The Relationship Between Implied And Realized Volatility

A Study On The Forecasting Value For European Index Funds

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Abstract

This study examines the relationship between implied volatility and future realized volatility in four European stock markets. In contrast to some previous studies implicating historical volatility to have higher forecasting value this study finds implied volatility to have the highest forecasting value. Findings show the implied volatility contains almost all of the information contained in historical volatility regarding the future forecast, but also contains some additional information on top of that. In this study the implied volatility forecast values also outperform those found in studies that found implied volatility to be the superior predictor. This study uses overlapping data and longer time-series than used in previous research ranging from early 2000 to late 2017. Findings also show positive average market returns in the 30 trading days before the implied volatility measurement to increase the forecast accuracy of implied volatility. No significant differences have been found between the different European markets except for the French CAC40 which has the least efficient volatility forecast of the four researched indices.

Chapter 1

Introduction

The implied volatility index on the S&P500, or VIX, is one of the lead indicators of trust in the financial markets. In 1993 the Chicago Board Options Exchange (CBOE) started quoting VIX in real-time. Since the introduction it gained a lot of attention and nowadays it is notoriously known as the 'fear gauge'. It has become the foundation for a wide range of tradable products and derived measurements of implied volatility for a variety of markets. In the summer of 2017 the VIX hit an all-time intraday low of 8.34 and VIX options volume spiked at record hights (CNBC, 2017). The implied volatility is one of the most closely watched indices in the market and the low-volatility bet has been one of this year's most popular wagers (Business Insider, 2017). That being said, the most important underlying fundamental of an implied volatility ticker is the assumption that it is a reliable forecast for the realized volatility in the next month. Whilst there has already been a substantial amount of research into the subject of predicting future volatility using implied volatility or other measures such as historical volatility, this has mostly focused on the US stock markets. Whether implied volatility outperforms historical volatility in terms of forecasting value and if the relationship between implied volatility and realized volatility holds in different markets however should be re-examined. Since the inception of the VIX a number of European stock indices have all gotten their own real-time volatility ticker using the same computation methods as VIX. Whether the forecasting ability of implied volatility in the US markets can be projected onto the European markets has not been researched in full.

1.1 Context

This study focuses on the European markets and examines the relationship between realized volatility (RV), implied volatility (IV) and historical volatility (HV) for the following stock market indices (between brackets are the respective implied volatility indices): the DAX (VDAX-NEW), the CAC40 (VCAC), the FTSE100 (VFTSE) and the AEX (VAEX). These IV indices are intended to make a reliable prediction about the RV in the coming period. Even though most of these were introduced in real-time around the financial crisis of 2007-2008 they have all been simulated retroactively until the beginning of the year 2000. To calculate the value of the IV all of these indices use roughly the same method originating from the VIX calculation. The exact calculation of these indices do not have to allign to compare them to each other as the most important thing is that they all make a prediction of the future realized volatility which can be measured in the same way. What is important as well is that they all make a forecast over the same period of time. For example the old VDAX used to forecast volatility over the next 45 days, which is non-comparable to the VFTSE which forecasts volatility over a 30 day period. Nevertheless with the introduction of the VDAX-NEW the IV for the DAX can also be used in this research as well as the other aforementioned indices since these all forecast a 30 day period. These values of implied volatility are based on a weighted sum of option prices rather than using the Black-Scholes model overcoming problems with the volatility skew. The exact calculation methods of the volatility indices are beyond the scope of this thesis but can be found on the websites of the respective stock exchanges. There has been a considerable amount of research on the topic of predicting realized volatility using this implied volatility and on the predicting value of implied volatility on stock returns. Nonetheless this research has mostly focused on the US market and especially the VIX and the S&P 500. In this study the predicting value of the implied volatility in European markets is researched with the aim of placing the forecast of RV in a broader perspective enhancing the understanding of the relationship between IV and RV. The IV will also be compared in terms of forecasting value with the historical volatility. Chapter 2 will explain why the HV in specific has been chosen as the independent variable to compare the IV forecasting value with.

