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Intraday Seasonality in EUR/SEK Returns

by

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Abstract: In this thesis the intraday seasonality in the EUR/SEK spot returns are investigated after the returns have been filtered from intraday volatility. This is done with five-minute returns from year 2007 to 2019. The returns are filtered using the Flexible Fourier Form regression and then intraday seasonality is tested using an ARMAX-GARCH model. The results reveal no significant intraday seasonality in the EUR/SEK spot return and therefore we can conclude that no seasonality exist in the filtered returns.

Keywords: Seasonality, intraday returns, intraday volatility, foreign exchange, EUR/SEK, Flexible Fourier Form, ARMAX-GARCH

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1 Introduction

Ever since the breakdown of Bretton Woods, where fixed exchange rates were abandoned in favor of floating exchange rates, one of the main goals in financial economics have been to understand the causes and consequences of movements in exchange rates (Evans, 2011). Being able to predict excess returns after adjusting for risk would be in violation of the Efficient Market Hypothesis (EMH), which state that security prices should reflect all available information in the market (Fama, 1991). Hence, as noted by Ranaldo (2007), any movement should be random and not follow a systematic or seasonal pattern. The foreign exchange (FX) market is by far the largest financial market in the world, with an estimated daily turnover of 6.6 trillion USD in 2019 (Bank of International Settlements, 2019). With characteristics such as high liquidity, low transaction costs, and trading on a 24-hour basis, the foreign exchange market should be a great contender for market efficiency (Ranaldo, 2007).

Previous studies have found that there are seasonal patterns in asset returns. While earlier studies used daily data, more recently, intraday data has been utilized. But, the number of papers are few, there is a lack of empirical consensus, and result show systematic patterns that put EMH into question. Cornett, Schwarz and Szakmary (1995) finds that the USD appreciate during the first and last trading hour of the U.S market. In contrast, both Khademalomoom and Narayan (2019) and Ranaldo (2009) find that this effect could stretch over several hours, and Breedon and Ranaldo (2013), Zhang (2018) and Jiang (2019) finds that this could hold over the whole local trading session for several currencies against the USD. At the same time, local currency has a tendency to depreciate during foreign trading sessions (Khademalomoom & Narayan, 2019; Ranaldo, 2009; Breedon & Ranaldo, 2013; Jiang, 2019). Khademalomoom and Narayan (2019) finds furthermore that the opening of the Asian and Pacific market result in depreciation of the foreign currencies against the USD and that overlapping trading hours between markets has an impact on currency returns. Krohn, Mueller and Whelan (2020) find that the G9 currencies with USD as the base currency exhibits a W-shape in returns during the day as a result of the major global currency fixes, which according to the authors and Evans (2018) is an event when transactions during a short time window at a predetermined time each day is collected to provide a benchmark for exchange rates. To conclude, there appears to be significant intraday seasonality in many of the currency pairs previously examined.

Earlier studies have for the most part not accounted for any seasonal component volatility that is present in returns. This is interesting since several lines of evidence suggest that intraday volatility have strong seasonal patterns (Müller et al., 1990; Dacorogna et al., 1993; Andersen & Bollerslev, 1997; Engle & Sokalska, 2012). Thus, any excess returns due to seasonal patterns in returns may be offset by increased volatility, which is a common proxy for risk. One should also note from a methodology viewpoint that it is important to correct for the seasonal patterns in intraday volatility (Andersen & Bollerslev, 1997).

The majority of the previous literature focuses on currency pairs with USD as the base currency, and the amount of studies where the EUR is used as the base currency against other currencies within the European region is sparse. In this thesis the intraday returns of the EUR/SEK will be dissected. Since, to the best of our knowledge no previous research has used the EUR/SEK. The EUR/SEK is the second most traded currency in Sweden (Bank of International Settlements, 2019) and information about intraday seasonality would not only be valuable from the perspective of traders but also for those market participants that actively must hedge their currency positions, for example Swedish exporters and importers.

With the motivations mentioned above in mind. The purpose of this thesis is to investigate to what extent EUR/SEK spot returns exhibit intraday seasonal patterns after the returns have been adjusted for intraday volatility.

The rest of the paper is structured as follows: section 2 presents a short introduction of the foreign exchange market which is followed by a literature overview, which cover literature on intraday seasonality in returns, volatility, and explanations that have been put forward for these patterns. Section 3 describe the data and how the data was processed. Section 4 presents the methodology used in the paper, that is the Flexible Fourier Form regression and the ARMAX-GARCH model. Section 5 presents and discuss the results. Section 6 concludes.

2 Theory and related literature

2.1 Foreign exchange market

The foreign exchange market has some unique characteristics compared to other markets. To begin with, and as already mentioned, the foreign exchange market is the largest financial market in the world. The average estimated daily turnover in 2019 was 6.6 trillion USD, where the 6.6 trillion are divided into trading in spot market, outright forwards, FX swaps, currency swaps, and options and other products (Bank of International Settlements, 2019). Bank of International Settlements also report that the most traded currency is the USD (88%) followed by EUR (32%) and JPY (17%). Note that the sum of the relative usage of all currencies is 200%, not 100%, since each trade always involve two currencies. Another key feature of the FX market is that trading occurs on a 24-hour basis, with the exception of weekends and holidays. That said, much of the trading activity is concentrated to daytime hours of the main financial centers (London, New York, Tokyo, Frankfurt), see figure 2.1 (Evans, 2011).

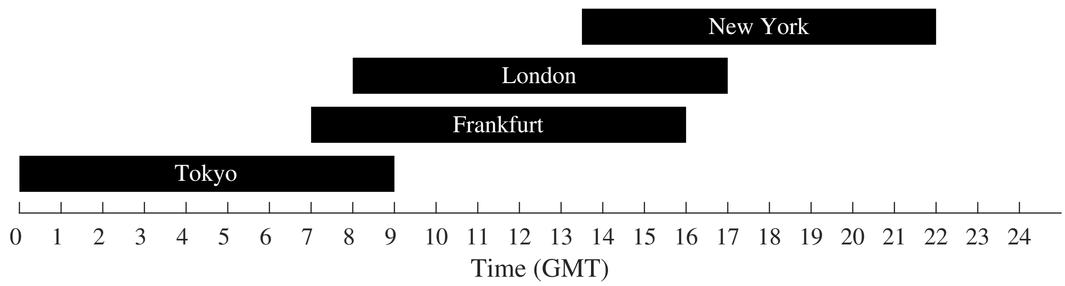


Figure 2.1: Trading hours

The foreign exchange market is a decentralized multiple-dealer market (Vega & Miller, 2011). This means that trading occurs on an over the counter (OTC) market, where dealers provide liquidity directly via a system of connected traders (Osler, 2011). This can for example result in the same exchange rate trading at different prices in different places (Vega & Miller, 2011). The increase in electronic trading over the two recent decades has resulted in an even further fragmentation and complexity of the market (Schrimpf & Sushko, 2019). Thus, the usual description of the FX market as a two-tier market, where according to Osler (2011) the trading between dealers and clients is the first tier and interdealer trading is the second tier, is somewhat less clear. Still, the two-tier structure provides a good foundation to understand the FX market. The clients are often divided into two groups, financial and non-financial corporations, and liquidity is provided by market makers (the dealers) (Osler, 2011). She further describes that in the interdealer market, in contrast, no liquidity provider exists and instead the interdealer must either trade with each other or through the brokerage system, which after 1992 started to provide electronic brokerage and not only voice brokerage. In this system the best limit orders are matched with the first market orders (Evans & Rime, 2019) and the counterparty of the trade is identified after the trade have occurred (Osler, 2011). But, as mentioned, the system has become much more complex and the customers have wide range of options in terms of trading venues (Evans & Rime, 2019).

To bring some clarity to the complex market structure, Figure 2.2 show the different participants and how they interact. The clients, dealers, voice brokerage (VB) and electronic brokerage (EB) have already been introduced. In addition to these there are single-bank platforms (SBP), multi-bank platforms (MBP), retail aggregators (RA), prime brokerage accounts (PB), and liquidity aggregators (LA) (King, Osler & Rime, 2012). They describe the role of these participants in the following way: single bank platforms allow the banks clients to trade through a proprietary trading system with the dealers, multi-bank platforms collect and distributes quotes from several dealers, retail aggregators is an online trading platform that aggregates retail investors trades to larger trades, and prime brokerage accounts as a place that allow customers to trade directly in the second tier, that is with the dealers or with the electronic brokerages. Liquidity aggregators combine multiple banks and venues in order to provide liquidity (Schrimpf & Sushko, 2019). Even though this might seem like a complex system, Evans and Rime (2019) show that interbank dealers remain the number one liquidity provider for the customers and especially for transactions at larger volumes. They note that the large trades to a large extent occurs in line with the old two-tier structure.

