly from its current price.

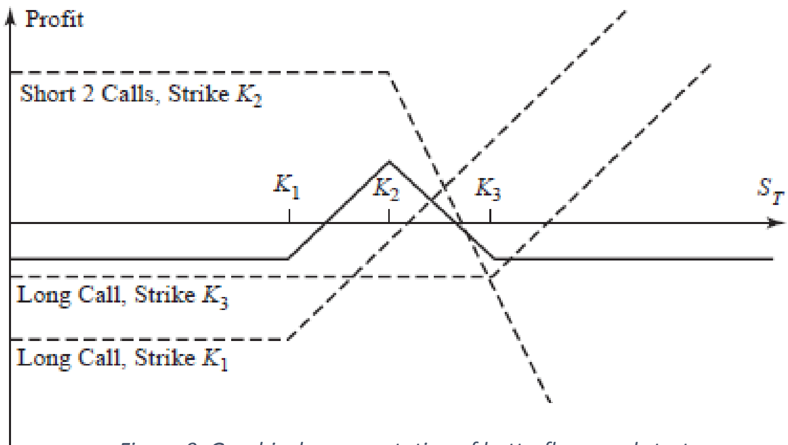


*Figure 9: Graphical representation of butterfly spread strategy*

At maturity, 4 outcomes can occur:

1. $S_T \leq K_1$. All options are out the money: No options are exercised. Investors make a loss equal to its initial investment. $In.Inv. = C_1 + C_3 - 2C_2$
2. $K_1 < S_T \leq K_2$. The call option with low strike price is exercised. Profit = $S_T - K_1 - In.Inv.$
3. $K_2 < S_T < K_3$. The Long call with strike $K_1$ and the 2 Short call with strike $K_2$ are exercised. Profit = $K_3 - S_T - In.Inv.$
4. $S_T \geq K_3$. All options are in the money and exercised. Profit = $-In.Inv.$ (Hull, 2012)

Contrary to the butterfly spread, t exists also more complex strategy which are based on the presence of volatility in the market such as straddle strategy. This strategy is put in place by buying one ATM European call and put with the same expiration date and strike price$(K)$. The strike price of both contracts is closed to the current asset price.  This strategy is profitable when the market is very volatile while the asset price at time T is far away from the strike price of the options. Figure 3 shows that straddle strategy provide a limited loss, equal to the purchasing of options, and unlimited profit for the investors.

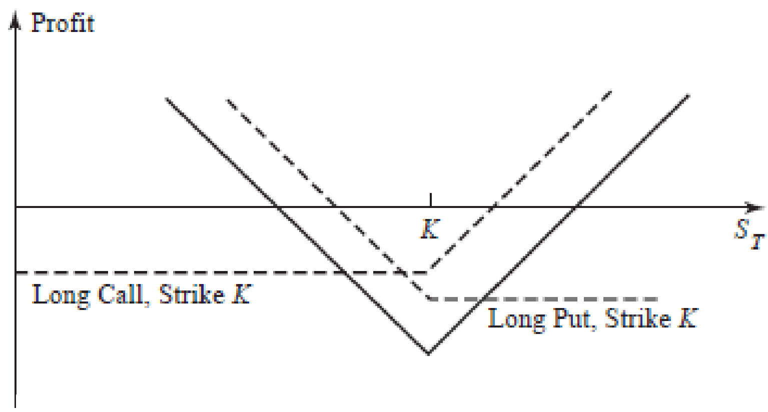


*Figure 10: Graphical representation of straddle strategy*

At maturity 3 situations can occur:

1. $S_T < K$. Put option is in the money and exercised. Profit = $K - S_T - In.Inv.$
2. $S_T = K$. No options are exercised. Investors make a loss equal to the initial investment (purchasing of call and put options). $In.Inv. = C + P$.

   On Figure 3, it is represented by the lowest point of the solid line.
3. $S_T > K_1$. Call option is in the money and exercised. Profit = $S_T - K_1 - In.Inv.$ (Hull, 2012)

Straddle strategy bets that the movement of an asset in both direction will be in the same order of magnitude. An investor can implement strategy that into account that a movement in a direction is more likely to occur, these strategies are the strip and strap. On the one hand, a strip strategy, composed of a long position in one call and two puts (same $K$ and $T$), is betting that a large asset price movement will arise but considers a large price decline is more likely to occur than a large increase. On the other hand, a strap strategy, composed of a long position in two calls and one put (same strike price $(K)$ and maturity $(T)$), is betting that an increase is more likely to occur than a decrease. In comparison to a straddle, these strategies are more expensive due to the purchase of an additional option (Hull, 2012).

Figure 4 shows the profit patterns from a strip and strap strategies. The profit patterns are quite the same with the straddle strategy but we can see a steep slope on the side where the additional option is purchased.

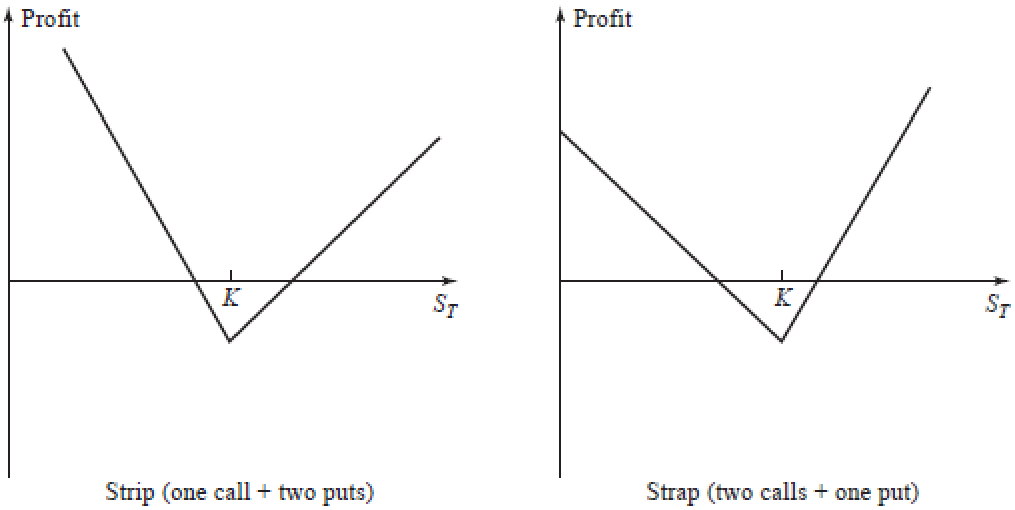



*Figure 11: Profit from Strip & Strap*

## Appendix 2: Kolmogorov-Smirnov Test

$$D_n = \sup|F_n(x) - F(x)|$$

$$F_n(x) = \frac{1}{n}\sum_{i=1}^{n} I_{[-\infty,x]}\,(X_i)$$

Where:

$F(x)$: Normal cumulative distribution function

$F_n(x)$: Distribution function of my data

$I_{[-\infty,x]}(X_i)$: Indicator function, equal to 1 if $X_i \ \leq x$ and 0 otherwise.

## Appendix 3: Time series analysis (Matlab Code)

```
%% TREND

%Plotting the data
plot(t,EURUSD);
legend('original data');
xlabel('time');
ylabel('Exchange rate');
title('EURUSD Exchange rate from 01/03/2015 to 31/12/2016')

%% First method (parametric)
detrend_data=detrend(EURUSD);
trend=EURUSD-detrend(EURUSD);

% Plotting the trend
hold on
plot(t,EURUSD);
plot(trend)
xlabel('time');
ylabel('Exchange rate');
title('Trend')

% Plotting the detrended data
plot(detrend_data)
xlabel('time');
ylabel('Exchange rate');
title('EURUSD Exchange rate without trend')

% -----------------------------NOTES----------------------------------

%% SEASONALITY
% How to find the period

sacf(detrend_data,100)   %
% How to find the seasonality
lagdata_season=lagmatrix(detrend_data,100);
x_season=lagdata_season - detrend_data;


sacf(x_season,100)

% Graph of the returns without seasonality
plot(x_season)
xlabel('Time')
ylabel('Returns')
title('Removed seasonality')

%% RETURNS WITHOUT TREND AND SEASONALITY
plot(x_season)
xlabel('time')
ylabel('returns')
title('Stock returns withtout trend and seasonality')
```

```
%% CHECK FOR INDEPENDANCE

% SAC function

sacf(x_season,100)

% --------------------------INTERPRETATION---------------------------
% we reject most of the lags
% the time dependency is not totally removed. Therefore, we cannot
% conclude of an independency between the data and we will confirm
% this assumption by doing the second test, the Ljung-Box test.

% --------------------------INTERPRETATION---------------------------

% Ljung-Box test
[q,pval]=ljungbox(x_season,6)
```

## Appendix 4: Normality analysis (Matlab Code)

```
% QQ Plot
qqplot(x_season)

% --------------------------INTERPRETATION---------------------------

% do not show normality

% --------------------------INTERPRETATION---------------------------

% Histogram
hist(x_season,51)
title('Histogram')

% Kolmogorov-smirnoff test
[stat,pval,h]=kolmogorov(x_season,0.05,'normcdf')
```

## Appendix 5: GARCH modelling (Matlab Code)

```
%%Define the model
Mdl = garch('Offset',NaN,'GARCHLags',1,'ARCHLags',1,'Distribution','t');

%% fit the model parameters
%estimate the parameters
[coeff,errors,eFit,sFit]=estimate(Mdl,EURUSDReturn);
[coeff]=estimate(Mdl,EURUSDReturn(1:264));

%value of estimated parameters, standard error of the estimation

%%now we have the model fit to the data, we can use function of garchpred
%to forecast the future mean and conditional standard deviation

%%Forecasting and simulation

%%
%Forecasting
horizon = 65; %Define the forecast horizon
Forecast_garch=forecast(coeff,horizon,'Y0',EURUSDReturn(1:264));
Forecast_garch1=forecast(coeff,horizon);


%% plot Garch graph
figure
plot(Simulate_garch,'Color',[.7,.7,.7])
hold on
plot(260:324,Forecast_garch,'r','LineWidth',2);
plot(260:324,Forecast_garch1,':','LineWidth',2);
title('Forecasted Conditional Variances at time t+1')
legend('Observed','Forecasts with Presamples',...
        'Forecasts without Presamples','Location','NorthEast')
hold off
```

## Appendix 6: Straddle (Matlab Code)

```
function[profit_straddle]=profit_straddle(EURUSD,
Option_price_call,Option_price_put)

Nb_row =length(EURUSD);
Last_column = size(EURUSD,2);
Nb_column = size(Option_price_call,2);
Strike_at_time_t = zeros(Nb_row-1,1);
Exchange_rate_at_maturity = zeros(Nb_row-1,1);
Initial_invest = zeros(Nb_row-1,1);
Upper_breakeven_point = zeros(Nb_row-1,1);
Lower_Breakeven_point = zeros(Nb_row-1,1);
profit_strategy = zeros(Nb_row-1,1);

for t=2:Nb_row
    for j=1:Nb_column
        %if loop check that the strike price of option are ATM
        if
EURUSD(t,Last_column)==Option_price_call(1,j)&&EURUSD(t,Last_column)==Option_
price_call(1,j)
            Strike_at_time_t(t-1)=EURUSD(t,Last_column);

            Exchange_rate_at_maturity(t-1)=EURUSD(Nb_row,2)*100;

            Cost = Option_price_call(t,j)+Option_price_put(t,j);%cost
strategy
            Initial_invest(t-1) = Cost*100;%contract size is 10 000€

            profit_strategy(t-1) = abs(EURUSD(Nb_row,2)*100-
EURUSD(t,Last_column))*100 - Cost*100;
            %calcul of profit (abs(spot_price - strike) -cost contract size
            %is 10 000€

            Upper_Breakeven = EURUSD(t,Last_column) + Cost;
            Lower_Breakeven = EURUSD(t,Last_column) - Cost;
            Upper_breakeven_point(t-1) = Upper_Breakeven;
            Lower_Breakeven_point(t-1) = Lower_Breakeven;

        end
    end
end
profit_strad =
[Strike_at_time_t;Exchange_rate_at_maturity;Initial_invest;Upper_breakeven_po
int;Lower_Breakeven_point;profit_strategy];
profit_straddle = reshape(profit_strad,Nb_row-1,6);
```