1.1.1 Academic Relevance

Predicting future values of volatility has been researched in numerous amounts of studies. Even though a lot of forecasting methods have been devised over time such as GARCH or ARIMA, the implied volatility is still one of the independent variables most relied on. The prior research on IV (Canina and

Figlewski, 1993; Christensen and Prabhala, 1998; Jorion, 1995; Martens and Zein, 2004; Szakmary et al., 2003; Äijo, 2008) has focused on a wide variety of markets using many different statistical techniques, yet in three ways this research still falls short and can be complemented.

The first one entails the prior research not covering enough markets. As previously said most research focuses on the US markets, with the VIX in special. Some research has been done in for example the currency markets (Jorion, 1995) or commodities (Szakmary et al., 2003), yet the European markets seem barely touched in comparison. There has been some research into the VDAX (Äijo, 2008) and an unpublished paper into the forecasting value of the VFTSE, but furthermore there can be found no literature into the VAEX or regarding the VCAC. This study aims to contribute by means of creating a broader foundation for the relationship between IV and RV in a European context. The findings of previous literature are tested in this study with the same regression formulas that were used to describe the original relationship and were found in the research papers of Szakmary et al. (2003), Christensen & Prabhala (1998) and Canina & Figlewski (1993).

The second way this study complements previous research is that next to testing the quality of the forecast by IV in a traditional way the data is split into groups based on the returns of the previous month. This shows if there are differences in forecasting value depending on whether the return of the underlying index has had positive or negative returns in the 30 trading days before the IV was recorded.

The third way of complementation also has to do with splitting the data into groups based on the returns of the index for which the IV is forecasting volatility and looks a lot like what has been described in the previous paragraph. The big difference here is that it is an a posteriori way of looking at things describing differences in the relationship depending on whether there have been positive or negative returns in the underlying index in the 30 trading days over which the IV makes the prediction. This of course has no practical relevance and is sheerly meant for the purpose of gaining more understanding of the implied volatility and its relationship regarding realized volatility.

1.1.2 Practical Relevance

This study could be of use to anyone who either trades in contracts on the IV, in derivative products using IV or in general anyone who needs to make a volatility forecast for the coming period. Because this study contributes to the enhancement of forecasting using implied volatility it could potentially help all entities earning money by interpreting the future volatility. For example someone selling an option on the AEX benefits from having a better understanding of what bias implied volatility has regarding future volatility. This study can help correct for such a bias making implied volatility a more precise predictor. For someone selling options knowing their bias and correcting the volatility level accordingly is important as this is one of the determinants of the price of an option contract. On the investors' side, having insights on whether IV is a good predictor or not, can help spot arbitrage, or at least it can help spot a possibility that arbitrage may be present which is potentially valuable information.

Another group to whom this study can be relevant in practice would be stock investors in a more general sense as better anticipation of stock market movement on a national or an international level can help them allocating their funds. In an international perspective it can be useful to know how well the RV is predicted by IV across different stock exchanges. Knowing there will be larger deviations in returns in the coming period might help them make market decisions on for example when and what to hedge in terms of risk management. The differences between the different stock markets in terms of the forecasting ability of the IV might also help determining where to park your money when volatility spikes.

Lastly, since the IV index is known as a thermometer of trust in the economy, a more reliable IV index means it is more reliable when it comes to measuring this trust. This can for example be used to better interpret how much worth should be attached to gloomy look-outs originating from sudden spikes of high implied volatility.

1.2 Research Questions

This thesis tries to describe the relationship between the IV and RV for the researched European index funds in the period between 4-1-2000 and 4-8-2017. To do so, the following questions have been formulated:

- What measure for predicting future volatility has a higher forecasting value on realized volatility in the sample; implied or historical volatility?

To answer this first question three different regressions are used to see how much explanatory power the IV and the HV have over the RV. These regressions can be found in chapter 3. The results show whether the relationship between the IV and RV is significant and to what extent the model explains the future values of RV. HV in this question is simply the realized volatility for the 30 trading days previous to the IV measurement.

- Is the relationship between implied volatility and realized volatility influenced by the index returns of the previous period?

- Does it retrospectively matter for the relationship between IV and RV whether the coming period has positive or negative index returns?