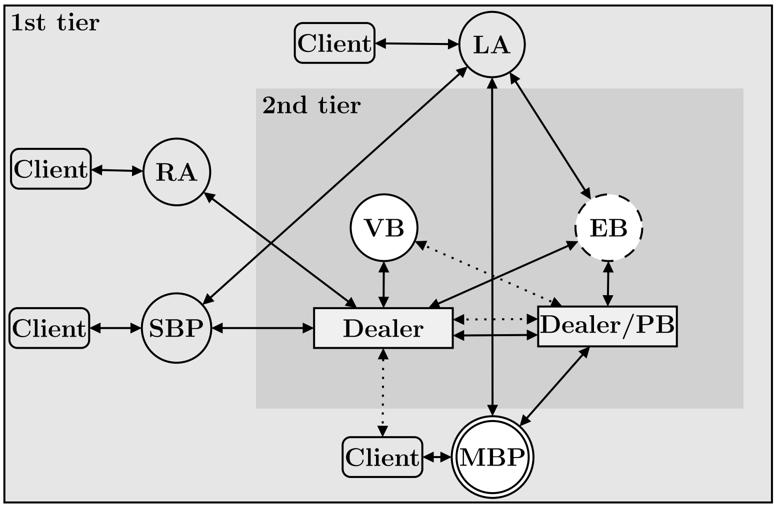


Figure 2.2: Overview of the FX market structure. SBP is single-bank platform, RA is retail aggregator, LA is liquidity aggregator, VB is voice brokerage, EB is electronic brokerage, PB is prime brokerage, MBP is multi-bank platform. Solid lines designates electronic execution methods. Dashed lines designates voice execution methods. Source: King, Osler and Rime (2012) and extension by Schrimpf and Sushko (2019)

2.2 Seasonality

One of the most prominent theories is the Efficient Market Hypothesis, which states that asset prices reflect all available information (Fama, 1991). This is the original strong version of the hypothesis, which among other things assume there are no trading- or informational costs (Fama, 1991). Since this do not reflect the economic reality, a weaker version of the hypothesis state that asset prices reflect information to a certain degree, when marginal benefits do not exceed marginal costs (Fama, 1991). This implies that when new information arrives, the market should in most cases immediately respond by adjusting the price to incorporate the new information. EMH is commonly paired with the hypothesis that asset prices follow a random walk. Hence, the arrival of unexpected news cause seemingly random movements in the asset price (Fama, 1965).

However, studies have found seasonal patterns seemingly contradicting this notion of randomness in the asset prices. Even though the structure of financial markets has changed over the years, some of the patterns remain unchanged. Empirically, seasonal patterns have been observed on different markets and across different asset types. For example, French (1980) found that returns have a day-of-the-week effect in the stock market. In addition, seasonalities have been found in the fixed income market (Zaremba, 2019), in the commodity market (Keloharju, Linnainmaa & Nyberg, 2016), and in the crypto currency market (Eross et al., 2019). In the

FX market, McFarland, Pettit and Sung (1982) found that the return distribution differs on different days of the week. This suggests that the patterns are not isolated to a specific time period or market setting.

The type of patterns we aim to explore are seasonal return patterns. One example of a seasonal return pattern is the well documented day-of-the-week effect, where there are significant differences in the returns on certain days. Examining the foreign exchange markets, McFarland, Pettit and Sung (1982) found that there are significant differences between certain days for almost all currencies in both spot and forward markets. By analyzing the distribution of FX returns, the authors find that all day-of-the-week distributions are highly non-normal with a stable distribution across different currencies. They conclude that the daily data is not conforming to a simple process and argue that daily data should be used with caution in financial research in exchange markets.

2.2.1 Seasonality in returns

Before proceeding to examine the FX intraday return literature, it is important to note that intraday patterns have been found on the stock market as well (Harris, 1986; Wood, McInish & Ord, 1985; Smirlock & Starks, 1986; Heston, Korajczyk & Sadka, 2010). With that said, let us now turn to the FX market. The research, which is presented below, point towards the notion that local and foreign trading sessions have major impact on the intraday returns. In addition, trading hours of the major markets and currency fixings seems to have an impact on the intraday returns for a wide variety of currencies.

The literature has shown that local trading sessions have an impact on the local currency returns. Wasserfallen (1989) documented early that the FX market exhibited intraday patterns, even though this was not the primary objective of the paper. Using five-minute returns from 09:00 to 17:00 local time during 1983 of the CHF/USD he finds that CHF depreciate in the first 30 minutes, depreciate during lunch time and appreciate during the afternoon. Cornett, Schwarz and Szakmary (1995) was though first with a thorough investigation of intraday returns in the FX market. They showed that the local currency (USD) appreciates the first hour after the local market has opened and the last hour before the market close, using intraday data from 1980 to 1991 on USD/DEM, USD/GBP, USD/CHF, USD/JPY, and USD/CAD future contracts. Khademalomoom and Narayan (2019) find to some extent similar result, using hourly spot returns of USD/AUD, USD/CAD, USD/CHF, USD/EUR, USD/GBP, USD/JPY from 2004 to 2014. But they find that the length of the appreciation after the market has opened is often longer and the results do not hold for the JPY, which appreciate during the whole local trading session. In contrast to this, Breedon and Ranaldo (2013) finds that the local currencies depreciate during the whole local trading session. They do this with data of spot returns from 1997 to 2007 on EUR/USD, USD/JPY, GBP/USD, EUR/JPY, USD/CHF, and AUD/USD. Similar results are found by Ranaldo (2009) who use spot rates of CHF/USD, GBP/USD, and JPY/USD from 1993 to 1995, EUR/USD and JPY/EUR from 1999 to 2005, and DEM/USD from 1993 to 1998. Using a fixed effect panel regression with the USD as base currency and four hours interval he finds that the local currency depreciates during the local trading session. Zhang (2018) use hourly spot returns of USD/AUD, USD/BRL, USD/CNY, USD/DKK, USD/EUR, USD/JPY, USD/INR, USD/NZD, USD/NOK, USD/RUB, USD/SGD, USD/ZAR, USD/SEK, USD/CHF, AND USD/GBP from 2010 to 2015 and finds that some currencies have significant depreciation during the local trading session. Lastly, Jiang (2019) use 30 minutes spot returns from 2007 to 2019 on USD/GBP, USD/EUR, USD/DKK, USD/AUD, USD/SEK, USD/CHF, USD/NZD, USD/NOK, USD/CNH, USD/CAD, USD/SGD, USD/HKD, and USD/JPY and finds that all local currencies, except JPY, depreciate during the local trading session.

In contrast to the local trading session, foreign trading session often result in an appreciation of the local currency. Khademalomoom and Narayan (2019) find that all currencies except JPY and CAD appreciate during the whole foreign trading session. Similar results are found by Ranaldo (2009), Breedon and Ranaldo (2013), Zhang (2018), and Jiang (2019).

In addition to local and foreign trading sessions, Khademalomoom and Narayan (2019) investigate how currency returns are affected when the major markets open, close, and when the trading sessions overlap. The authors find that the opening and closing of the Asian market have a major impact on the returns, where all currencies depreciate during the three hours after the Asian market opens and European currencies appreciate during the three hours after the American market have opened.

Regarding overlapping trading sessions, they find that when the Asian and European market overlaps all currencies, except the GBP, appreciate. On the other hand, they find that currencies depreciate when the American and Pacific market overlaps. Zhang (2018) also investigate the impact of overlapping trading session and finds that the overlapping trading session between New York and London have an impact on several currencies.

Krohn, Mueller and Whelan (2020) find a W-shape pattern in intraday returns, using 5 minutes spot returns from 1999 to 2018 of USD/AUD, USD/CAD, USD/CHF, USD/EUR, USD/GBP, USD/JPY, USD/NOK, USD/NZD, and USD/SEK. They find that this pattern is a result of the Tokyo, ECB and London currency fixings, observing large volume spikes, and where the USD appreciate before the fixings and depreciate after. The same W-pattern could not be found in non-USD cross exchange rates, but the authors still find other intraday patterns, which they leave for future research to explore.

Some of the recently mentioned research has also investigated to what extent one could trade on these patterns. The findings are to some extent different, resulting from different definitions of trading costs. Khademalomoom and Narayan (2019) find strategies earning 18% in annualized returns, but Krohn, Mueller and Whelan (2020) conclude that only traders who can trade at tight bid ask spreads can exploit the intraday patterns around the currency fixings.