## Appendix 7: Strip (Matlab Code)

```
function[profit_strip]=profit_strip(EURUSD,
Option_price_call,Option_price_put)

Nb_row =length(EURUSD);
Last_column = size(EURUSD,2);
Nb_column = size(Option_price_call,2);
Strike_at_time_t = zeros(Nb_row-1,1);
Exchange_rate_at_maturity = zeros(Nb_row-1,1);
Initial_invest = zeros(Nb_row-1,1);
Upper_breakeven_point = zeros(Nb_row-1,1);
Lower_Breakeven_point = zeros(Nb_row-1,1);
profit_strategy = zeros(Nb_row-1,1);

for t=2:Nb_row
    for j=1:Nb_column
        %if loop check that the strike price of option are ATM
        if
EURUSD(t,Last_column)==Option_price_call(1,j)&&EURUSD(t,Last_column)==Option_
price_put(1,j)
            Strike_at_time_t(t-1)=EURUSD(t,Last_column);

            Exchange_rate_at_maturity(t-1)=EURUSD(Nb_row,2)*100;

            Cost = Option_price_call(t,j)+ 2*Option_price_put(t,j);%cost
strategy
            Initial_invest(t-1) = Cost*100;

            if EURUSD(Nb_row,2)*100<= EURUSD(t,Last_column)
                profit_strategy(t-1) = 2*(EURUSD(t,Last_column)-
EURUSD(Nb_row,2)*100)*100 - Cost*100;
            elseif EURUSD(Nb_row,2)*100> EURUSD(t,Last_column)
                profit_strategy(t-1)= ((EURUSD(Nb_row,2)*100)-
(EURUSD(t,Last_column)))*100 - Cost*100;
            end
            %calcul of profit of strip

            Upper_Breakeven = EURUSD(t,Last_column) + Cost;
            Lower_Breakeven = EURUSD(t,Last_column) - (Cost/2);
            Upper_breakeven_point(t-1) = Upper_Breakeven;
            Lower_Breakeven_point(t-1) = Lower_Breakeven;

        end
    end
end
profit_stri =
[Strike_at_time_t;Exchange_rate_at_maturity;Initial_invest;Upper_breakeven_po
int;Lower_Breakeven_point;profit_strategy];
profit_strip = reshape(profit_stri,Nb_row-1,6);
```

## Appendix 8: Strap (Matlab Code)

```
function[profit_strap]=profit_strap(EURUSD,
Option_price_call,Option_price_put)

Nb_row =length(EURUSD);
Last_column = size(EURUSD,2);
Nb_column = size(Option_price_call,2);

Strike_at_time_t = zeros(Nb_row-1,1);
Exchange_rate_at_maturity = zeros(Nb_row-1,1);
Initial_invest = zeros(Nb_row-1,1);
Upper_breakeven_point = zeros(Nb_row-1,1);
Lower_Breakeven_point = zeros(Nb_row-1,1);
profit_strategy = zeros(Nb_row-1,1);

for t=2:Nb_row
    for j=1:Nb_column
        %if loop check that the strike price of option are ATM
        if
EURUSD(t,Last_column)==Option_price_call(1,j)&&EURUSD(t,Last_column)==Option_
price_put(1,j)
            Strike_at_time_t(t-1)=EURUSD(t,Last_column);

            Exchange_rate_at_maturity(t-1)=EURUSD(Nb_row,2)*100;

            Cost = 2*Option_price_call(t,j)+ Option_price_put(t,j);%cost
strategy
            Initial_invest(t-1) = Cost*100;

            if EURUSD(Nb_row,2)*100<= EURUSD(t,Last_column)
                profit_strategy(t-1) = abs((EURUSD(Nb_row,2)*100-
EURUSD(t,Last_column)))*100 - Cost*100;
            else
                profit_strategy(t-1)= 2*abs((EURUSD(t,Last_column)-
EURUSD(Nb_row,2)*100))*100- Cost*100;
            end
            %calcul of profit of strap

            Upper_Breakeven = EURUSD(t,Last_column) + (Cost/2);
            Lower_Breakeven = EURUSD(t,Last_column) - Cost;
            Upper_breakeven_point(t-1) = Upper_Breakeven;
            Lower_Breakeven_point(t-1) = Lower_Breakeven;

        end
    end
end
profit_stra =
[Strike_at_time_t;Exchange_rate_at_maturity;Initial_invest;Upper_breakeven_po
int;Lower_Breakeven_point;profit_strategy];
profit_strap = reshape(profit_stra,Nb_row-1,6);
```

## Appendix 9: Butterfly Spread (Matlab Code)

```
function[profit_butterfly]=profit_butterfly(EURUSD,
Option_price_call,Spread_length)
L = Spread_length;%length of spread

Nb_row =length(EURUSD);
Last_column = size(EURUSD,2);
Nb_column = size(Option_price_call,2);
Strike_at_time_t = zeros(Nb_row-1,1);%ATM option
Strike_lower_option = zeros(Nb_row-1,1);%ITM lower option
Strike_upper_option = zeros(Nb_row-1,1);%OTM upper option
Exchange_rate_at_maturity = zeros(Nb_row-1,1);
Initial_invest = zeros(Nb_row-1,1);%initial investment
Upper_breakeven_point = zeros(Nb_row-1,1);
Lower_Breakeven_point = zeros(Nb_row-1,1);
profit_strategy = zeros(Nb_row-1,1);

for t=2:Nb_row
    for j=1:Nb_column
        %'if' loop check that the strike price of option are ATM
        if EURUSD(t,Last_column)==Option_price_call(1,j)
            Strike_at_time_t(t-1)=Option_price_call(1,j);%sell 2 ATM call
            Strike_lower_option(t-1)=Option_price_call(1,j-L);%buy 1 ITM call
            Strike_upper_option(t-1)=Option_price_call(1,j+L);%buy 1 OTM call
            Exchange_rate_at_maturity(t-1)=EURUSD(Nb_row,2)*100;

            Cost = -2*Option_price_call(t,j)+ Option_price_call(t,j-
L)+Option_price_call(t,j+L);%cost strategy
            Initial_invest(t-1) = Cost*100;

            if EURUSD(Nb_row,2)*100 <= Option_price_call(1,j-L)
                profit_strategy(t-1)= -Cost*100;
            elseif EURUSD(Nb_row,2)*100 >= Option_price_call(1,j+L)
                profit_strategy(t-1)= -Cost*100;
            elseif EURUSD(Nb_row,2)*100 > Option_price_call(1,j-L) &&
EURUSD(Nb_row,2)*100 <= Option_price_call(1,j)
                profit_strategy(t-1)= (EURUSD(Nb_row,2)*100 -
Option_price_call(1,j-L))*100 - Cost*100;
            else
                profit_strategy(t-1)= (Option_price_call(1,j+L) -
EURUSD(Nb_row,2)*100)*100 - Cost*100;
            end
            %calcul of profit of butterfly
            Upper_Breakeven = Option_price_call(1,j+L) - Cost;%upper strike
            Lower_Breakeven = Option_price_call(1,j-L) + Cost;%lower strike
            Upper_breakeven_point(t-1) = Upper_Breakeven;
            Lower_Breakeven_point(t-1) = Lower_Breakeven;
        end
    end
end
profit_but =
[Strike_lower_option;Strike_at_time_t;Strike_upper_option;Exchange_rate_at_ma
turity;Initial_invest;Upper_breakeven_point;Lower_Breakeven_point;profit_stra
tegy];
profit_butterfly = reshape(profit_but,Nb_row-1,8);
```

## Appendix 10: Bull Spread (Matlab Code)

```
function[profit_bull_spread]=profit_bull_spread(EURUSD,
Option_price_call,Spread_length)

L = Spread_length;%length of spread

Nb_row =length(EURUSD);
Last_column = size(EURUSD,2);
Nb_column = size(Option_price_call,2);

Price_at_time_t = zeros(Nb_row-1,1);%exchange rate at time t
Strike_lower_option = zeros(Nb_row-1,1);%ITM lower option
Strike_upper_option = zeros(Nb_row-1,1);%OTM upper option
Exchange_rate_at_maturity = zeros(Nb_row-1,1);
Initial_invest = zeros(Nb_row-1,1);%initial investment
breakeven_point = zeros(Nb_row-1,1);
profit_strategy = zeros(Nb_row-1,1);

for t=2:Nb_row
    for j=1:Nb_column
        %'if' loop check that the strike price of option are ATM
        if EURUSD(t,Last_column)==Option_price_call(1,j)
          Price_at_time_t(t-1)=EURUSD(t,Last_column);%exchange rate at time t
          Strike_lower_option(t-1)=Option_price_call(1,j-L);%buy 1 ITM call
          Strike_upper_option(t-1)=Option_price_call(1,j+L);%sell 1 OTM call

            Exchange_rate_at_maturity(t-1)=EURUSD(Nb_row,2)*100;

            Cost = Option_price_call(t,j-L)- Option_price_call(t,j+L);%cost
strategy
            Initial_invest(t-1) = Cost*100;

            if EURUSD(Nb_row,2)*100 <= Option_price_call(1,j-L)
                profit_strategy(t-1)= -Cost*100;
            elseif EURUSD(Nb_row,2)*100 >= Option_price_call(1,j+L)
                profit_strategy(t-1)= (Option_price_call(1,j+L) -
Option_price_call(1,j-L))*100 - Cost*100;
            else
                profit_strategy(t-1)= (EURUSD(Nb_row,2)*100 -
Option_price_call(1,j-L))*100 - Cost*100;
            end
            %calcul of profit of Bull

            Breakeven = Option_price_call(1,j-L) + Cost;%Breakeven strike
price of long call - premium paid
            breakeven_point(t-1) = Breakeven;

        end
    end
end
8profit_bull =
[Price_at_time_t;Strike_lower_option;Strike_upper_option;Exchange_rate_at_mat
urity;Initial_invest;breakeven_point;profit_strategy];
profit_bull_spread = reshape(profit_bull,Nb_row-1,7);
```

## Appendix 11: Bear Spread (Matlab Code)

```
function[profit_bear_spread]=profit_bear_modified(EURUSD,
Option_price_call,Spread_length)

L = Spread_length;%length of spread

Nb_row =length(EURUSD);
Last_column = size(EURUSD,2);
Nb_column = size(Option_price_call,2);

Strike_lower_option = zeros(Nb_row-1,1);%ATM lower option
Strike_upper_option = zeros(Nb_row-1,1);%OTM upper option
Exchange_rate_at_maturity = zeros(Nb_row-1,1);
Initial_invest = zeros(Nb_row-1,1);%initial investment
breakeven_point = zeros(Nb_row-1,1);
profit_strategy = zeros(Nb_row-1,1);

for t=2:Nb_row
    for j=1:Nb_column
        %'if' loop check that the strike price of option are ATM
        if EURUSD(t,Last_column)==Option_price_call(1,j)
            Strike_lower_option(t-1)=Option_price_call(1,j-L);%sell 1 ITM
call
            Strike_upper_option(t-1)=Option_price_call(1,j);%buy 1 ATM call

            Exchange_rate_at_maturity(t-1)=EURUSD(Nb_row,2)*100;

            Cost = Option_price_call(t,j)- Option_price_call(t,j-L);%cost
strategy
            Initial_invest(t-1) = Cost*100; % cost is positive, no initial
investment

            if EURUSD(Nb_row,2)*100 <= Option_price_call(1,j-L)
                profit_strategy(t-1)=  -Cost*100; %ok
            elseif EURUSD(Nb_row,2)*100 >= Option_price_call(1,j)
                profit_strategy(t-1)= (Option_price_call(1,j) -
Option_price_call(1,j-L))*100 + Cost*100;
            else
                profit_strategy(t-1)= (EURUSD(Nb_row,2)*100 -
Option_price_call(1,j-L))*100 + Cost*100;
            end
            %calcul of profit of Bear

            Breakeven = Option_price_call(1,j-L) - Cost;%Breakeven strike
price of long call - premium paid
            breakeven_point(t-1) = Breakeven;
        end
    end
end
profit_bull =
[Strike_lower_option;Strike_upper_option;Exchange_rate_at_maturity;Initial_in
vest;breakeven_point;profit_strategy];
profit_bear_spread = reshape(profit_bull,Nb_row-1,6);
```

***Result:***

## Appendix 12: Basic probability computation on the EURUSD Returns

| ***Period*** | **01/03/2015-31/12/2015** |
|---:|---:|
| *Number of trading days* | 263 |
| *Mean* | 1,10258109 |
| *Standard deviation* | 0,02292582 |
| *Variance* | 0,0005276 |
| *Median* | 1,10099423 |
| *Minimum* | 1,04816306 |
| *Maximum* | 1,15830564 |
| *Skewness* | -0,1337496 |
| *Excess Kurtosis* | -0,7326611 |
| *Min Pips* | 105,0 |
| *Max Pips* | 116,0 |

*Table 10: EURUSD Returns - basic probability computation*

## Appendix 13: Regression on the EURUSD Returns

***01/03/15-31/12/15***

RAPPORT DÉTAILLÉ

| *Statistiques de la régression* | |
|---|---:|
| Coefficient de détermination multiple | 0,000891242 |
| Coefficient de détermination R^2 | 7,94312E-07 |
| Coefficient de détermination R^2 | -0,00383062 |
| Erreur-type | 0,007007783 |
| Observations | 263 |

ANALYSE DE VARIANCE

| | *Degré de liberté* | *Somme des carrés* | *Moyenne des carrés* | *F* |
|---|---:|---:|---:|---:|
| Régression | 1 | 1,01811E-08 | 1,01811E-08 | 0,000207316 |
| Résidus | 261 | 0,012817454 | 4,9109E-05 | |
| Total | 262 | 0,012817464 | | |

| | *Coefficients* | *Erreur-type* | *Statistique t* | *Probabilité* |
|---|---:|---:|---:|---:|
| Constante | -6,06877E-05 | 0,000866707 | -0,070020943 | ***0,944230609*** |
| Period | -8,19515E-08 | 5,69168E-06 | -0,014398457 | ***0,988523091*** |