To answer question 2 and 3 the data is split into four different groups per market. These groups are formed on the basis of positive or negative returns of the market indices in the previous or following period of the corresponding IV. To answer question 2 the two groups with positive or negative market returns in the period previous to the corresponding IV are used. For question 3 the two groups with positive or negative market returns in the period after the corresponding IV are used. The three regressions from the first question are ran again on the new groups for both of the questions.

- Is there a difference between the relationship of IV and RV for the different index funds?

To obtain an answer to the last question the regression results of the first three questions are compared to each other. The differences in the coefficients between the markets provide fundamental information to answer the main research question.

1.3 Structure

The remaining part of this thesis is structured in the following way:

Chapter 2 gives a broad review of the currently available literature on forecasting future volatility. Section 2.1 is used to review some of the methods described in the literature to predict volatility. It also gives an explanation as to why implied volatility in specific has been chosen for this study. Besides it reviews some literature on linkages between foreign markets regarding implied volatility. Section 2.2 gives an overview of the research gaps in previous literature. Section 2.3 presents how this study is of added value to the current literature.

Chapter 3 describes the specifics on how this study was carried out. Section 3.1 shows how the data was prepared for further processing. This section also reports some descriptive statistics and elaborates on the stationarity tests that were performed on the sample. Section 3.2 provides the experimental setup meaning the regression analyses used, the hypotheses and the criteria to which these hypotheses are held in order to reject or accept.

Chapter 4 contains the regression results of this study. In this chapter all of the research questions will be answered. Section 4.1 will run the regressions as specified in chapter 3. In section 4.2 the data will be split on the basis of average market returns for the past and following 30 trading days. Section 4.3 will deal with the comparison between the different researched market indices. Section 4.4 will be used to describe the bigger picture taking a step back, analyzing the results from a behavioral standpoint.

Chapter 5 summarizes the main findings in section 5.1. Next it discusses the limitations of this research in section 5.2 and the added value of this paper in section 5.3. Lastly, this chapter will give some recommendations for further research into the IV-RV relationship in section 5.4.

Chapter 2

Related Work

Ever since the fundamentals of a theoretical framework for implied volatility were laid by (Brenner and Galai, 1986) and the following introduction of the VIX by the Chicago Board Options Exchange in 1993, a large amount of effort has been put into describing the characteristics of implied volatility. After the creation of VIX lots of new indices measuring implied volatility have been created on foreign stock exchanges as well. Like the stock market, other financial markets such as those for bonds, currencies and commodities nowadays also make use of IV, laying the foundation for a large derivatives market trading IV as the underlying product. Next to studies trying to predict future stock returns based on IV values such as (Banerjee et al., 2007), most existing literature regarding implied volatility indices or the corresponding derivatives markets focuses on how well the IV can predict future realized volatility.

The existing literature has tried predicting future realized volatility in a number of ways, using different statistical techniques and models, but implied volatility seems to remain one of the important predicting factors throughout. Examples of studies using the IV in some form are: (Agnolucci, 2009; Busch et al., 2011; Canina and Figlewski, 1993; Christensen and Prabhala, 1998; Corrado and Miller, 2005; Koopman et al., 2005; Lamoureux and Lastrapes, 1993; Li and Yang, 2008; Martens and Zein, 2004; Szakmary et al., 2003). These papers do not necessarily claim IV is the best predictor, yet in multiple studies IV was found to have the most predictive power. However, the previous literature is not unanimous about what method forecasts volatility best. A summarizing study found IV to come out on top if compared to other methods (Poon and Granger, 2003).

2.1 Previous Work

The amount of studies on forecasting future volatility has grown substantially over the last decades. In the following subsections the most important papers of the existing literature will be discussed. The studies have been divided into groups separated by their main method of forecasting future realized volatility. The last forecasting method to be discussed is IV as this is the method used in this paper. Since this study also aims at comparing the implied volatility among different stock markets the last subsection describes the literature treating integration between markets.