Table 2.1: Literature review

Author	Time period	Currency pairs	Methodology	Data frequency	Main findings
Cornett, Schwarz & Szakmary (1995)	1980-1991	USD/DM, USD/GBP, USD/CHF, USD/CAD, USD/JPY	Dummy regression	Hourly frequency	First and last hour positive returns; middle of the day negative returns
Ranaldo (2009)	1993-2005; 1999-2005; 1993-1998	CHF/USD, DEM/USD, EUR/USD, GBP/USD, JPY/EUR, JPY/USD	Two-sample t-test; dummy regression; GARCH(1,1)	Five-minute frequency	Local currencies depreciate during domestic hours; appreciate during foreign hours
Breedon & Ranaldo (2013)	1997-2007	EUR/USD, USD/JPY, GBP/USD, EUR/JPY, USD/CHF, AUD/USD	Two-sample t-test; dummy GARCH; sign test	Hourly frequency	Local currencies depreciate during domestic hours; appreciate during foreign hours
Zhang (2018)	2010-2015	USD/AUD, USD/BRL, USD/CNY, USD/DKK, USD/EUR, USD/JPY, USD/INR, USD/NZD, USD/NOK, USD/RUB, USD/SGD, USD/ZAR, USD/SEK, USD/CHF, USD/GBP	Two-sample t-test; dummy regression	Hourly frequency	Local currencies depreciate during domestic hours; depreciate during LDN-NY overlap; appreciate during U.S. trading hours after London close
Jiang (2019)	2007-2019	USD/GBP, USD/EUR, USD/DKK, USD/AUD, USD/SEK, USD/CHF, USD/NZD, USD/NOK, USD/CNH, USD/CAD, USD/SGD, USD/HKD, USD/JPY	OLS regression	30-min frequency	Local currencies depreciate during domestic hours; appreciate during foreign hours
Khademalomoom & Narayan (2019)	2004-2014	USD/AUD, USD/CAD, USD/CHF, USD/EUR, USD/GBP, USD/JPY	Dummy regression	Hourly frequency	Post-opening/closing hours depreciation; overlapping times affect returns
Krohn, Mueller & Whelan (2020)	1999-2018	USD/AUD, USD/CAD, USD/CHF, USD/EUR, USD/GBP, USD/JPY, USD/NOK, USD/NZD, USD/SEK	Two sided t-test	Five-minute frequency	Local currencies depreciates before FX fixings; appreciates after

2.2.2 Seasonality in volatility

There is extensive empirical evidence of intraday patterns in the return volatility across several asset markets. Wasserfallen (1989) investigates the properties of foreign exchange rates using higher frequency, intraday data, allowing for a finer estimation of the distribution. The author finds that the foreign exchange rates are much more volatile in the short term than previously thought. Harvey and Huang (1991) further examined volatility patterns in the FX market using intraday data and find empirical evidence that intraday volatility varies by day-of-the-week. However, the authors also find that there are volatility differences depending on the time-of-the-day, which motivated further research with intraday data. Wood, McInish and Ord (1985) were among the first to document high volatility during opening and closing time, and low during the middle of the day, creating a distinct U-shaped pattern in the return volatility of stock market returns. Müller et al. (1990) later finds that the volatility pattern exists on the foreign exchange market as well.

In addition, Andersen and Bollerslev (1998) finds that the pattern of intraday volatility in DEM/USD has a strong connection to market activity, such as opening and closing from different trading centers and lunch time in Asian markets. Ito and Hashimoto (2006) shows that there is a difference in the intraday volatility patterns between the EUR/USD and JPY/USD, where the EUR/USD have two U-shapes during 24 hours whereas JPY/USD have three U-shapes. In addition to cyclical patterns, there is a large amount of literature showing that macro news announcement and other market events is associated with large spikes in the intraday volatility (Osler, 2011). The seasonal component in the volatility results in a distinct U-shape in the autocorrelation of the volatility (Laakkonen, 2014). This have been documented several times and across several currencies (Andersen & Bollerslev, 1998; Laakkonen, 2014; Vatter et al., 2015) even though slightly differences in the U-shapes have been reported.

2.2.3 Explanations for the intraday seasonality

It is clear that seasonal intraday patterns are a well-documented phenomenon in empirical studies. Given how complex the foreign exchange market is, there are certainly many factors to consider when attempting to explain intraday seasonal patterns. Several factors are related to market microstructure, which focus on the formation of prices (Goodhart & O'Hara, 1997). While there are multiple frameworks for market microstructure, the common denominator is that they all attempt to incorporate characteristics of the market participants, such as adverse selection and risk aversion (Biais, Glosten & Spatt, 2005). As we are interested in theories related to why patterns emerge over the day, we focus on factors which could explain seasonalities.

Ranaldo (2007) argue that there are two main factors contributing to intraday return patterns: information flow and inventory risk. Firstly, movements could originate from the flow of new information reaching market participants. Public news, such as macroeconomic announcements, is a source of new information known to cause movements in the exchange rates (e.g. Andersen et al., 2003; Bauwens, Omrane & Gioat, 2005; Rosa, 2011). Macroeconomic announcements are often scheduled and released at a certain time of the day, which according to Admati and Pfleiderer (1988) help shape trading patterns. Another source of information comes from the order flow, which contain information about the transaction volume and whether the transaction is initiated by a buyer or a seller (Evans & Rime, 2019). They argue that the order flow is more important than news when it comes to explaining foreign exchange movements. In contrast, Breedon and Vitale (2004) found that the relationship mostly stems from liquidity effects rather than the information content of the order flow, which is related to the second main factor: inventory risk. Ranaldo (2007) discusses how many banks limit the amount of trading allowed during the night, hence in order to avoid inventory risk the dealers hedge before closing. With a net zero position overnight, they restore their inventory in the early morning (Lyons, 1998; Ranaldo, 2007).

Furthermore, Ranaldo (2007) suggest two behavioral biases explaining intraday patterns. The first bias he suggests is the domestic-currency bias, where traders in a specific country tend to hold assets in their own local domestic currency. Since domestic traders typically hold domestic assets in their portfolios, the domestic currency will prevail over other foreign currencies, paralleling to the idea of home-bias in international economic literature which has previously been found in equity markets (Ranaldo, 2007). The second bias he suggests is the domestic-time bias where, similar to the proximity bias seen in the equity market (e.g. Massa & Simonov, 2006), traders prefer to trade mainly in the working hours of their own country.

2.3 Summary

To summarize, the foreign exchange market is vast, complex, and trade on a 24 hours basis. This have resulted in research documenting significant intraday seasonality in returns as a consequence from when different market participants trades, when global trading hours overlap, and during major global currency fixings. At the same time, it is widely documented that intraday volatility exhibit seasonal pattern where the U-shape during the local trading hours is the most recognized pattern. Several explanations have been put forward to these seasonalities, relating to information flow, order flow, inventory risk, and biases. We bring the seasonality patterns in the returns and the volatility together by investigating intraday seasonal patterns in the filtered returns.

3 Data

3.1 Data description

We collected foreign exchange data covering the time period between 2007-01-01 and 2019-12-31 from Dukascopy Bank SA. Dukascopy provide historical FX spot rates in several frequencies, ranging from yearly quotes to tick-by-tick quotes. Referring back to figure 2.2, Dukascopy's foreign exchange trading platform (Swiss FX Marketplace) is a liquidity aggregator. Thus, it combines liquidity from other marketplaces and banks to match their clients bid/ask orders (Dukascopy, 2019). Arguably all currency trading does not go through Dukascopy's trading platform, but when comparing with Bloomberg data[1], who use several data sources to compute the high frequency quotes (Bloomberg, 2016), the differences are negligible. Differences start to occur at the third or the fourth decimal and this is also expected given the decentralized structure of the foreign exchange market. In that respect, we consider the data sample to be representative.

One of the main issues with high frequency data is that it is prone to contain errors, mainly stemming from either delayed or straight up erroneous recording of trading information (Hautsch, 2012). While the data obtained from Dukascopy is pre-filtered to a discrete minute-by-minute frequency, certain data cleaning measures are taken to ensure the quality of the sample. Following previous literature, negative bid-ask spreads are removed. Weekends and holidays around Christmas (24 to 26 December) and New Year (31 December to 1 January) are removed from the sample due to little trading activity. The weekend is defined as the time between 22:00 GMT Friday to 22:00 GMT Sunday. It is important to consider that the shift to daylight savings time (DST) occur at a different date in different regions (e.g. second Sunday in March in the U.S. and last Sunday in March in the U.K.). Quotes from Dukascopy switch to DST according to the U.S. system. Hence, weekends are removed based on this fact.

[1]Bloomberg provide 140 days of historical intraday data.

Finally, in order to accommodate for the one-hour parallel shift that the DST creates, the timestamp is converted from universal coordinated time to GMT (Andersen & Bollerslev, 1998).