*Table 11: EURUSD Return - detailed OLS regression*

## Appendix 14: ACF and PACF plot on Returns

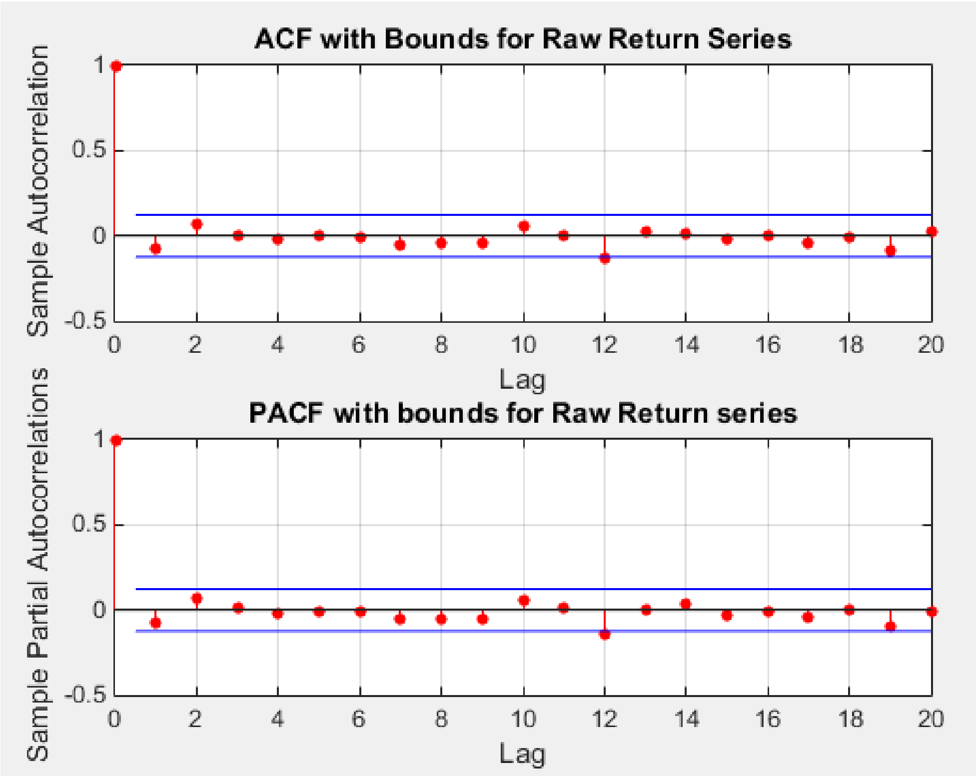



*Figure 12: ACF and PACF plot of the Returns*

## Appendix 15: CME Euro FX futures contract settlement price

| ***Date*** | **Futures contract settlement price** |
|---|---|
| *2015-12-31* | 1,0884 |
| *2016-01-04* | 1,0852 |
| *2016-01-05* | 1,0765 |
| *2016-01-06* | 1,0805 |
| *2016-01-07* | 1,0954 |
| *2016-01-08* | 1,0939 |
| *2016-01-11* | 1,0874 |
| *2016-01-12* | 1,08725 |
| *2016-01-13* | 1,08955 |
| *2016-01-14* | 1,0872 |
| *2016-01-15* | 1,0942 |
| *2016-01-19* | 1,09365 |
| *2016-01-20* | 1,09055 |
| *2016-01-21* | 1,08995 |

| | |
|---|---|
| *2016-01-22* | 1,08065 |
| *2016-01-25* | 1,0862 |
| *2016-01-26* | 1,0866 |
| *2016-01-27* | 1,09075 |
| *2016-01-28* | 1,09535 |
| *2016-01-29* | 1,0845 |
| *2016-02-01* | 1,0902 |
| *2016-02-02* | 1,0928 |
| *2016-02-03* | 1,1122 |
| *2016-02-04* | 1,1216 |
| *2016-02-05* | 1,11705 |
| *2016-02-08* | 1,12045 |
| *2016-02-09* | 1,13035 |
| *2016-02-10* | 1,13025 |
| *2016-02-11* | 1,1329 |
| *2016-02-12* | 1,12635 |
| *2016-02-16* | 1,1144 |
| *2016-02-17* | 1,11445 |
| *2016-02-18* | 1,1104 |
| *2016-02-19* | 1,11335 |
| *2016-02-22* | 1,10355 |
| *2016-02-23* | 1,10245 |
| *2016-02-24* | 1,10195 |
| *2016-02-25* | 1,103 |
| *2016-02-26* | 1,0939 |
| *2016-02-29* | 1,08935 |
| *2016-03-01* | 1,0877 |
| *2016-03-02* | 1,0873 |
| *2016-03-03* | 1,09645 |
| *2016-03-04* | 1,10115 |
| *2016-03-07* | 1,1014 |
| *2016-03-08* | 1,10135 |
| *2016-03-09* | 1,09995 |
| *2016-03-10* | 1,1178 |
| *2016-03-11* | 1,1145 |
| *2016-03-14* | 1,1108 |

*Table 12: CME Euro FX futures contract settlement price*

## Appendix 16: QQ-plot of the residuals

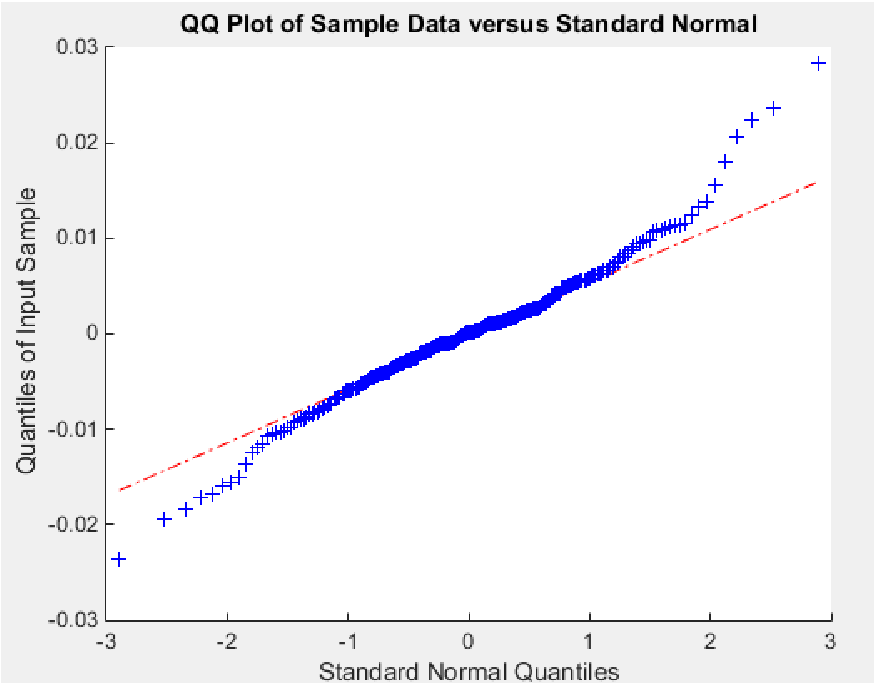



*Figure 13: EURUSD residuals - QQ-plot*

## Appendix 17: Histogram of the residuals

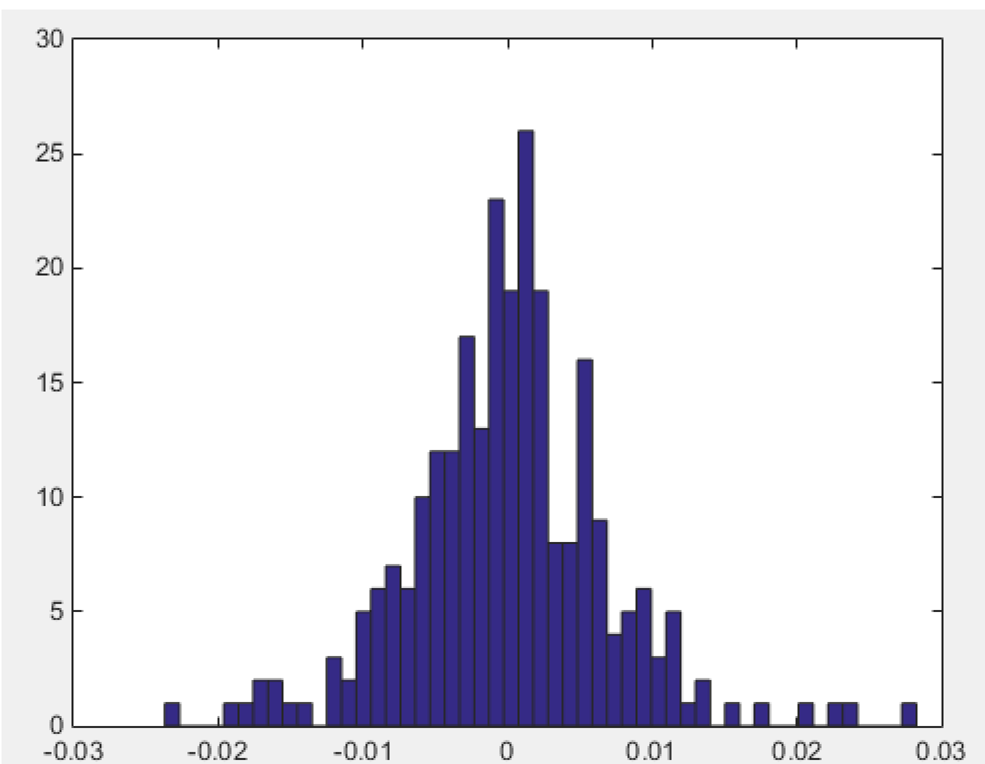



*Figure 14: EURUSD residuals - Histogram*

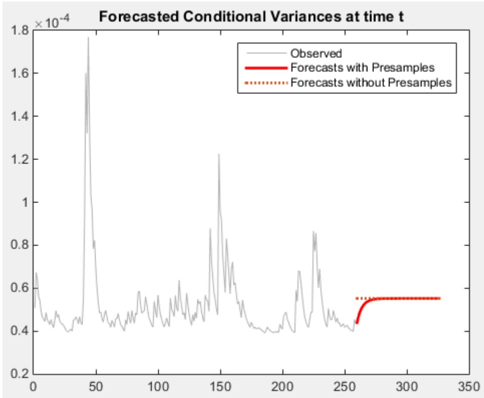
## Appendix 18: GARCH: parameter estimation

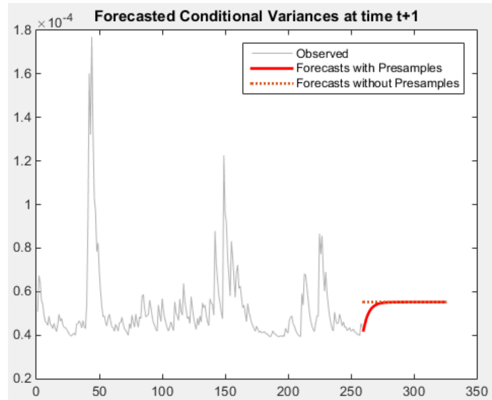
| | GARCH | ARCH | Unconditional Variance | Constant | Offset | Distribution |
|---|---|---|---|---|---|---|
| *t* | 0,621 | 0,0996 | 5,52E-05 | 1,20E-05 | -1,54E-04 | t |
| *t+1* | 0,6908 | 0,0999 | 5,52E-05 | 1,15E-05 | -1,39E-04 | t |
| *t+2* | 0,69760541 | 0,10050541 | 5,52E-05 | 1,11E-05 | -0,00015713 | t |
| *t+3* | 0,70505666 | 0,1015098 | 5,53E-05 | 1,07E-05 | -0,00017476 | t |
| *t+4* | 0,6958307 | 0,09915283 | 5,46E-05 | 1,12E-05 | -0,00020764 | t |
| *t+5* | 0,70288665 | 0,09880314 | 5,45E-05 | 1,08E-05 | -0,0001923 | t |
| *t+6* | 0,67999868 | 0,09804178 | 5,52E-05 | 1,23E-05 | -0,00015658 | t |
| *t+7* | 0,68182119 | 0,0970476 | 5,50E-05 | 1,22E-05 | -0,00017712 | t |
| *t+8* | 0,67662156 | 0,09773464 | 5,46E-05 | 1,23E-05 | -0,00015099 | t |
| *t+9* | 0,67279429 | 0,09833974 | 5,43E-05 | 1,24E-05 | -0,00017657 | t |
| *t+10* | 0,67682245 | 0,09657459 | 5,41E-05 | 1,23E-05 | -0,00018609 | t |
| *t+11* | 0,67618746 | 0,09641832 | 5,38E-05 | 1,22E-05 | -0,00016455 | t |
| *t+12* | 0,67478239 | 0,09716082 | 5,38E-05 | 1,23E-05 | -0,00018044 | t |
| *t+13* | 0,6719309 | 0,09808421 | 5,36E-05 | 1,23E-05 | -0,00015668 | t |
| *t+14* | 0,6724342 | 0,09989557 | 5,36E-05 | 1,22E-05 | -0,0001406 | t |
| *t+15* | 0,67585788 | 0,10101107 | 5,35E-05 | 1,19E-05 | -0,00015477 | t |
| *t+16* | 0,67914086 | 0,10286158 | 5,35E-05 | 1,17E-05 | -0,00014154 | t |
| *t+17* | 0,67935439 | 0,10387801 | 5,34E-05 | 1,16E-05 | -0,00016186 | t |
| *t+18* | 0,68701408 | 0,10603146 | 5,37E-05 | 1,11E-05 | -0,00017137 | t |
| *t+19* | 0,6934963 | 0,10868277 | 5,40E-05 | 1,07E-05 | -1,81E-04 | t |
| *t+20* | 0,69316543 | 0,10803241 | 5,36E-05 | 1,07E-05 | -0,00020753 | t |
| *t+21* | 0,68960064 | 0,10686136 | 5,31E-05 | 1,08E-05 | -0,00017781 | t |
| *t+22* | 0,69793171 | 0,10802517 | 5,33E-05 | 1,03E-05 | -0,00016928 | t |
| *t+23* | 0,69866471 | 0,10728276 | 5,28E-05 | 1,03E-05 | -0,0001446 | t |
| *t+24* | 0,70486804 | 0,10800202 | 5,29E-05 | 9,90E-06 | -0,00012342 | t |
| *t+25* | 0,70798627 | 0,1082807 | 5,28E-05 | 9,70E-06 | -0,00014313 | t |
| *t+26* | 0,70039195 | 0,10625849 | 5,22E-05 | 1,01E-05 | -0,00017429 | t |
| *t+27* | 0,69252491 | 0,10575815 | 5,18E-05 | 1,04E-05 | -0,00014311 | t |
| *t+28* | 0,69936685 | 0,10511004 | 5,17E-05 | 1,01E-05 | -0,00012879 | t |
| *t+29* | 0,68269343 | 0,10626398 | 5,31E-05 | 1,12E-05 | -0,00010564 | t |
| *t+30* | 0,66850759 | 0,11185086 | 5,32E-05 | 1,17E-05 | -8,39E-05 | t |
| *t+31* | 0,76554552 | 0,09850523 | 5,60E-05 | 7,61E-06 | -0,00038844 | t |
| *t+32* | 0,71351661 | 0,11010022 | 5,36E-05 | 9,46E-06 | -0,00022129 | t |
| *t+33* | 0,67083298 | 0,10646063 | 5,23E-05 | 1,16E-05 | -7,99E-05 | t |
| *t+34* | 0,67431196 | 0,10506109 | 5,22E-05 | 1,15E-05 | -5,40E-05 | t |
| *t+35* | 0,67723082 | 0,10397401 | 5,21E-05 | 1,14E-05 | -5,40E-05 | t |
| *t+36* | 0,67573979 | 0,10411066 | 5,18E-05 | 1,14E-05 | -3,57E-05 | t |
| *t+37* | 0,6709113 | 0,10541341 | 5,18E-05 | 1,16E-05 | -4,86E-05 | t |
| *t+38* | 0,67377849 | 0,10364469 | 5,14E-05 | 1,14E-05 | -7,33E-05 | t |