2.1.1 Historical Volatility

The most obvious predictor of future volatility is historical volatility. The use of historical volatility as one of the independent forecasting variables is widespread, yet in general it does not seem to hold the most predictive power. In fact, (Poon and Granger, 2003) found the historical volatility to be a better predictor than GARCH (see the following subsection), but it predicts future volatility worse than implied volatility in the compared papers. Nevertheless there are some studies that have found historical volatility as the best predicting variable. One of the earlier studies into the forecasting value of IV done by (Canina and Figlewski, 1993) found that for S&P100 index options the IV had almost no correlation with future realized volatility. They find historical volatility to be superior to implied volatility and recommended using more input factors in the calculation of expected volatility. The usage of non-overlapping data in this paper reduces the power of the statistical tests. (Lamoureux and Lastrapes, 1993) Also found that historical volatility had more predictive power than IV in a sample consisting of individual stock options. However in later research the findings of these papers were disputed, hence historical volatility is included in the regression analyses, but is not expected to be the most significant factor.

2.1.2 GARCH

The Generalized Autoregressive Conditional Heteroskedasticity model or GARCH is an econometric tool to analyze and forecast future volatility. The oridinary least squares method and the GARCH or ARCH models used in previous research differ on the perspective of the error term. OLS assumes the squared error term is the same throughout the data, or in other words homoskedasticity. GARCH models on the other hand assume heteroskedasticity and model the variance in the data. Even in its simplest form, it has proven surprisingly successful in predicting conditional variances (Engle, 2001). One of the few studies finding GARCH to be a better predictor than IV is (Agnolucci, 2009). The study examined the WTI future contract, which is the futures contract on crude oil quoted at the NYMEX. The findings show GARCH models to make a better future RV forecast, yet the researcher does recommend combining both time-series models as well as IV models since IV forecasts do contain some information that is not present in GARCH-type models. In general however GARCH is not found to be a better forecast than IV. Most research, as mentioned in the next subsection, find GARCH to hold less predictive power than IV and often finds GARCH yields the same or worse predictions.

2.1.3 Implied Volatility

The last, but most important variable discussed in this chapter is the implied volatility. The available literature throughout the years shows IV remains the most important, or one of the most important factors in all types of markets. A study by (Li and Yang, 2008) examined the forecasting value of IV from option prices on future realized volatility. They studied the Australian market and found IV to be superior to historical volatility. Their research can be described as a follow up on (Christensen and Prabhala, 1998) who studied the IV on OEX options. Christensen and Prabhala found the Black-Scholes option pricing model to be a good measure for interpreting the IV and found IV to be a better predictor of realized volatility than historical volatility. They found standard OLS to produce the same or better outcomes than GARCH or ARCH models. These two studies by (Li and Yang, 2008) and (Christensen and Prabhala, 1998) are the main foundation for this study.

Furthermore, research by (Christensen and Prabhala, 1998) refuted findings of (Canina and Figlewski, 1993) who showed that historical volatility outperformed implied volatility in their research. They give several explanations as to why Canina and Figlewski obtained these results. They believe the biggest reason their research refutes earlier findings is the use of nonoverlapping data. The extreme degree of overlap in data and the highly autocorrelated errors with a low Durbin-Watson statistic (0.2) of the Canina and Figlewski research is very likely the main reason they came to this conclusion. In the research by Christensen and Prabhala it is shown that when applying the new method on the same sample the earlier research used, IV is biased, but still the most efficient forecast of volatility.

In different markets such as the futures market, research on the IV was done by (Szakmary et al., 2003). This study compared a GARCH model to the IV for 35 futures markets. Their research concluded that GARCH does not add predictive power for most of the futures markets, when it does, in most cases it does not add much and the predictive power of IV remains strong throughout. Hence this research also confirms and extends the evidence of (Jorion, 1995) from the currency futures market. In a study across markets, forecasting RV in stocks, bonds and currencies by (Busch et al., 2011) IV was found to have incremental information in all three markets. The study examined jump components and found IV to be an unbiased predictor of future volatility. The results in an out-of-sample experiment confirmed their findings.