A common practice in high frequency FX literature is to use indicative quotes as a proxy for transaction quotes and that will be used in this thesis as well, since that is what Dukascopy provides. As stressed by Breedon and Ranaldo (2013) shortcomings exist with indicative quotes. This statement is reasonable since the quotes are not the actual transaction quotes, but indicative quotes representing the prices at which the second-tier market were willing to buy or sell currency (Evans, 2011). He argues that the spread between the indicative ask and bid prices are larger than the bid ask spread in the second-tier market, but that the midpoint is reasonably accurate. Danielsson and Payne (2002) further show that at five-minute intervals many of the shortcomings from the indicative quotes disappear completely. Thus, to avoid potential problem with indicative quotes, five-minute returns will be used in this thesis.

3.2 Foreign exchange returns

From indicative five-minute quotes, the logarithmic returns can be calculated. First, the mid-quote price is calculated as

$$P_t = \frac{P_t^A + P_t^B}{2} \tag{3.1}$$

where P_t^A and P_t^B are the five minute closing price for ask and bid, respectively. Thus, the five minute logarithmic return is defined as

$$R_t = \ln \frac{P_t}{P_{t-1}} \tag{3.2}$$

Before proceeding it should be mentioned that the EUR is used as the base currency in this thesis. This means when the exchange rate increases the value of the SEK decrease, resulting in a depreciation of the SEK and an appreciation of the EUR. The reverse holds when the exchange rate decrease.

4 Methodology

4.1 Dealing with intraday seasonality

We have established that intraday returns exhibit strong daily seasonal patterns in the volatility, forming a U-shaped pattern during the day in the correlogram. See figure 4.1 for an example of the autocorrelation function of five-minute absolute return plotted over 24 hours for the EUR/SEK. It has been argued that if this is not taken into consideration when analyzing intraday returns, it could skew the statistical inference of the results (Laakkonen, 2014). The empirical evidence of intraday seasonality has been known for a long time (Wood, McInish & Ord, 1985), however the seasonality component has not yet been explicitly modeled in previous studies examining intraday return patterns. In other research areas it is a well-established practice where several methods have been developed.

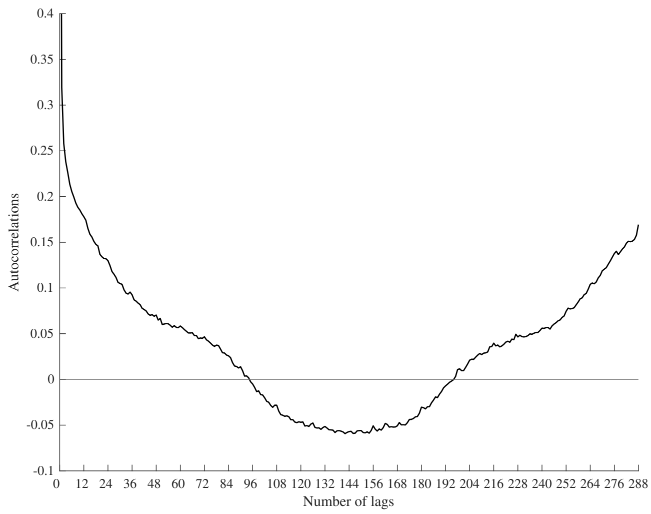


Figure 4.1: Example of the correlogram over a day for the absolute 5 minute returns for the EUR/SEK spot exchange rate. Each day contain 288 lags.

The earliest methods attempted to incorporate seasonality with traditional econometric models. Baillie and Bollerslev (1991) introduced a GARCH model with hourly dummies in order to account for seasonality observed in hourly data. This type of method has previously only been used once in the context of examining intraday FX return patterns (Breedon & Ranaldo, 2013). Another approach is to explicitly model the seasonal component of volatility and filter out the seasonality from the returns. These types of methods have previously been used in other contexts, for example when studying the impact of macroeconomic announcements on FX volatility (e.g. Andersen & Bollerslev, 1998; Chatrath, Christie-David & Moore, 2006; Laakkonen, 2014). Considering that we use a higher frequency than most of the previous studies in FX return patterns, we opt for the second approach which is more efficient.

The Flexible Fourier Form (FFF), first developed by Gallant (1981) and later introduced in this context by Andersen and Bollerslev (1997), is a commonly used method to filter out the seasonal component in FX literature. Andersen and Bollerslev (1997) argue that given the seasonal nature of the intraday volatility, the return dynamics can be estimated using a combination of trigonometric and polynomial functions. The trigonometric part uses a Fourier transformation, fitting the seasonal pattern using different frequencies of multiple sine and cosine functions (Laakkonen, 2014). The polynomial part allows the volatility to vary in overall level and after the seasonal component of the volatility have been properly modeled, we can get filtered returns by dividing the raw returns with the estimated seasonal component (Andersen & Bollerslev, 1997).

One drawback with the FFF approach stems from the assumption that the seasonal component of the intraday pattern is time-invariant (Vatter et al., 2015). As market behavior and institutional settings change over time this might be a too strong assumption. For example, Andersen, Thyrsgaard and Todorov (2019) show that the intraday volatility seasonality of E-mini S&P 500 futures contract changes over time. The fact that E-mini S&P 500 futures contract do not have time-invariant intraday volatility does not necessarily suggest that this is the case for the EUR/SEK spot returns. Still, we need to consider this possibility and therefore a careful investigation of the intraday volatility was made before implementing the Flexible Fourier Form.

4.2 Flexible Fourier Form regression

Following Andersen and Bollerslev (1997), the return is decomposed as

$$R_{t,n} = E[R_{t,n}] + \frac{\sigma_t s_{t,n} Z_{t,n}}{N^{\frac{1}{2}}} \tag{4.1}$$

where $E(R_{t,n})$ is the unconditional mean, N is the number of return intervals per day, σ_t is the daily conditional volatility, $s_{t,n}$ is the intraday seasonal component and $Z_{t,n} \sim IID(0,1)$.

They show that by squaring and taking the log of equation 4.1, we get

$$\begin{aligned} x_{t,n} \equiv 2\log\left(\frac{|R_{t,n} - E(R_{t,n})|}{\sigma_t^2}\right) + \log N &= \log s_{(k),t,n} + \log Z_{(k),t,n} \\ &= f(\theta; t, n) + u_{(k),t,n} \end{aligned} \tag{4.2}$$

Where $u_{t,n} \equiv \log Z_{t,n}^2 - E[\log Z_{t,n}^2]$ is the zero mean i.i.d error term.

The FFF regressor is obtained by

$$x_{t,n} = \sum_{q=0}^{Q} \mu_q (\frac{n}{N})^q + \sum_{d=1}^{D} \lambda_d I_d(t,n) + \sum_{p=1}^{P} (\delta_{c,p} \cdot \cos\frac{p2\pi n}{N} + \delta_{s,p} \cdot \sin\frac{p2\pi n}{N}) \tag{4.3}$$

Where the δ coefficients will capture the overall intraday pattern. The dummy variables I will allow us to capture specific points in time that is not in line with the overall seasonal pattern (Andersen & Bollerslev, 1997). This could for example be macroeconomic news or events that is pre-scheduled (Andersen & Bollerslev, 1998).

To implement the FFF model, we follow the two-step procedure suggested by Andersen and Bollerslev (1997). They state that the first step is get the estimated counterpart of $x_{t,n}$ in equation 4.2, that is $\hat{x}_{t,n}$. This is done by substituting $E(R_{t,n})$ with sample mean of the five-minute return $\bar{R}$, and substituting the daily variance $\hat{\sigma}_t^2$ with an estimate $\hat{\sigma}_t^2$. In this case the realized volatility will be used for $\hat{\sigma}_t^2$, which is defined as $\hat{\sigma}_t^2 = \sum_{n=1}^{N} R_{t,n}^2$. Another alternative is to use a one-day head forecast from a GARCH model, but as noted by Vo (2019) this method has the drawback of requiring a correct specification of the GARCH model and by using realized volatility one circumvents that problem. The second step is to estimate equation 4.3 with $\hat{x}_{t,n}$ as the dependent variable, using OLS (Andersen & Bollerslev, 1997).

The authors state that determining the exact form of equation 4.3 is not straight forward and requires a good deal of judgement as well as trial and error to obtain a good fit.

With a correct specification of equation 4.3 the period component $\hat{s}_{t,n}$ could be obtained by noting that the normalization factor is $T^{-1}\sum_{n=1}^{N}\sum_{t=1}^{T/N}\hat{s}_{t,n}$ and therefore the intraday period component is

$$\tilde{s}_{t,n} = \frac{T \cdot \hat{s}_{t,n}}{\sum_{t=1}^{[T/N]}\sum_{n=1}^{N}\hat{s}_{t,n}} \tag{4.4}$$

The filtered return $\tilde{R}_{t,n}$ is then obtained by dividing the raw returns with the intraday periodic component

$$\tilde{R}_{t,n} = \frac{R_{t,n}}{\tilde{s}_{t,n}} \tag{4.5}$$

In that sense, the intraday filtered return could be viewed as an intraday risk adjusted return due to the fact that the seasonal component of the volatility has been filtered out. Since the return is divided by the seasonal component of volatility, one could also view the filtered returns as a Sharpe ratio since the risk free-rate is approximately zero at five minute interval.