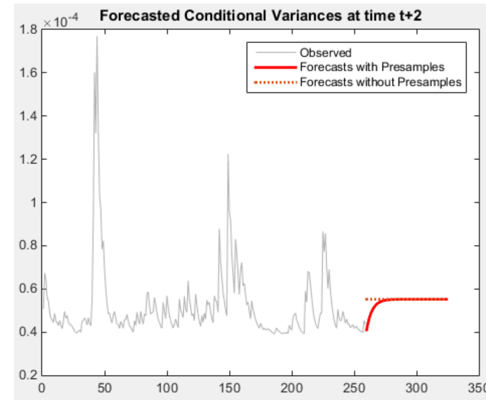
| | | | | | | |
|---|---|---|---|---|---|---|
| *t+39* | 0,67342319 | 0,10328733 | 5,12E-05 | 1,14E-05 | -9,54E-05 | t |
| *t+40* | 0,67320965 | 0,10421166 | 5,11E-05 | 1,14E-05 | -0,00011033 | t |
| *t+41* | 0,67477295 | 0,1056197 | 5,12E-05 | 1,12E-05 | -0,00012408 | t |
| *t+42* | 0,67855875 | 0,10753871 | 5,12E-05 | 1,10E-05 | -0,00013386 | t |
| *t+43* | 0,68162765 | 0,10976676 | 5,13E-05 | 1,07E-05 | -0,00013206 | t |
| *t+44* | 0,68613902 | 0,11270351 | 5,16E-05 | 1,04E-05 | -0,00012797 | t |
| *t+45* | 0,67752051 | 0,10819015 | 5,12E-05 | 1,10E-05 | -0,00015725 | t |
| *t+46* | 0,68725071 | 0,10780171 | 5,13E-05 | 1,05E-05 | -0,00016021 | t |
| *t+47* | 0,69340618 | 0,10868815 | 5,14E-05 | 1,02E-05 | -0,00016786 | t |
| *t+48* | 0,69763458 | 0,11282462 | 5,29E-05 | 1,00E-05 | -0,00016563 | t |
| *t+49* | 0,70207894 | 0,1123819 | 5,18E-05 | 9,62E-06 | -0,00017107 | t |
| *t+50* | 0,69561622 | 0,108881 | 1,00E-05 | 1,00E-05 | -0,00019907 | t |
| *t+51* | 0,70022546 | 0,10856358 | 5,12E-05 | 9,79E-06 | -0,00021692 | t |
| *t+52* | 0,70419595 | 0,10956895 | 5,13E-05 | 9,56E-06 | -0,00022499 | t |
| *t+53* | 0,71200101 | 0,11081453 | 5,16E-05 | 9,13E-06 | -0,0002322 | t |
| *t+54* | 0,70590389 | 0,10764114 | 5,10E-05 | 9,51E-06 | -0,00019956 | t |
| *t+55* | 0,71393828 | 0,1075522 | 5,11E-05 | 9,13E-06 | -0,0002044 | t |
| *t+56* | 0,71157558 | 0,10657901 | 5,07E-05 | 9,21E-06 | -0,00017893 | t |
| *t+57* | 0,71628628 | 0,10671131 | 5,06E-05 | 8,96E-06 | -0,00016574 | t |
| *t+58* | 0,71932666 | 0,10764395 | 5,07E-05 | 8,77E-06 | -0,00017085 | t |
| *t+59* | 0,72655908 | 0,10944214 | 5,11E-05 | 8,38E-06 | -0,00017876 | t |
| *t+60* | 0,7115648 | 0,10746391 | 5,31E-05 | 9,61E-06 | -0,00016193 | t |
| *t+61* | 0,71034154 | 0,10765031 | 5,28E-05 | 9,61E-06 | -0,00017509 | t |
| *t+62* | 0,70994294 | 0,10712102 | 5,25E-05 | 9,60E-06 | -0,00015677 | t |
| *t+63* | 0,70916976 | 0,10699125 | 5,22E-05 | 9,59E-06 | -0,00017549 | t |
| *t+64* | 0,70886894 | 0,10601263 | 5,20E-05 | 9,62E-06 | -0,00017297 | t |
| *t+65* | 0,71289334 | 0,10513749 | 5,21E-05 | 9,48E-06 | -0,00014504 | t |
| *t+66* | 0,76163659 | 0,09451495 | 5,23E-05 | 7,53E-06 | -0,00014644 | t |

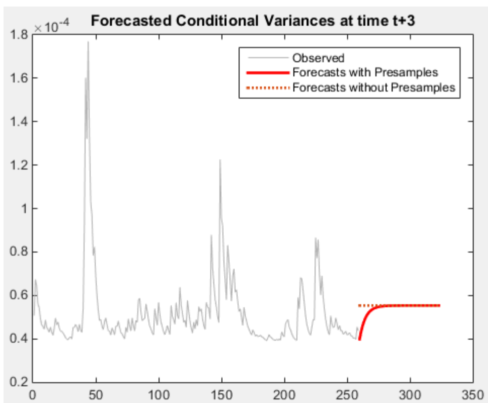
*Table 13: GARCH parameters estimation*

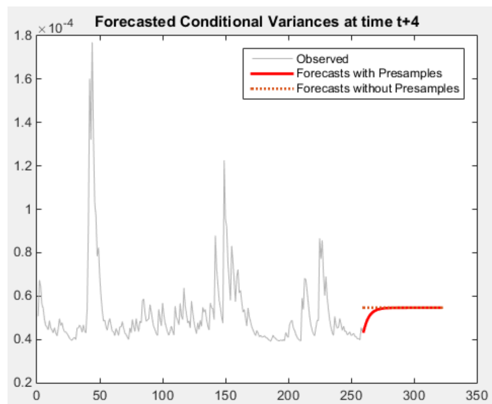
## Appendix 19: Graphical result of GARCH forecasting

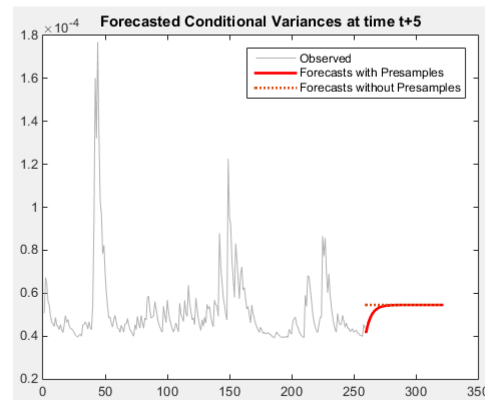

Forecasted Conditional Variances at time t
Observed
Forecasts with Presamples
Forecasts without Presamples

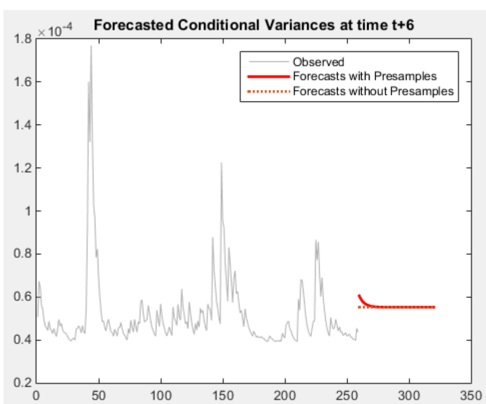

Forecasted Conditional Variances at time t+1
Observed
Forecasts with Presamples
Forecasts without Presamples

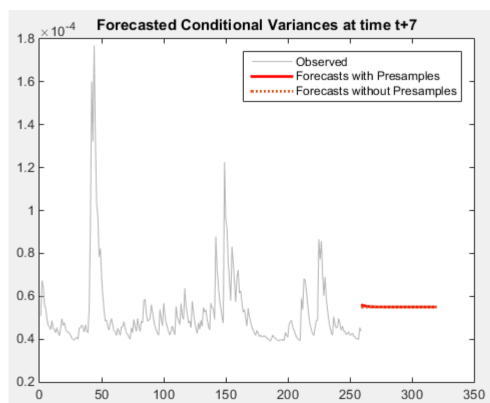

Forecasted Conditional Variances at time t+2
Observed
Forecasts with Presamples
Forecasts without Presamples

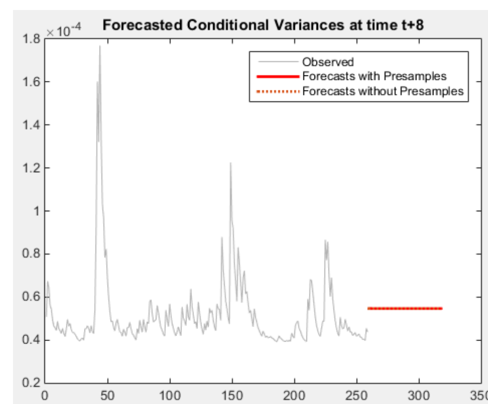

Forecasted Conditional Variances at time t+3
Observed
Forecasts with Presamples
Forecasts without Presamples