Other evidence provided by (Martens and Zein, 2004) shows implied volatility providing superior forecasts over the GARCH(1,1) model. They researched three different asset classes, equity, foreign exchange and commodities. Their research adheres to what (Jorion, 1995) and (Christensen and Prabhala, 1998) found in previous studies. Martens and Zein suggest using a composite forecast combining implied volatility and ARFIMA (Autoregressive Fractionally Integrated Moving Average) to generate the best volatility forecast. In following research by (Koopman et al., 2005) who compared different methods for the S&P 100 index it was found that the log ARFIMA-RV provided better forecasting than the GARCH model as well.

Research conducted by (Corrado and Miller, 2005) found that the implied volatility provided better qualitity forecasts than the GJR-GARCH model in almost all tests for the volatility indices of the S&P 100, the S&P 500 and the Nasdaq 100. They also found that CBOE provided volatility index data has improved since 1995, reducing the bias in forecasts.

As shown, the amount of literature supporting IV as having the most forecasting value is overwhelming. A research paper by (Poon and Granger, 2003) reviewed 93 papers on the topic of forecasting volatility and found that historical volatility outperformed GARCH in 56 percent of the reviewed studies. Implied volatility was the better predictor over historical volatility in 76 percent of the studies. When comparing GARCH directly to the IV it showed that in 17 out of 18 studies, or 94 percent, IV was superior. Considering this it seems rational to assume IV is the most significant factor in forecasting volatility.

2.1.4 Market Comparison

For this study the relationship between IV and RV is examined for the DAX, CAC40, FTSE100 and the AEX. The regressions used to value the variables are compared between the different exchanges. To put this in perspective it is important to note some important studies on implied volatility in an international comparative setting.

There are only a few studies doing research on implied volatility term structure integration between European stock markets. For example the study by (Äijo, 2008) who researched the old volatility index for the DAX, the VDAX, and compared it to the VSMI and VSTOXX volatility indices. The researcher found that the term structures of the volatility indices were closely correlated. The DAX was found to play a leading role in predicting volatility term structures of European markets. Another study focused on the integration of stock markets between the United States, the United Kingdom, Germany and Finland found that there is a great deal of integration with respect to market uncertainty (Nikkinen and Sahlström, 2004). The study also found the U.S. stock market to be the leading source of uncertainty in the markets as changes in the volatility there are transmitted to the other researched markets.

2.2 Research Gaps

To the best of my knowledge, there has been little research on the implied volatility relationship for European index funds. Whilst there have been some studies on different types of markets such as the bond or currency markets, in the stock markets most research has focused on the US with the S&P 500 in special. In the European market there has been some research on the DAX and the FTSE 100, but the CAC 40 and the AEX have not been researched until now. Even though the research in for example the US market is expected to be relevant and applicable to the European volatility tickers it can not be assumed to hold naturally. Therefore the lack of studies concerning Europe can be identified as a research gap. Also, there has been little research on differences in the predictive values of the implied volatility indices between different foreign markets. The current literature generally examines the IV relationship for a certain market but rarely describes linkages or compares the relationship between different foreign markets.

Another gap in the current research is that there has not been much research using stock returns as a moderating variable in the forecasting relationship between implied and realized volatility. There has been research on the relationship between implied volatility and stock index returns in a causal way, for example (Giot, 2005) researched this relationship for the S&P 100 and the NASDAQ 100 finding a negative and statistically significant relationship between the stock index returns and the corresponding volatility indices. Yet, it has not been researched in full how the stock index returns of the previous month influence the implied volatility prediction on realized volatility for the following month.

In contrast to (Giot, 2005), there has also been some previous research regarding the relationship between IV and future portfolio returns of S&P 500 companies by (Banerjee et al., 2007) who found the opposite. A positive relationship between VIX-levels and future excess returns was found and demonstrated to be most present at portfolios with high betas. A study by (Sornette et al., 2017) who researched 40 asset bubbles to see whether the implied volatility can predict crashes found volatility to be neither a reliable indicator of the maturity of such bubbles, but also found it unreliable in predicting crashes. Nevertheless this study also found eleven cases of very low implied volatility right before a bubble burst. This implies that in some cases implied volatility was a good predictor of coming volatility and in some cases it was not, but it does not show how well implied volatility works as a forecast method a posteriori. The influence of future returns on current implied volatility has not been researched yet, and however it does not hold any economic value, it is an academic research gap.