4.3 ARMAX-GARCH model

Using the filtered returns, an ARMAX(3,3)-GARCH(1,1) model will be implemented. Thus, the conditional mean is specified with lags of the filtered returns and error terms to remove any linearly dependence in the time series (Tsay, 2010). The number of lags is based on the model which gives the lowest Bayesian Information Criterion (BIC). In addition, exogenous variables will be included in terms of dummy variables for each hour, making it possible to capture the five-minute average of the excess filtered returns corresponding to each hour. A GARCH model is used since it takes into account heteroscedasticity and volatility clustering commonly seen in financial data (Brooks, 2014). One alternative specification of the conditional variance would be a Fractional Integrated (FI)-GARCH model. This model considers a hyperbolic decay rate, also known as long memory, of the autocorrelation rather than an exponential decay rate (Baillie, Bollerslev & Mikkelsen, 1996). But, to conduct such analysis is out of scope in this thesis.

With that said, the ARMAX(3,3)-GARCH(1,1) model is expressed as

$$\tilde{R}_{t,n} = \sum_{h=1}^{24} \lambda_h d_h + \sum_{p=1}^{3} \phi_p \tilde{R}_{t,n-p} + \sum_{q=1}^{3} \theta_q \varepsilon_{t,n-q} + \varepsilon_{t,n} \tag{4.6}$$

$$\sigma_{t,n}^2 = \omega + \alpha \varepsilon_{t,n-1}^2 + \beta \sigma_{t,n-1}^2 \tag{4.7}$$

Where d_h is a dummy variable for every hour that is equal to 1 at hour h, and zero otherwise. The coefficients of the dummy variables λ_h, will capture the average five-minute excess return for respective hour. Thus, this will allow us to investigate the statistical significance of the intraday filtered returns.

5 Results

5.1 Intraday raw returns

5.1.1 Descriptive statistics

To begin with, in figure 5.1 the five-minute return of the EUR/SEK exchange rate is plotted from 2007 to 2019. From this figure it could be noted that that the five-minute returns are centered around the mean of zero and roughly range from –1.4 percent to 1.6 percent. The return series also show clear patterns of volatility clustering, especially following the financial crisis 2007-2008. There also seems to be a tendency of higher kurtosis from year 2013 and onwards.

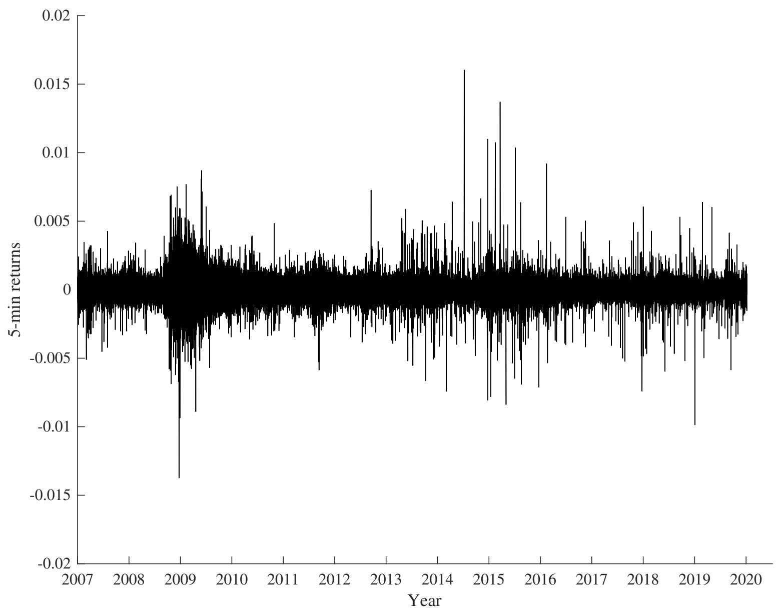


Figure 5.1: Five-minute raw returns between 2007 and 2019

In table 5.1, descriptive statistics of the EUR/SEK spot rate is shown divided into the whole sample, and to give an overview of how the spot rate characteristics differs over the trading day, three-hour intervals are also included. To formally test whether the returns are normally distributed a Jarque-Bera test have been performed; significant results indicate non-normality. The kurtosis of 40.4 over the whole sample suggests the returns have a leptokurtic distribution. Kurtosis of this magnitude is not uncommon in high frequency data, it is more of a rule than an exception. For example, Krohn, Mueller and Whelan (2020) report a kurtosis of 56 in the USD/SEK. The kurtosis differs throughout the day, ranging from 12.8 between the 15:00 and 18:00 interval to 56.2 between the 06:00 and 09:00 interval. Regarding symmetry of the distribution, the skewness over the whole sample is 0.1 and throughout the day it ranges between -0.3 to 0.4. The mean of the returns, which is expressed in annualized terms in the table, also change throughout the day. For example, the average five-minute returns over the domestic working hours is positive whereas the mean returns tend to be negative or close to zero during the non-domestic working hours. Across the whole sample the annualized average five-minute return is 1.5 percent. Even though an Augmented Dickey-Fuller test confirms that the returns are stationary, autocorrelation is still present in the returns. After investigating the autocorrelation by visually inspecting the correlograms, provided in appendix A.1, it could be confirmed that a statistically significant negative autocorrelation exists. This autocorrelation could be a consequence of the bid-ask bounce effect (Andersen & Bollerslev, 1997). To further confirm this, a Ljung-Box test was performed up to 20 lags and provided statistically significant results as well.

Table 5.1: The table show descriptive statistics of the EUR/SEK five-minute raw returns from 2007 to 2019. The mean is expressed in annualized figures, that is the average five-minute returns times 252 times 288. 252 represents number of trading days and 288 number of five minute returns during a day. The standard deviation is expressed in annualized terms, that is the standard deviation of the average five-minute returns times the square root of 252 times the square root of 288. P-values for the Jarque-Bera (JB) test, the Augmented Dickey-Fuller (ADF) test, and the Ljung-Box Q (LBQ) test.

	Whole sample	**00:00-03:00**	**03:00-06:00**	**06:00-09:00**	**09:00-12:00**	**12:00-15:00**	**15:00-18:00**	**18:00-21:00**	**21:00-24:00**
Mean	0.015	-0.007	0.037	-0.037	0.053	0.059	0.160	-0.070	-0.071
Median	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Std	0.093	0.074	0.069	0.116	0.098	0.103	0.103	0.077	0.096
Skewness	0.145	0.096	0.182	0.471	-0.252	0.437	0.138	-0.015	-0.311
Kurtosis	40.427	38.596	35.150	56.228	29.800	35.678	12.845	23.014	40.227
JB (p-value)	<0.001								
ADF (p-value)	<0.001								
LBQ 1:20 lags (p-value)	<0.001								

5.1.2 Cumulative returns

Moving on, the five-minute returns for the whole sample is visually examined in order to investigate the intraday EUR/SEK spot rate movements. Figure 5.2 plots the annualized average cumulative returns across the trading day. The intervals with the largest appreciation occur between 06:00 and 07:00 and between 15:00 and 16:00. While there are no definitive working hours for the foreign exchange market (Breedon & Ranaldo, 2013), it is reasonable to assume that European working hours start at the opening of the Frankfurt Stock Exchange, 07:00 (Krohn, Mueller & Whelan, 2020). Hence, the appreciation of the EUR/SEK spot rate between 06:00 and 07:00 could be in anticipation of the European market opening. The most significant appreciation happens between 15:00 and 16:00. This corresponds to the appreciation before the London currency fix, as seen in currencies against the USD (e.g. Krohn, Mueller & Whelan, 2020). However, the Tokyo fix and the ECB fix, which along with the London fix created the 'W' return pattern seen in Krohn, Mueller and Whelan (2020), appear to have little effect on the EUR/SEK spot rate. This is in line with their findings that the pattern is not seen in currency pairs who do not have USD as its base currency. The largest interval of depreciation happens after the European trading hours, between 19:00 and 22:30.