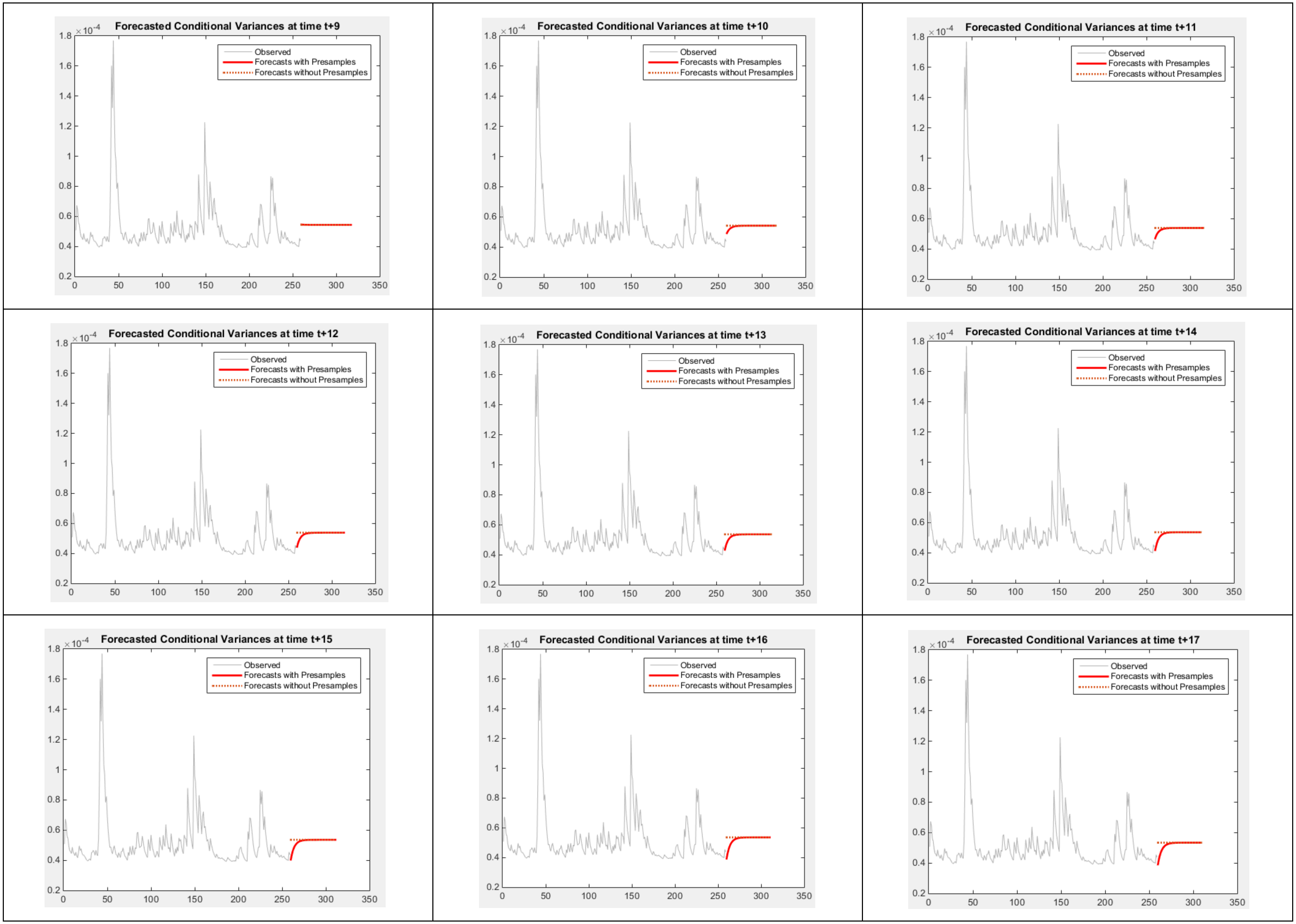

Forecasted Conditional Variances at time t+4
Observed
Forecasts with Presamples
Forecasts without Presamples

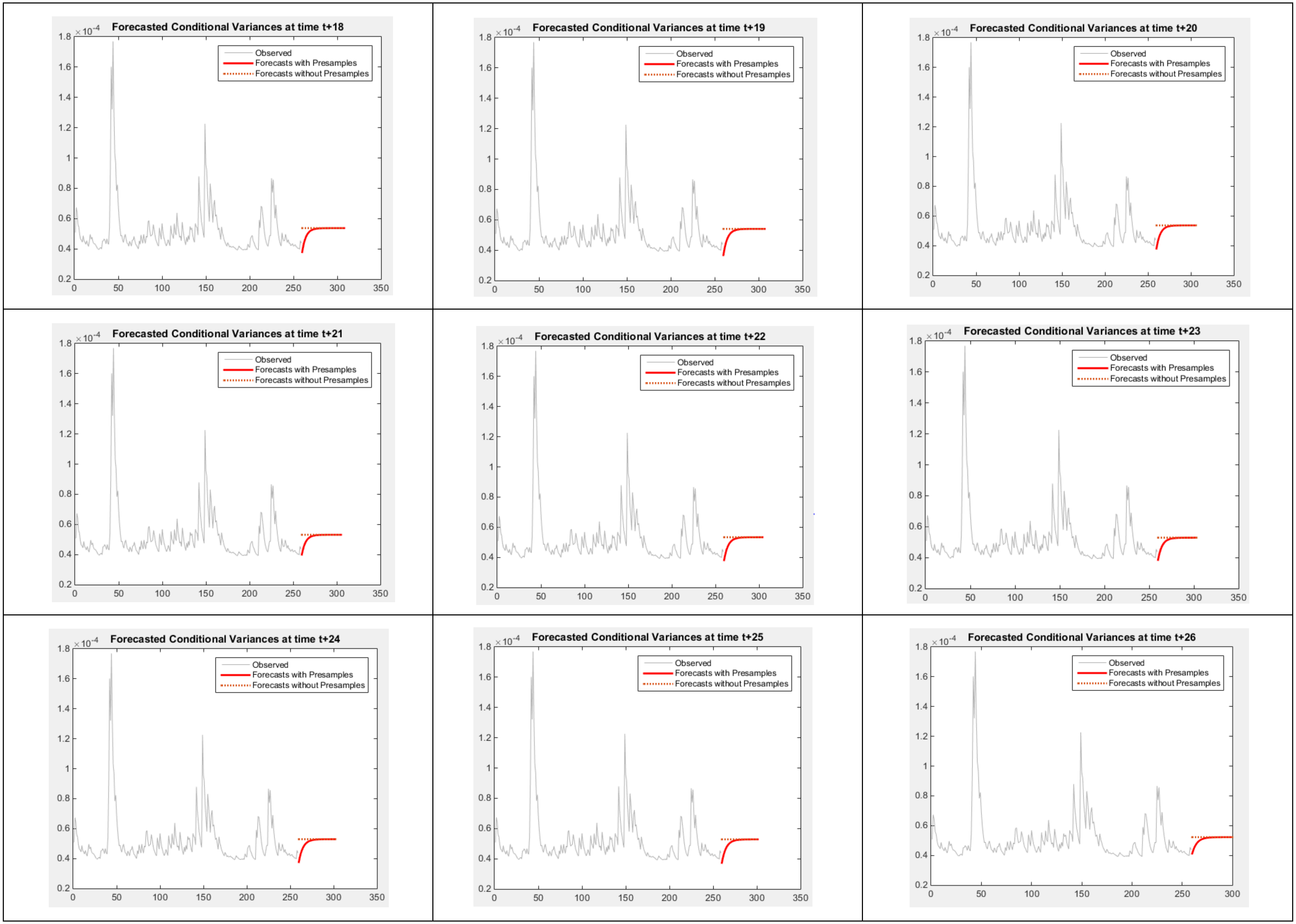

Forecasted Conditional Variances at time t+5
Observed
Forecasts with Presamples
Forecasts without Presamples

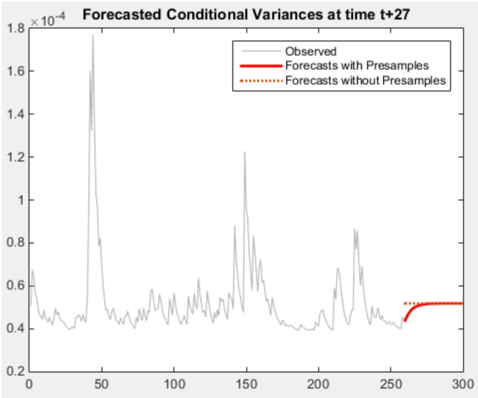

Forecasted Conditional Variances at time t+6
Observed
Forecasts with Presamples
Forecasts without Presamples

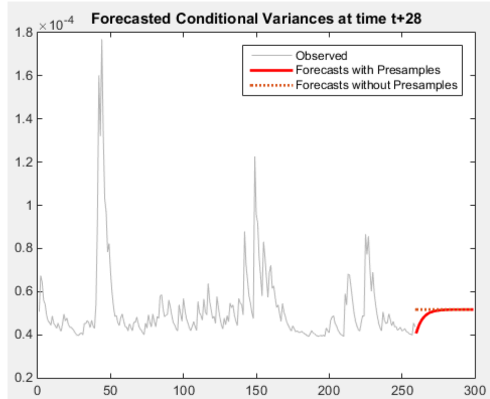

Forecasted Conditional Variances at time t+7
Observed
Forecasts with Presamples
Forecasts without Presamples

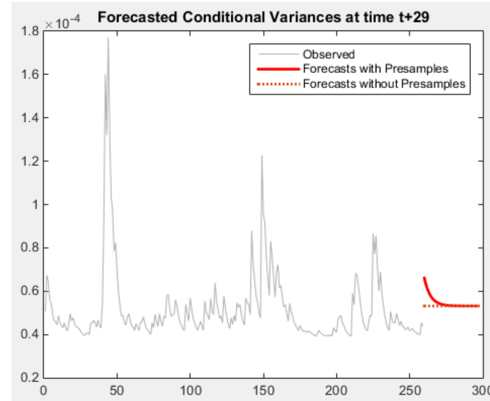

Forecasted Conditional Variances at time t+8
Observed
Forecasts with Presamples
Forecasts without Presamples

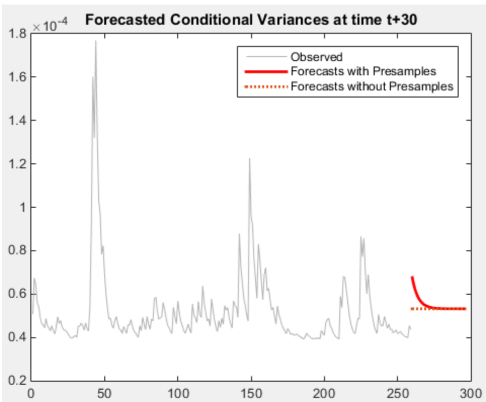

Forecasted Conditional Variances at time t+9
Observed
Forecasts with Presamples
Forecasts without Presamples
Forecasted Conditional Variances at time t+10
Observed
Forecasts with Presamples
Forecasts without Presamples
Forecasted Conditional Variances at time t+11
Observed
Forecasts with Presamples
Forecasts without Presamples
Forecasted Conditional Variances at time t+12
Observed
Forecasts with Presamples
Forecasts without Presamples
Forecasted Conditional Variances at time t+13
Observed
Forecasts with Presamples
Forecasts without Presamples
Forecasted Conditional Variances at time t+14
Observed
Forecasts with Presamples
Forecasts without Presamples
Forecasted Conditional Variances at time t+15
Observed
Forecasts with Presamples
Forecasts without Presamples
Forecasted Conditional Variances at time t+16
Observed
Forecasts with Presamples
Forecasts without Presamples
Forecasted Conditional Variances at time t+17
Observed
Forecasts with Presamples
Forecasts without Presamples

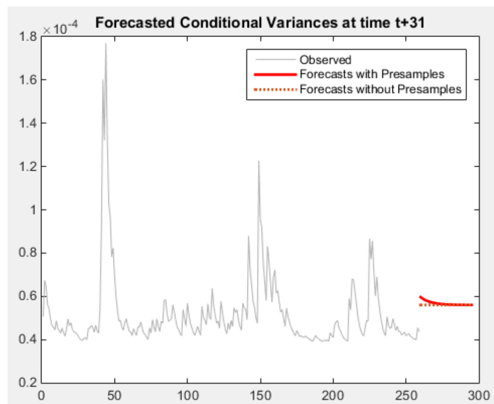

Forecasted Conditional Variances at time t+18
Forecasted Conditional Variances at time t+19
Forecasted Conditional Variances at time t+20
Forecasted Conditional Variances at time t+21
Forecasted Conditional Variances at time t+22
Forecasted Conditional Variances at time t+23
Forecasted Conditional Variances at time t+24
Forecasted Conditional Variances at time t+25
Forecasted Conditional Variances at time t+26
Observed
Forecasts with Presamples
Forecasts without Presamples
×10⁻⁴

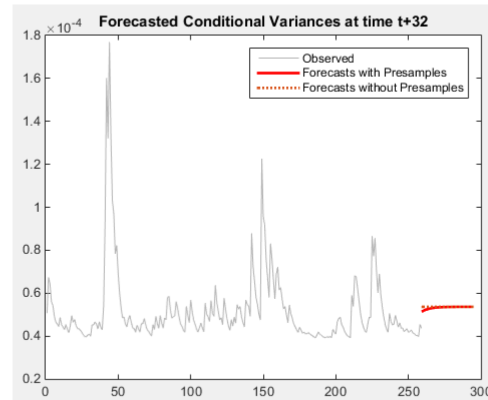

Forecasted Conditional Variances at time t+27
×10-4
Observed
Forecasts with Presamples
Forecasts without Presamples

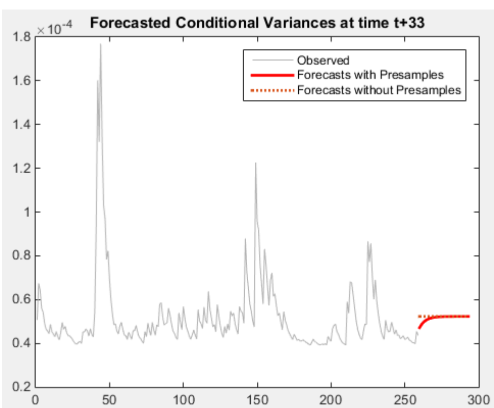

Forecasted Conditional Variances at time t+28
×10-4
Observed
Forecasts with Presamples
Forecasts without Presamples

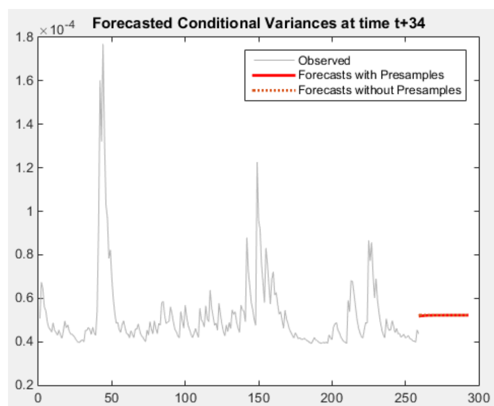

Forecasted Conditional Variances at time t+29
×10-4
Observed
Forecasts with Presamples
Forecasts without Presamples

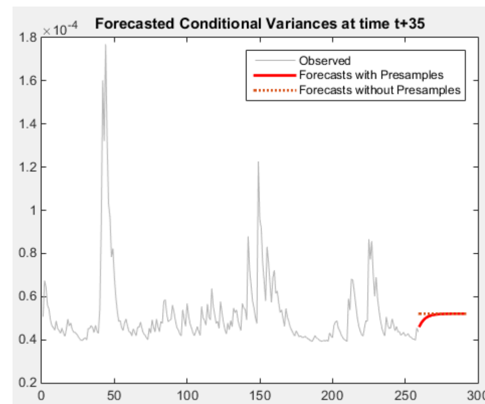

Forecasted Conditional Variances at time t+30
×10-4
Observed
Forecasts with Presamples
Forecasts without Presamples

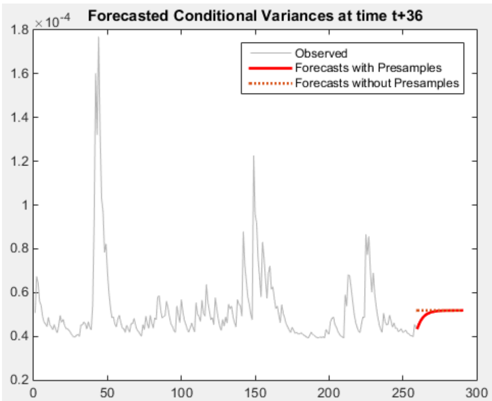

Forecasted Conditional Variances at time t+31
×10-4
Observed
Forecasts with Presamples
Forecasts without Presamples

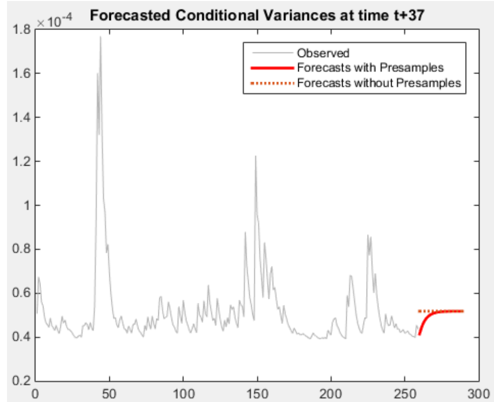

Forecasted Conditional Variances at time t+32
×10-4
Observed
Forecasts with Presamples
Forecasts without Presamples

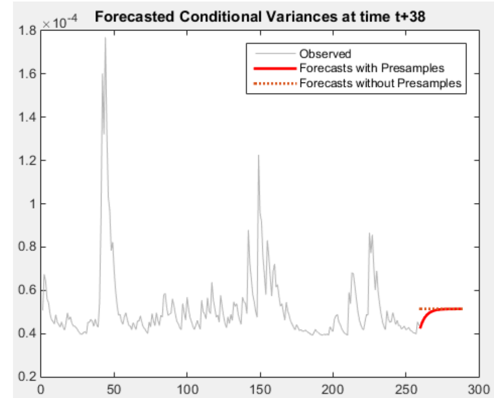

Forecasted Conditional Variances at time t+33
×10-4
Observed
Forecasts with Presamples
Forecasts without Presamples

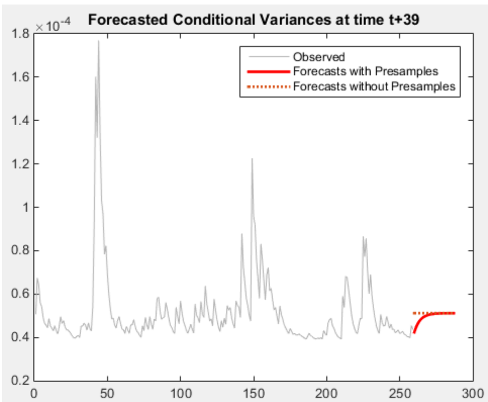

Forecasted Conditional Variances at time t+34
×10-4
Observed
Forecasts with Presamples
Forecasts without Presamples

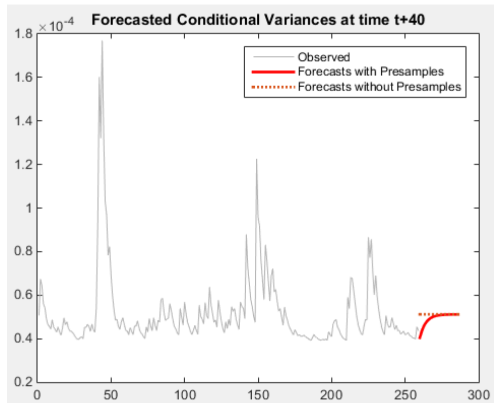

Forecasted Conditional Variances at time t+35
×10-4
Observed
Forecasts with Presamples
Forecasts without Presamples

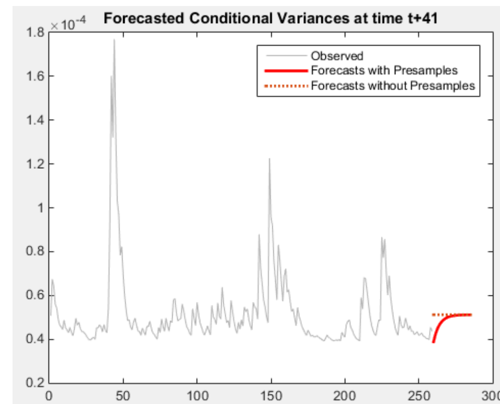

Forecasted Conditional Variances at time t+36
Observed
Forecasts with Presamples
Forecasts without Presamples

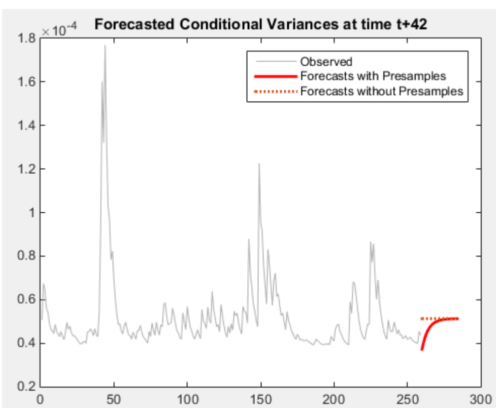

Forecasted Conditional Variances at time t+37
Observed
Forecasts with Presamples
Forecasts without Presamples

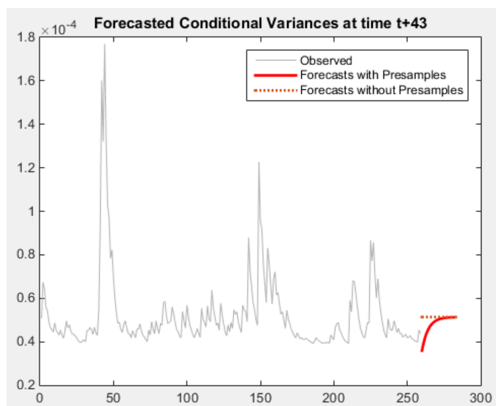

Forecasted Conditional Variances at time t+38
Observed
Forecasts with Presamples
Forecasts without Presamples

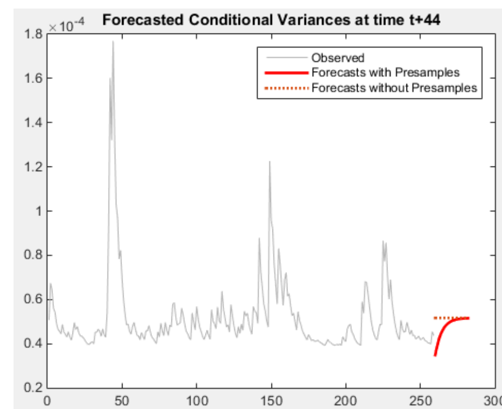

Forecasted Conditional Variances at time t+39
Observed
Forecasts with Presamples
Forecasts without Presamples

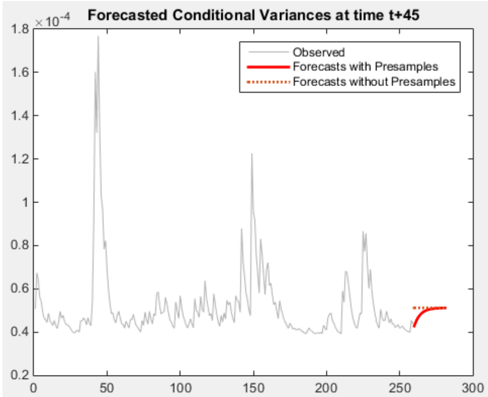

Forecasted Conditional Variances at time t+40
Observed
Forecasts with Presamples
Forecasts without Presamples

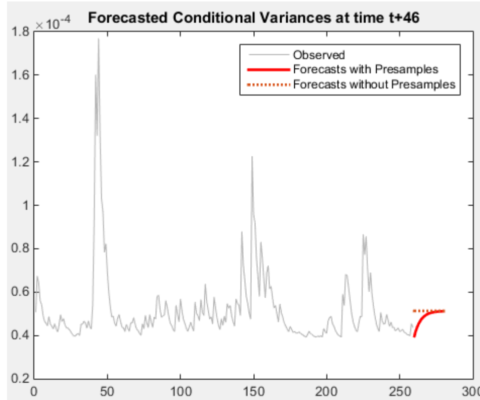

Forecasted Conditional Variances at time t+41
Observed
Forecasts with Presamples
Forecasts without Presamples

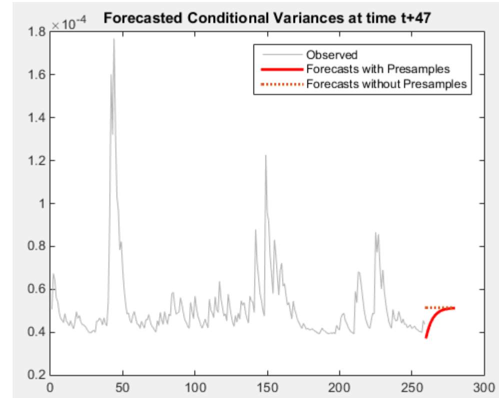

Forecasted Conditional Variances at time t+42
Observed
Forecasts with Presamples
Forecasts without Presamples

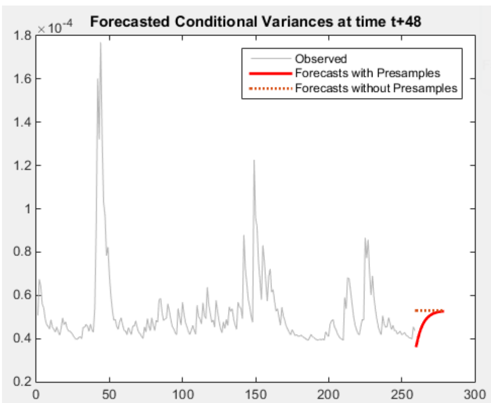

Forecasted Conditional Variances at time t+43
Observed
Forecasts with Presamples
Forecasts without Presamples

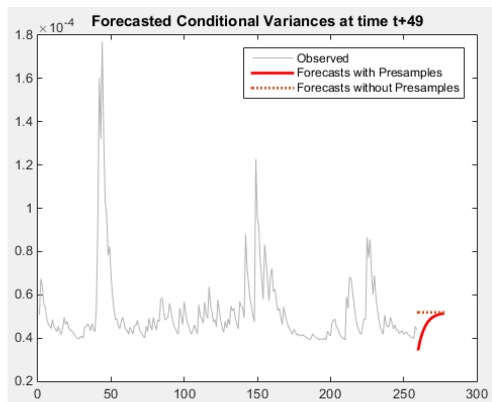

Forecasted Conditional Variances at time t+44
Observed
Forecasts with Presamples
Forecasts without Presamples

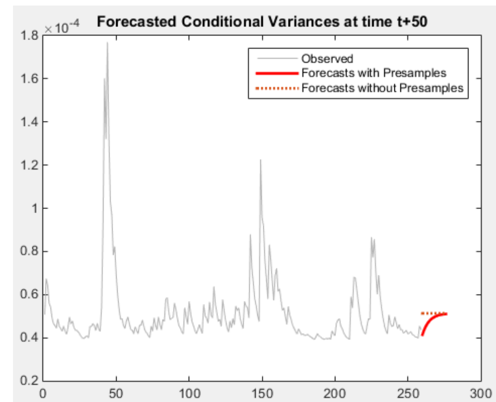

Forecasted Conditional Variances at time t+45
$\times 10^{-4}$
Observed
Forecasts with Presamples
Forecasts without Presamples
1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2
0 50 100 150 200 250 300