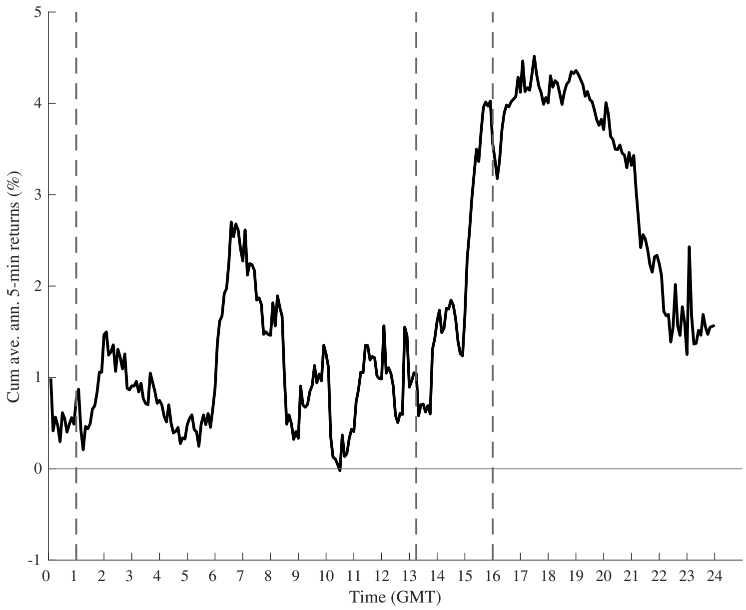


Figure 5.2: Cumulative Annualized Average 5 min return for the EUR/SEK over the time period 2007-01-01 to 2019-31-12. Where the vertical lines represent the Tokyo fix, ECB fix, and London fix, respectively.

While it is hard to pinpoint a specific event, the end of U.S. trading hours at 22:00 could be a contributing factor. Another factor that might contribute to this drop is the fact that the last trading before, and first trading after, the weekend occurs at 22:00.

5.1.3 Absolute returns

Over the whole sample period, that is between 2007 and 2019, the intraday volatility has a strong seasonal component and is shown in figure 5.3. The figure plots the average absolute five minute returns. The first thing to note is the U-shape during the domestic working hours, a pattern that is widely documented across different currencies pairs (Andersen & Bollerslev, 1997; Andersen & Bollerslev, 1998; Müller et al., 1990; Ito & Hashimoto, 2006), followed by another U-shape during the non-domestic working hours. Furthermore, there are three large spikes in the volatility, first one at 08:30, second at 16:00, and third at 22:00. The most likely explanation of the spike at 16:00 is the London currency fix, which according to Krohn, Mueller and Whelan (2020) is associated with a large spike in volume as well. One possible explanation of the spike at 08:30 could be that a number of important macroeconomic data is released at 08:30. This includes for example figures of monthly and quarterly CPI, quarterly GDP, monthly and quarterly PPI, unemployment rate, trade balance, export, and import for Sweden (Thomson Reuters Eikon, 2020). This would be in line with the literature that Osler (2011) present regarding volatility and macro news release. The spike at 22:00 is less obvious, but one explanation could be that the market closes at 22:00 on Friday. As suggested by Lyon's (1998) model, dealers want to eliminate inventory risk when they do not trade and since the market close on Friday this effect might be the strongest during this time period. Comparing figure 5.2 and 5.3 one could note that the EUR/SEK appreciate before the London fix 16:00 and this is the case for the volatility as well, suggesting that increased risk is compensated by increased returns. The connection at 08:30 seem though to be less clear.

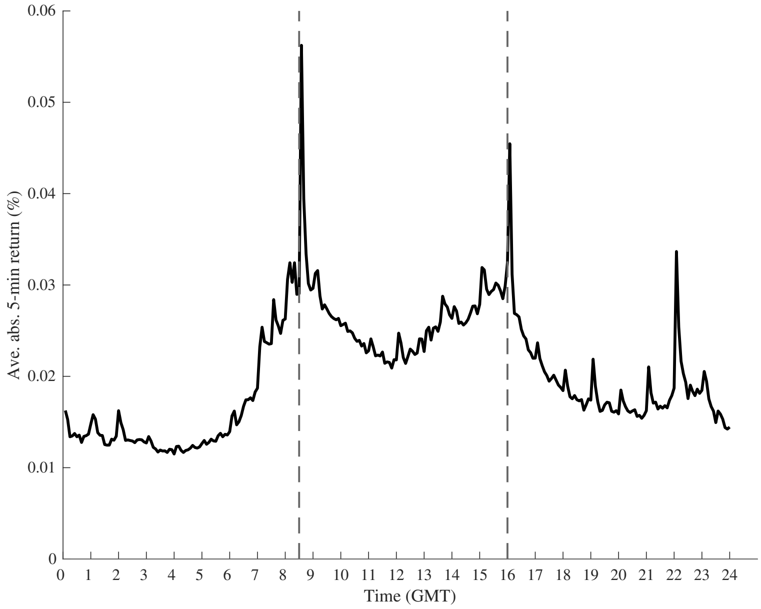


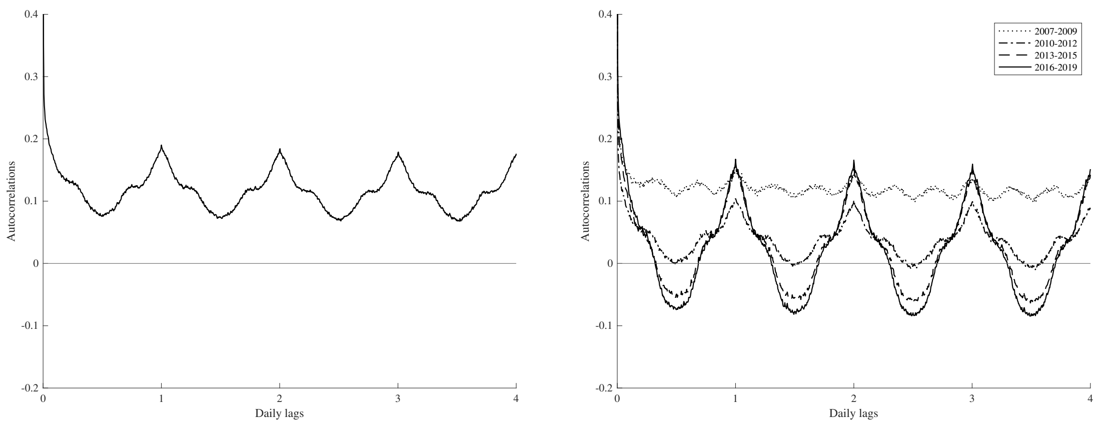
Figure 5.3: Average absolute 5-min return for the EUR/SEK over the time period 2007-01-01 to 2019-12-31. The vertical lines mark 8:30 and 16:00, respectively.

After a closer investigation of the intraday volatility it could be confirmed that the above mention pattern has not been constant over time, with the exception of the U-shape during the working hours that exist with varying degrees. See appendix A.2 for the yearly average absolute return plotted individually for each year between 2007 and 2019. During 2007, the seasonal pattern is very weak compared to the other years. Between 2008 and 2010, and during 2012 there are two U-shaped patterns during the non-domestic working hours. These patterns are similar to those seen in the JPY/USD spot exchange rate, as reported by Ito and Hashimoto (2006). Another interesting fact is that from 2016 and onwards there are distinct spikes between 19:00 to 24:00, the actual cause of these spikes remains unknown.

Arguably, based on visual analysis, the intraday seasonality in volatility is not time-invariant, supporting the findings of Andersen, Thyrsgaard and Todorov (2019). Referring back to the methodology part, this puts some restriction on this thesis since FFF assumes a time-invariant intraday volatility. To deal with this issue (and given the limited amount of time), a specific period will be chosen where the FFF regression can eliminate the seasonal component in a proper way. We leave the rest for future research.

Since the seasonal pattern in the volatility also cause a seasonal pattern in the autocorrelation (Laakkonen, 2014), we should expect the autocorrelation of the EUR/SEK to change over time. This is also what we find, as shown in figure 5.4. Over the whole sample one could note the well-known seasonal pattern in the autocorrelation, and the autocorrelation is always non-negative. The pattern is more similar to what Vatter et al. (2015) find in the JPY/USD rather than what he finds in the CHF/USD, EUR/USD, GBP/USD, and what Andersen and Bollerslev (1997) find in the DEM/USD. Dividing the sample into three years intervals, it seems that the non-negative autocorrelation over the whole sample is a result of the first years in the sample.

As time passes by in the sample the U-shape increases, and the autocorrelation turns negative during the domestic trading hours each day. In that sense it appears that both the volatility and its autocorrelation have changed from patterns similar to those seen in the JPY/USD to those seen in the EUR/USD. The fact that the seasonal pattern of the volatility change over time for the EUR/SEK and that the seasonal component in the autocorrelation have increased over time is interesting and something that at least we have not seen in previous literature.



(a) 2007-2019 **(b)** 3-year intervals

Figure 5.4: Absolute return correlogram for different time periods. Each day contains 288 lags.