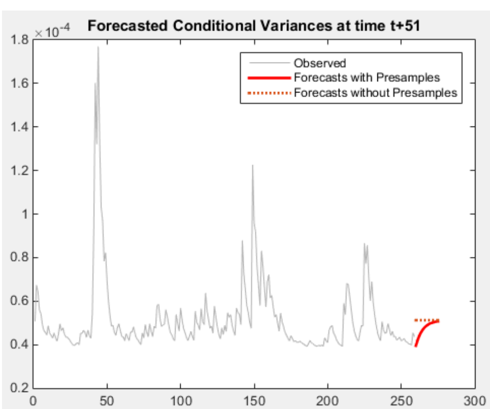

Forecasted Conditional Variances at time t+46
$\times 10^{-4}$
Observed
Forecasts with Presamples
Forecasts without Presamples
1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2
0 50 100 150 200 250 300

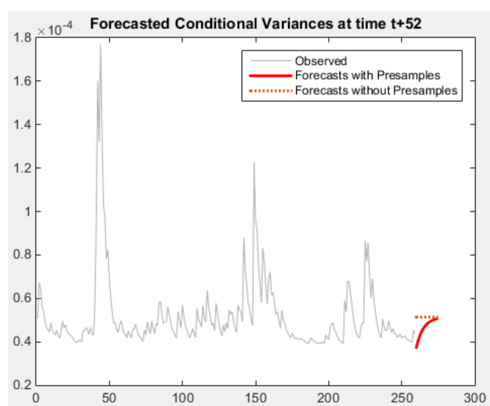

Forecasted Conditional Variances at time t+47
$\times 10^{-4}$
Observed
Forecasts with Presamples
Forecasts without Presamples
1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2
0 50 100 150 200 250 300

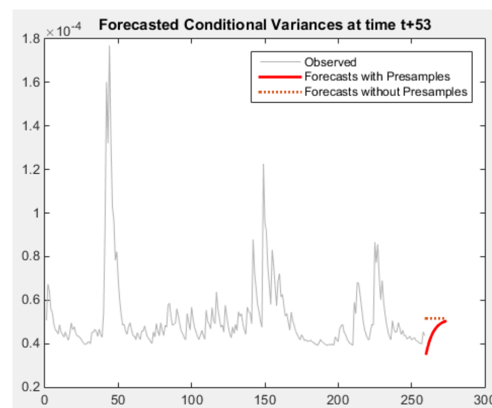

Forecasted Conditional Variances at time t+48
$\times 10^{-4}$
Observed
Forecasts with Presamples
Forecasts without Presamples
1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2
0 50 100 150 200 250 300

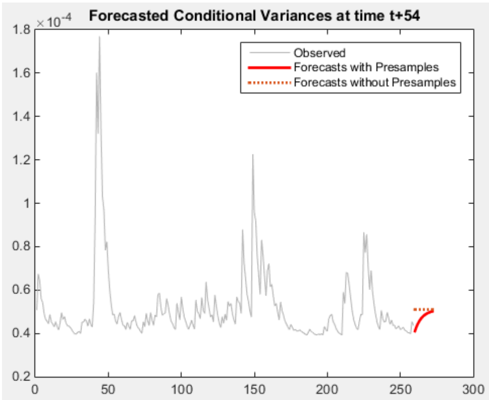

Forecasted Conditional Variances at time t+49
$\times 10^{-4}$
Observed
Forecasts with Presamples
Forecasts without Presamples
1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2
0 50 100 150 200 250 300

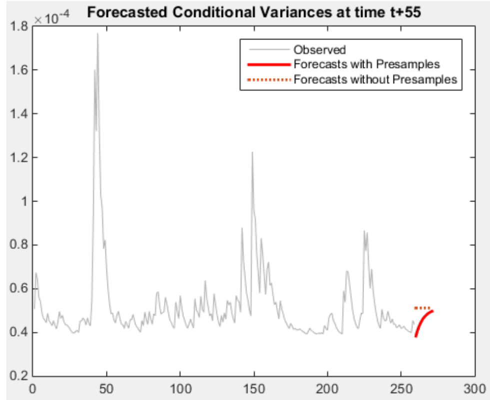

Forecasted Conditional Variances at time t+50
$\times 10^{-4}$
Observed
Forecasts with Presamples
Forecasts without Presamples
1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2
0 50 100 150 200 250 300

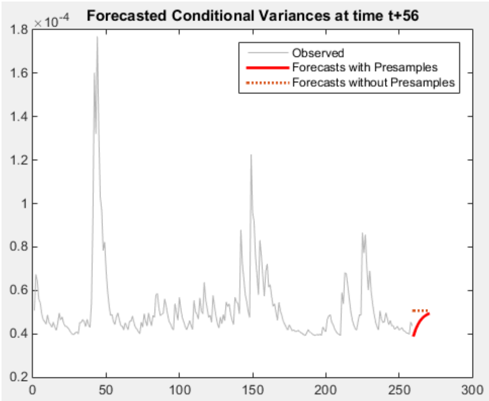

Forecasted Conditional Variances at time t+51
$\times 10^{-4}$
Observed
Forecasts with Presamples
Forecasts without Presamples
1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2
0 50 100 150 200 250 300

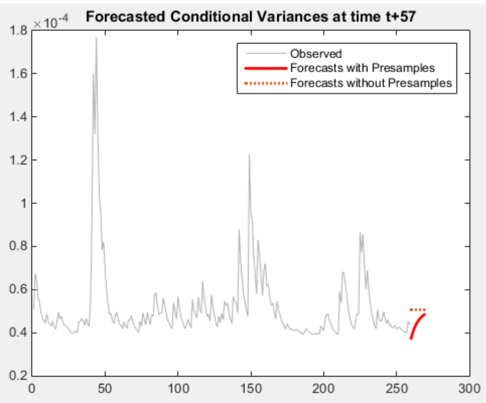

Forecasted Conditional Variances at time t+52
$\times 10^{-4}$
Observed
Forecasts with Presamples
Forecasts without Presamples
1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2
0 50 100 150 200 250 300

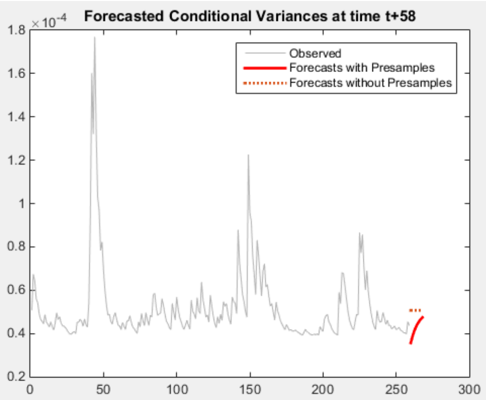

Forecasted Conditional Variances at time t+53
$\times 10^{-4}$
Observed
Forecasts with Presamples
Forecasts without Presamples
1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2
0 50 100 150 200 250 300

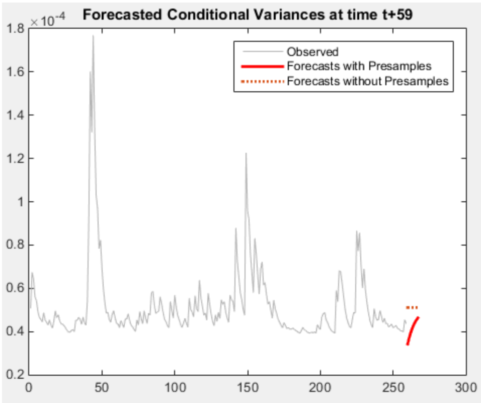

Forecasted Conditional Variances at time t+54
×10^-4
Observed
Forecasts with Presamples
Forecasts without Presamples

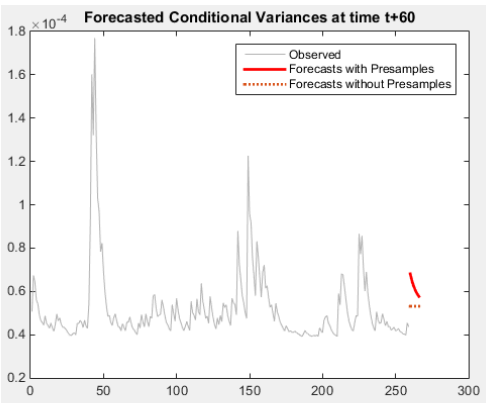

Forecasted Conditional Variances at time t+55
×10^-4
Observed
Forecasts with Presamples
Forecasts without Presamples

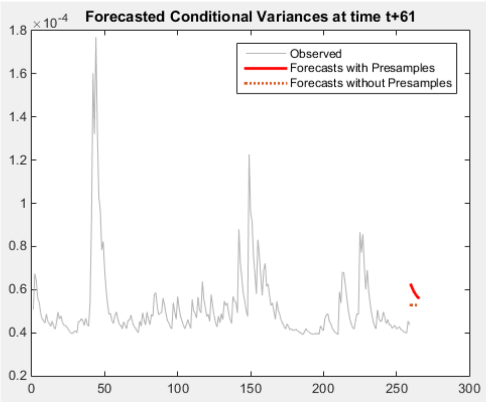

Forecasted Conditional Variances at time t+56
×10^-4
Observed
Forecasts with Presamples
Forecasts without Presamples

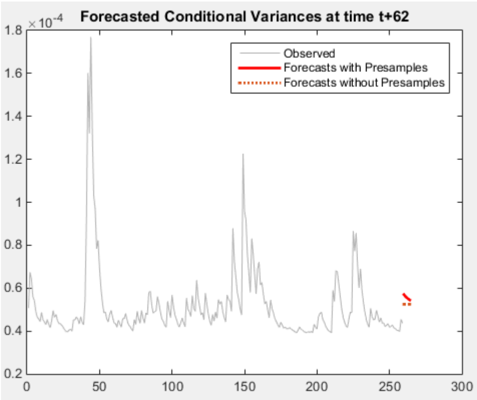

Forecasted Conditional Variances at time t+57
×10^-4
Observed
Forecasts with Presamples
Forecasts without Presamples

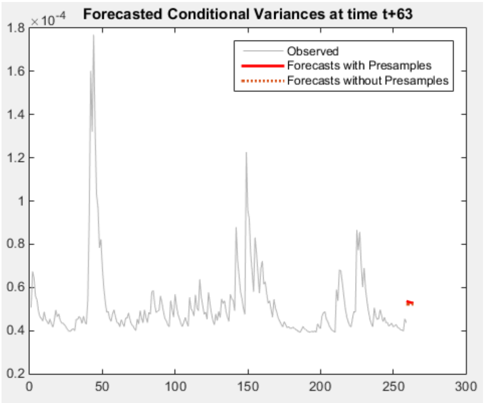

Forecasted Conditional Variances at time t+58
×10^-4
Observed
Forecasts with Presamples
Forecasts without Presamples

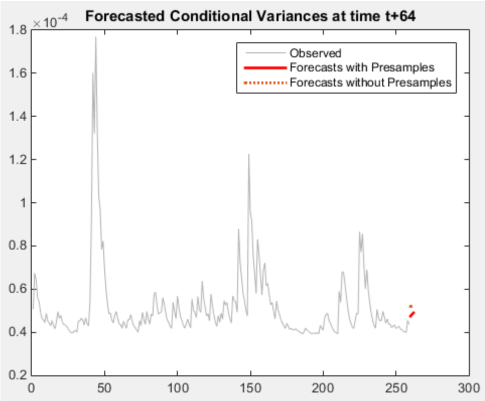

Forecasted Conditional Variances at time t+59
×10^-4
Observed
Forecasts with Presamples
Forecasts without Presamples

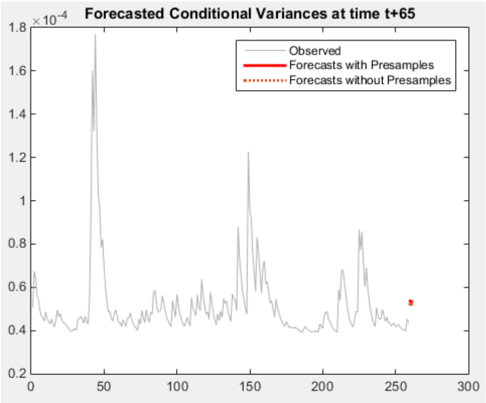

Forecasted Conditional Variances at time t+60
×10^-4
Observed
Forecasts with Presamples
Forecasts without Presamples

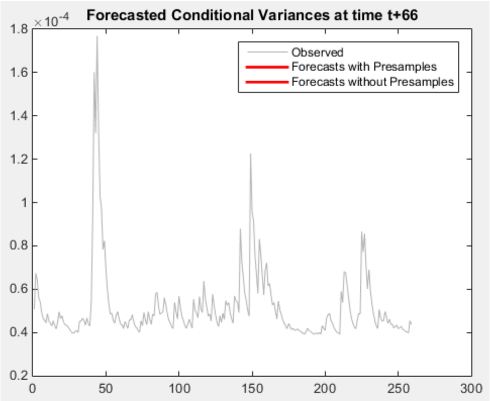

Forecasted Conditional Variances at time t+61
×10^-4
Observed
Forecasts with Presamples
Forecasts without Presamples


Forecasted Conditional Variances at time t+62
×10^-4
Observed
Forecasts with Presamples
Forecasts without Presamples


Forecasted Conditional Variances at time t+63
×10⁻⁴
Observed
Forecasts with Presamples
Forecasts without Presamples
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
0
50
100
150
200
250
300


Forecasted Conditional Variances at time t+64
×10⁻⁴
Observed
Forecasts with Presamples
Forecasts without Presamples
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
0
50
100
150
200
250
300


Forecasted Conditional Variances at time t+65
×10⁻⁴
Observed
Forecasts with Presamples
Forecasts without Presamples
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
0
50
100
150
200
250
300


Forecasted Conditional Variances at time t+66
×10⁻⁴
Observed
Forecasts with Presamples
Forecasts without Presamples
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
0
50
100
150
200
250
300

## Bibliography and references

Alessandria, G., & Kaboski, J. (2004). *Violating Purchasing Power Parity.* Philadephia: Federal Reserve Bank of Philadelphia.