5.2 Intraday filtered returns

5.2.1 Flexible Fourier Form regression

Given the previously mentioned fact that the seasonal component does not remain constant over time, and that the FFF regression itself requires a lot of experimentation to fit the data well, we have to set a specific time period to use before fitting the FFF regression. The chosen time period is between year 2013 and 2019 and this is based on the fact that the intraday volatility roughly follows the same intraday pattern during these years (see figure 2 and 3 in appendix A.2). With a time period set and after testing several model specifications, we arrived with a model containing five sine, five cosine, and two polynomial parameters. To account for the volatility spikes at 08:30 and at the London currency fix, additional dummy variables are included for those time periods. In line with Andersen and Bollerslev (1998) we include also dummy variables for early Monday and Friday close. Table 5.2 show that all variables are highly statistically significant, suggesting a good fit of the model.

Table 5.2: Estimated coefficients from the Flexible Fourier Form regression. The λ coefficients correspond to morning macroeconomic announcements, 8:15 - 8:45 GMT, late Friday, 18:00 - 22:00 GMT, Monday morning, 22:00-23:30 GMT, and London Fix, 15:45 - 16:15 GMT, respectively. $x_{t,n} = \sum_{q=0}^{1} \mu_q (\frac{n}{N})^q + \sum_{d=1}^{4} \lambda_d I_d(t,n) + \sum_{p=1}^{5} (\delta_{c,p} \cdot \cos \frac{p2\pi n}{N} + \delta_{s,p} \cdot \sin \frac{p2\pi n}{N})$
Robust standard errors are reported in parenthesis. The standard errors are estimated according to the Newey and West method. *** indicates significance at a 1% confidence level.

Parameter	Coefficient (Standard error)	Parameter	Coefficient (Standard error)
μ_0	-3,0055***	$\delta_{c,3}$	0,5318***
	(0,0371)		(0,0110)
μ_1	0,2349***	$\delta_{c,4}$	-0,3847***
	(0,0377)		(0,0094)
λ_1	0,2494***	$\delta_{c,5}$	-0,1505***
	(0,0289)		(0,0087)
λ_2	-0,4836***	$\delta_{s,1}$	-0,4578***
	(0,0776)		(0,0259)
λ_3	0,2738***	$\delta_{s,2}$	-0,3689***
	(0,0367)		(0,0153)
λ_4	0,5052***	$\delta_{s,3}$	0,1258***
	(0,0279)		(0,0120)
$\delta_{c,1}$	-1,7440***	$\delta_{s,4}$	0,1738***
	(0,0133)		(0,0107)
$\delta_{c,2}$	0,1696***	$\delta_{s,5}$	-0,0920***
	(0,0123)		(0,0096)

5.2.2 ARMAX-GARCH

If the FFF-regression have worked properly, the seasonal component of the auto-correlation in the absolute returns should have decreased. Figure 5.5 show the autocorrelation for both the absolute raw returns and the absolute filtered returns for the chosen time period from year 2013 to 2019. As could be noted, the seasonal component is drastically reduced.

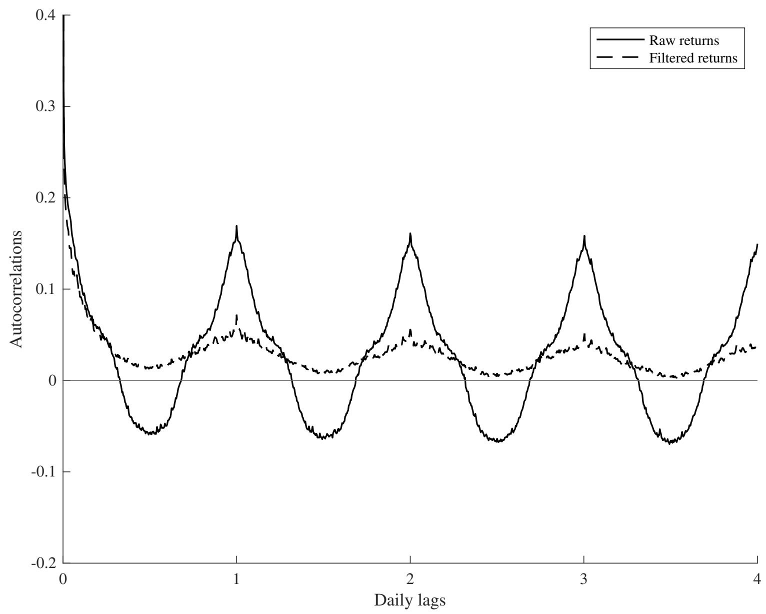


Figure 5.5: Absolute return correlogram for the EUR/SEK over the time period 2013-01-01 to 2019-12-31. Each day contain 288 lags.

As mentioned in the methodology section, the filtered return has no seasonal component in the volatility. Thus, if the filtered returns view any clear intraday patterns then one could argue there exists a seasonal component in the returns after correcting for the seasonal component of the volatility. To see if this is the case an ARMAX(3,3)-GARCH(1,1) model with dummy variables for each hour in the mean equation is performed, where the number of lags are based on the model giving the lowest BIC value. Table 5.3 show the result of the model and none of the coefficients are significant, with exception of the first two lags of the filtered returns. Other model specifications, in terms of number of lags in the mean equation, have been tested as well without changing the conclusion of the results. Furthermore, the signs of the coefficients do not appear to change in accordance with home bias theory (Ranaldo, 2007) although this should be interpreted with caution since the coefficients are not significant. The results are in contrast with earlier studies that have found significant intraday patterns in the raw returns, such as depreciation of the local currency in during the first and last trading hours (Cornett, Schwarz & Szakmary, 1995), during the whole local trading session (Breedon & Ranaldo (2013), the depreciation before and appreciation after associated with major global markets currency fixes (Krohn, Mueller & Whelan, 2020), among other patterns. In that sense it may be argued that the significant intraday patterns that have been found earlier may not yield the same results after correcting for the seasonal component in the intraday volatility. Given these result it also seems that one could not systematically exploit intraday pattern in risk adjusted returns, supporting EMH.

Table 5.3: Estimated coefficients from the ARMAX(3,3)-GARCH(1,1) model with dummy variables for each hour. $\tilde{R}_{t,n} = \sum_{h=1}^{24} \lambda_h d_h + \sum_{p=1}^{3} \phi_p \tilde{R}_{t,n-p} + \sum_{q=1}^{3} \theta_q \varepsilon_{t,n-q} + \varepsilon_{t,n}$
Standard error is in parenthesis. *** indicates significance at a 1% confidence level.

Parameter	Coefficient (Standard error)	Parameter	Coefficient (Standard error)
λ_1	0,0004	λ_{16}	0,0003
	(0,0005)		(0,0010)
λ_2	0,0002	λ_{17}	0,0003
	(0,0007)		(0,0009)
λ_3	-0,0002	λ_{18}	0,0000
	(0,0009)		(0,0008)
λ_4	-0,0002	λ_{19}	0,0002
	(0,0009)		(0,0010)
λ_5	-0,0001	λ_{20}	-0,0003
	(0,0010)		(0,0013)
λ_6	0,0009	λ_{21}	-0,0002
	(0,0009)		(0,0011)
λ_7	0,0007	λ_{22}	0,0000
	(0,0010)		(0,0008)
λ_8	-0,0008	λ_{23}	0,0003
	(0,0009)		(0,0006)
λ_9	-0,0004	λ_{24}	-0,0001
	(0,0009)		(0,0006)
λ_{10}	-0,0001	ϕ_1	-13,8750***
	(0,0012)		(0,3231)
λ_{11}	0,0002	ϕ_2	-5,0465***
	(0,0013)		(0,7869)
λ_{12}	0,0002	ϕ_3	-1,7094
	(0,0015)		(2,4578)
λ_{13}	0,0001	θ_1	-0,0277
	(0,0016)		(0,3082)
λ_{14}	0,0000	θ_2	-0,1120
	(0,0015)		(0,7522)
λ_{15}	0,0004	θ_3	-0,3139
	(0,0013)		(2,4274)

6 Conclusion

This thesis set out to investigate to what extent intraday patterns exist in the returns, after adjusting for intraday volatility, in the EUR/SEK spot rate. Practically, this is done in two steps. Firstly, the filtered returns are obtained by dividing the raw returns with seasonal components, which are estimated from a Flexible Fourier Form regression. After this, the filtered returns are examined using an ARMAX-GARCH model with dummies corresponding to each hour of the day. Our main empirical findings are that no significant intraday patterns exist when using returns filtered for seasonal volatility. Since the dummies are not significant, one could not reject the EMH. This is in contrast to earlier studies that have used raw returns (Breedon & Ranaldo, 2013; Cornett, Schwarz & Szakmary, 1995; Jiang 2019; Khademalomoom & Narayan, 2019; Ranaldo, 2009). Our findings instead suggest that their results may partly be driven by the intraday seasonal component in the volatility rather than a true seasonal component in the returns. In that sense, it is questionable if one could reject EMH based on their results. Despite the aim to investigate filtered returns, it is important to highlight our findings regarding intraday volatility in the EUR/SEK, since it have not been documented in the literature before. Our data show that one cannot assume a time-invariant intraday volatility, in that sense that the volatility in the EUR/SEK have moved from a pattern that is close to the JPY/USD to become more similar to EUR/USD. The same holds for the seasonal component of the autocorrelation in volatility, that have increased throughout the years.

For the future we see several interesting and import areas to investigate further. First, the methodology could be further developed to account for the time-invariant seasonal component of the volatility. This will allow for more data in the sample. Second, the previous studies that have confirmed statistical intraday pattern in the mean returns could be revisited, using filtered returns instead. Finally, it would be highly relevant and interesting to investigate to what extent time-varying seasonal component exist in intraday volatility and the autocorrelation of it and how this might change over time and across asset classes. In terms of the foreign exchange rate it would be interesting to see if there is any link between a time-varying pattern and the institutional development of the foreign exchange market, which have become increasingly more complex and fragmented over time.

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Appendix A

A.1 Correlograms of raw returns

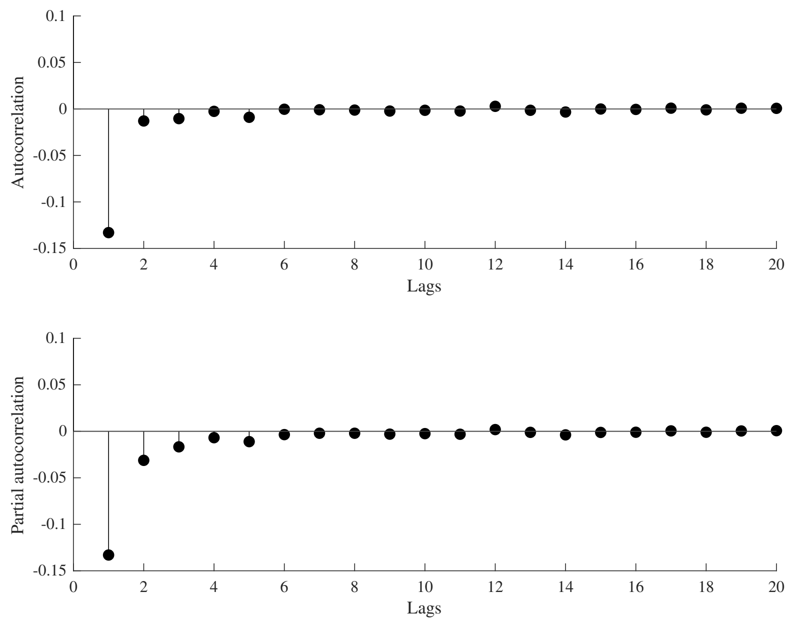
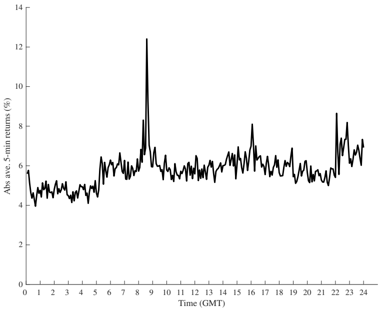
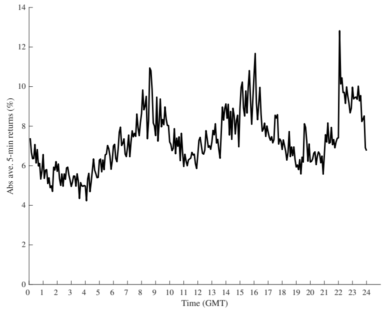


Figure 1: Autocorrelation function and partial autocorrelation function for raw returns, 2007-2019

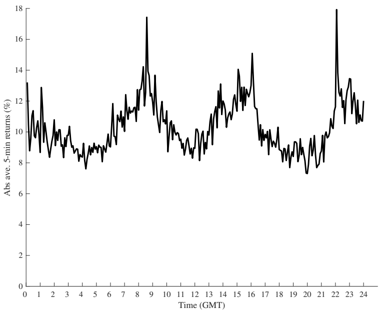
A.2 Yearly average absolute return



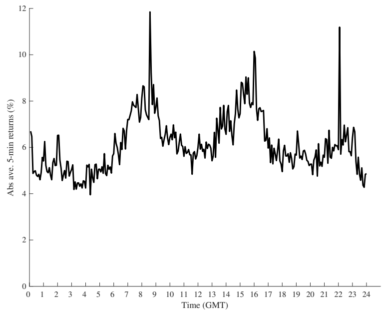
(a) 2007



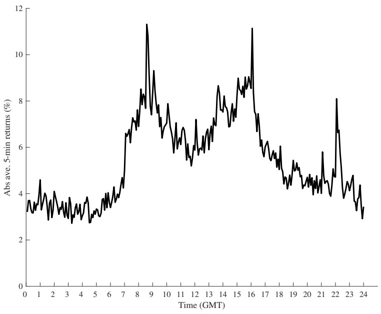
(b) 2008



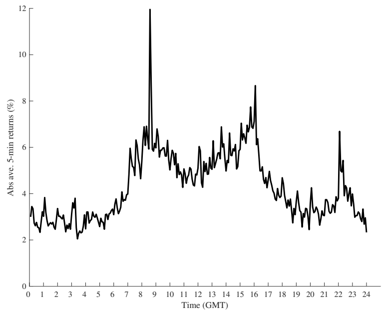
(c) 2009



(d) 2010

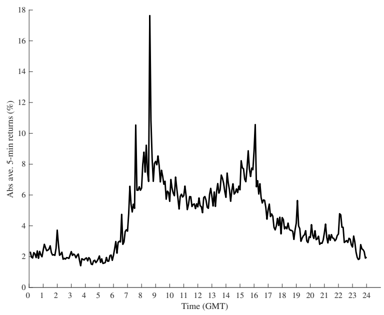


(e) 2011

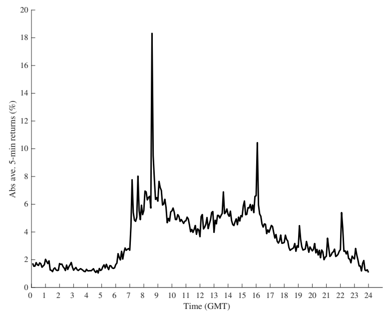


(f) 2012

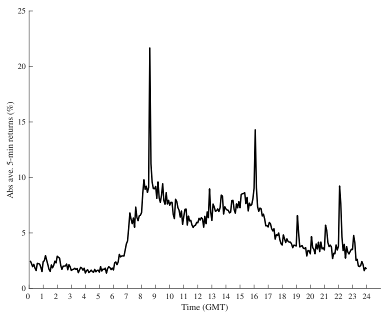
Figure 2: Plots of average absolute annualized 5-minute returns for the EUR/SEK over the different years.



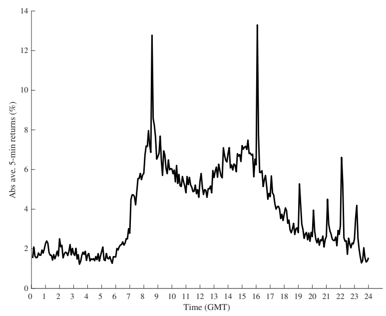
(a) 2013



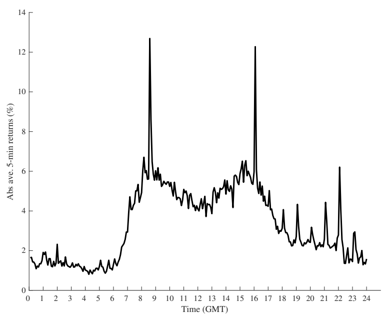
(b) 2014



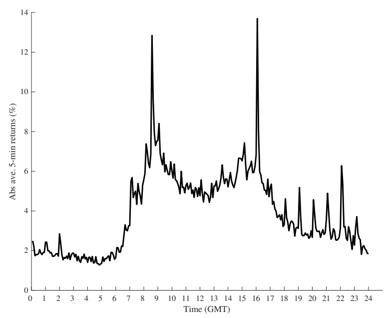
(c) 2015



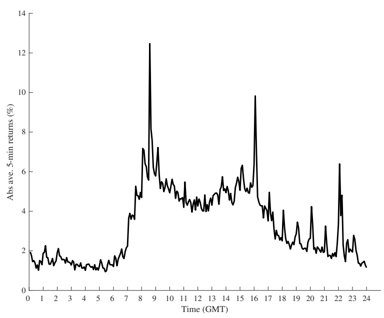
(d) 2016



(e) 2017



(f) 2018



(g) 2019

Figure 3: Plots of average absolute annualized 5-minute returns for the EUR/SEK over the different years.