Alexander, C., & Lazar, E. (2006, April). Normal Mixture GARCH(1,1): Applications to Exchange Rate Modelling. *Journal of Applied Econometrics, Vol. 21, No. 3*, pp. 307-336.

Andersen, T. G., & Bollerslev, T. (1998, November). Answering the Skeptics: Yes, Standard Volatility Models do Provide Accurate Forecasts. *International Economic Review*, pp. 885-905.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2000, March). *The Distribution of Realized Exchange Rate Volatility.* National Bureau of Economic Research.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Vega, C. (2003, March). Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange. *The American Economic Review, Vol. 93, No. 1*, pp. 38-62.

Baillie, R. T., & Bollerslev, T. (1990). Intra-day and Inter-Market Volatility in Foreign Exchange Rates. *The Review of Economic Studies, Vol. 58, No. 3*, pp. 565-585.

Bailliu, J., & King, M. R. (2005). *What Drives Movements in Exchange Rates.* Bank of Canada Review.

Bank for International Settlements. (2013). *Triennal Central Bank Survey - Foreign exchange turnover in April 2013: preliminary global results.* Bank for International Settlements.

Bank of England. (2009). *Paper on the Foreign Exchange Market.* London.

Bayoumi, T., & Eichengreen, B. (1992). *Macroeconomic Adjustement under Bretton Woods and the Post-Bretton Woods Float: An Impulse-response analysis.* Massachussets: National Bureau of Economic Research.

Beckmann, J., Czudaj, R., & Pilbeam, K. (2015). Causality and volatility patterns between gold prices and exchanges rates. *North American Journal of Economics and Finance*, pp. 292-300.

Berge, T., Jorda, O., & Taylor, A. M. (2010). Currency Carry Trades. *NBER International Seminar on Macroeconomics, Vol. 7, No. 1*, pp. 357-388.

Bishop, P., & Dixon, D. (1992). *Foreign Exchange Handbook.* Baskerville: McGraw-Hill's Professional Book Group.

Bjonnes, G. H., Rime, D., & Solheim, H. O. (2005). Liquidity provision in the overnight foreign exchange market. *Journal of International Money and Finance, Vol. 24*, pp. 175-196.

Bollerslev, T. (1987, August). A Conditionally Heteroskedastic Time Series Model for Speculative Prices and Rates of Return. *The Review of Economics and Statistics, Vol. 69, No. 3*, pp. 542-547.

Bollerslev, T., & Zhou, H. (2006). Volatility puzzles: a simple framework for gauging return-volatility regressions. *Journal of Econometrics, Vol. 131*, pp. 123-150.

Buttenwood. (2015, February). *Why currency volatility has got worse*. Retrieved from Economist: http://www.economist.com/blogs/economist-explains/2015/02/economist-explains-2

Chang, E. C., & Wong, K. P. (2003, September). Cross-Hedging with Currency Options and Futures. *Journal of Financial and Quantitative Analysis, Vol. 38, No. 3*, pp. 555-574.

Conrad, J., & Kaul, G. (1998, Autumn). An Anatomy of Trading Strategies. *The Review of Financial Studies, Vol. 11, No 3*, pp. 489-519.

Coudert, V., Couharde, C., & Mignon, V. (2015). *On the impact of volatility on the real exchange rate - terms of trade nexus: Revisiting commodity currencies.* Journal of International Money and Finance.

Coval, J. D., & Shumway, T. (2001, June). Expected Option Returns. *The Journal of Finance, Vol. 56, No. 3*, pp. 983-1009.

Dimitris, K., Papadamou, S., & Dimitriou, D. (2015). *Intraday exchange rate volatility transmissions across QE announcements.* Finance Research Letters.

Eichengreen, B. (1992). *Three Perspectives on the Bretton Woods System.* Massachussets: National Bureau of Economic Research.

Elliot, G., Rothenberg, T. J., & Stock, J. H. (1996, July). Efficient Tests for an Autoregressive Unit Root. *Econometrica, Vol. 64, No. 4*, pp. 813-836.

Fama, E. F. (1965, January). The Behavior of Stock-Market Prices. *The journal of Business, Vol. 38, No. 1*, pp. 34-105.

Forni, M., Gambetti, L., Lippi, M., & Sala, L. (2014). *Noisy News in Business Cycles.*

Frankel, J. A., Galli, G., & Giovannini, A. (1996). *The microstructure of foreign exchange markets.* Chicago: National Bureau of Economic Research Conference Report.

Galagedera, D. U., & Kitamura, Y. (2012). Effect of exchange rate return on volatility spill-over across trading regions. *Japan and the World Economy, Vol. 24*, pp. 254-265.

Garber, P. M. (1993). The Collapse of the Bretton Woods Fixed Exchange Rate System. In M. D. Eichengreen, *A Retropsective on the Bretton Woods System : Lessons for International Monetary Reform* (pp. 461-494). Chicago: University of Chicago Press.

Gaske, D. (1992, Winter). Teaching Interactions between Foreign Exchange Markets and Balance-of-Payments Flows: An Alternative Graphical Approach. *The Journal of Economic Education, Vol. 23, No. 1*, pp. 48-52.

Geczy, C., Minton, B. A., & Schrand, C. (1997, September). Why Firms Use Currency Derivatives. *The Journal of Finance, Vol. 52, No. 4*, pp. 1323-1354.

Gorbachev, O., Stoffels, N., & Tille, C. (2001, August). To What Extent Does Productivity Drive the Dollar. *Current Issues in Economics and Finance, Vol. 7, No. 8*.

Hopper, G. P. (1997). *What Determines the Exchange Rate: Economic Factors or Market Sentiment?* Philadelphia: Business Review - Federal Reserve Bank of Philadelphia.

Hull, J. C. (2012). *Options, Futures and other Derivatives - 8th Edition.* Boston: Prentice Hall.

Isakov, D., & Morard, B. (2001). Improving portfolio performance with option strategies: Evidence from Switzerland. *European Financial Management, Vol. 7, No. 1*, pp. 73-91.

Jorion, P. (1995, June). Predicting Volatility in the Foreign Exchange Market. *The Journal of Finance, Vol. 50, No. 2*, pp. 507-528.

King, M. R., Osler, C. L., & Rime, D. (2013). The market microstructure approach to foreign exchange : Looking back and looking forward. *Journal of International Money and Finance, Vol. 38*, pp. 95-119.

Levinson, M. (2005). *Guide to financial markets.* London: Economist in association with Profile Books.

Lothian, J. R., & Taylor, M. P. (2008, October). Real Exchange Rates over the past two centuries : How imporant is the Harrod-Balassa-Samuelson effect? *The Economic Journal, Vol. 118, No. 532*, pp. 1742-1763.

Mathworks. (n.d.). *Mathworks - adftest*. Retrieved from Mathworks: http://nl.mathworks.com/help/econ/adftest.html?refresh=true

Meese, R. (1990). Currency Fluctuations in the Post-Bretton Woods. *Journal of Economic Perspectives, Volume 4*, pp. 117-134.

Melvin, M., & Melvin, B. P. (2003, August). The global transmission of volatility in the foreign exchange market. *The Review of Economics and Statistics, Vol. 85, No. 3,* pp. 670-679.

Mendoza, E. G. (1995, Feb). The Terms of Trade, the Real Exchange Rate, and Economic Fluctuations. *International Economic Review, Vol. 36, No. 1*, pp. 101-137.

Menkhoff, L., Sarno, L., Schmeling, M., & Schrimpf, A. (2012a, April). Carry Trades and Global Foreign Exchange Volatility. *The Journal of Finance, Vol. 67, No. 2*, pp. 681-718.

Menkhoff, L., Sarno, L., Schmelling, M., & Schrimpf, A. (2012b). *The Cross-Section of Currency Order Flow Porfolios.* Hannover: Leibniz University - Working Paper.

Merton, R. C., Scholes, M. S., & Gladstein, M. L. (1978, April). The Returns and Risk of ALternative Call Option Portfolio Investment Strategies. *The Journal of Business, Vol. 51, No. 2*, pp. 183-242.

Moore, M. J., & Payne, R. (2011, May). On the sources of private information in FX markets. *Journal of Banking & Finance, Vol. 35, No. 5,* pp. 1250-1262.

Müller-Plantenberg, N. A. (2010, January). Balance of payments accounting and exchange rate dynamics. *International Review of Economics & Finance, Vol. 19, No. 1*, pp. 46-63.

NASDAQ. (n.d.). *FX Options Product Specifications*. Retrieved from NasdaqTrader: http://www.nasdaqtrader.com/Micro.aspx?id=phlxwcoproductspecs

Okunev, J., & White, D. (2003, June). Do Momentum-Based Strategies Still Work in Foreign Currency Markets? *The Journal of Financial and Quantitative Analysis, Vol. 38. No 2,* pp. 425-447.

Orlov, V. (2016). Currency momentum, carry trade, and market illiquidity. *Journal of Banking & Finance*.

Poon, S.-H., & Granger, C. W. (2003, June). Forecasting Volatility in Financial Markets: A Review. *Journal of Economic Literature, Vol.41, No.2*, pp. 478-539.

Quek, C., & Tung, W. (2011). Financial volatility trading using a self-organising neural fuzzy semantic network and option straddle-based approach. *Expert Systems with Applications, Vol. 38,* pp. 4668-4688.

Redl, C. (2015). Noisy news and exchange rates: A SVAR approach. *Journal of Internal Money and Finance 58*, pp. 150-171.

Rime, D. (2001). *Trading in Foreign Exchange Markets : Four Essays on the Microstructure of Foreign Exchange.* Oslo: Nordberg Hurtigtrykk.

Santa-Clara, P., & Saretto, A. (2009). Option strategies: Good deals and margin calls. *Journal of Financial Markets, Vol. 12*, pp. 391-417.

Sarno, L., & Taylor, M. P. (2001). *The Microstructure of the foreign-exchange market : A selective survey of the literature.* Princeton: Princeton Studies in International Economics.

Sarno, L., & Taylor, M. P. (2002). *Purchasing Power Parity and the Real Exchange Rate.* IMF Staff Papers.

Taylor, A. M., & Taylor, M. P. (2004, Autumn). The Purchasing Power Parity Debate. *The Journal of Economic Perspectives, Vol. 18, No. 4*, pp. 135-158.

Tsay, R. S. (2005). *Analysis of Financial Time Series, Second Edition.* John Wiley & Sons, Inc.

Wang, K.-L., Fawson, C., Barrett, C. B., & McDonald, J. B. (2001, July-August). A Flexible Parametric GARCH Model with an Application to Exchange Rates. *Journal of Applied Econometrics, Vol. 16, No. 4,* pp. 521-536.

# Table of contents

# Executive Summary

In this paper, I try to establish a procedure to invest in EURUSD currency pair during a period where there is monetary policy shifting in Europe and USA. As remarked by Redl (2015), this kind of transition period conducts to imperfect information circulation and disconnection between the currencies exchange rate level and market fundamentals. There are many reasons to explain the increase in volatility which started at the beginning of 2015 for the EURUSD currency pair. One of them is the different monetary policy followed by the Federal Reserve System (FED) and European Central Bank (ECB). At the beginning of 2015, FED has stopped its quantitative easing (QE) program and has also tightened its monetary policy by increasing the interest rate; meanwhile the ECB has started its QE program (Buttenwood, 2015). In this market situation, traditional strategy such as momentum failed to make profit. In this paper, I look at volatility as my friend and not my enemy and try to develop active management based on option strategy.

This master thesis tries to understand and model the factors influencing options strategies. These factors are the underlying price, change in volatility and the time to maturity. This paper proposes different models to try to estimate these factors, such as ARMA, GARCH modelling to propose, at the end, a methodology to invest in a market where high volatility is encountered.

The results of my different models have showed that firstly, the residuals of the EURUSD exchange rate is a white noise and therefore, cannot be modelled with an ARMA model. This has led to another approach to forecast the expected exchange rate. In response to that, I have used the Market-Based approach to forecast exchange rate level with Euro FX futures contracts. Secondly, GARCH modelling provides me a way to forecast the volatility tendency. The methodology, combining information gathered from the Euro FX futures contracts and GARCH modelling, demonstrates that most of the implemented strategies has a positive profit when options are exercised at maturity.

**Key words:** EURUSD; Options strategies; Volatility; GARCH modelling