The last identified research gap is the passed time since most of the important studies in the field were done. Most of the studies concerning IV come from before or around the year 2000, with only a few important papers around the financial crisis, but since 2008 there has been very little research on volatility indices. This means most of the existing literature has focused on older samples of implied volatility whilst the global economy has changed fundamentally over the last decade.

2.3 Current Study

This study will contribute to the currently existing research as it will focus on the relationship between IV and RV for the European markets. Because there has been little attention for the implied volatility forecasting value for the AEX, the CAC 40, the DAX and the FTSE 100, this study will focus on those indices. All of the research questions mentioned in section 1.2 will be answered with regard to the international perspective. Next to this, this research will examine how past returns of the underlying index influence the forecasting value of the corresponding implied volatility index. The influence of the stock index returns on the forecasting value of IV will also be examined in an a posteriori manner purely for academic purposes as this has no value in financial practice. This study will also fill the time gap between the different relevant research papers using parts of the methodology of existing literature and applying it on a fresh dataset. The two main studies that will be used as the foundation for this research are (Christensen and Prabhala, 1998) and (Li and Yang, 2008). These papers form the basis for the methodology used in this research as will be explained in the next chapter.

Chapter 3

Methodology

This chapter will discuss the methodological framework that was used in order to provide answers to the research questions.

3.1 Dataset

For this study, the daily quotation data from all four researched indices (AEX, CAC40, FTSE100 and DAX) was retrieved as well as the daily level of their respective implied volatility indices (VAEX, VCAC40, VFTSE100 and VDAX-NEW). To obtain this time-series data the Datastream database was used. Even though all of the volatility indices have different introduction dates and some of the volatility indices have not been around for long, they have been calculated back to 1-1-2000 using past market data. The data from the market indices depict the daily price level at market close. For both the market indices as well as the implied volatility indices data from 4-1-2000 until 4-8-2017 was obtained and used in this study. This means this study was carried out over a sample of 36,712 data points divided over 8 different tickers. The data obtained in Datastream has no missing values or other irregularities that had to be accounted for.

3.1.1 Data Processing

To make the obtained data useful for this study the daily price levels of the four market indices are used to generate new variables containing the daily logreturns of the indices. To do so the following formula was used:

$$r_t = ln\Big(\frac{Price_t}{Price_{t-1}}\Big) \tag{3.1}$$

The daily returns showed 0 on the days that the stock market was closed in the respective countries hosting the stock indices. These days were dropped from the dataset as the implied volatility is a prediction over the next 30 trading days. Days with zero return on the general index contaminate the results as the implied volatility will remain the same these days meaning they weigh more heavily in the regressions. After the daily returns have been computed the 30-day standard deviation or realized volatility of these returns were generated as a new variable. The standard deviation is expressed using the following formula:

$$\sigma_{rv} = \sqrt{\frac{1}{30}\sum_{n=1}^{30}(r_t - \bar{r_t})^2} \tag{3.2}$$

Using this formula a rolling time-series of 30-day volatility for the entire sample was produced for the four market indices. The 30-day volatility is used in this study as historical volatility and realized volatility depending on the relative position toward the implied volatility measurements. The historical volatility series is in essence the same as the realized volatility series from 30 trading days earlier. Both of these volatility series had to be annualized multiplying them by the square root of the average yearly trading days from the sample. Also, to make the obtained new variables less skewed and usable for the OLS regressions the level series have to be transformed to natural logarithm series. After this point all references to the different volatility series actually describe the logvolatility series.

3.1.2 Exploratory Data Analysis

To get some some basic understanding of the data used in this study, some descriptive statistics have been added in the tables below.

Table 3.1: Descriptive Statistics on the Market Index Returns

Stats	AEX	DAX30	FTSE100	CAC40
Min (%)	-9.59	-8.87	-9.27	-9.47
Max (%)	10.03	10.80	9.38	10.59
Mean (%)	0.00	0.01	0.00	0.00
σ (%)	1.44	1.51	1.20	1.47
Skewness	-0.09	-0.05	-0.15	-0.03
Kurtosis	9.34	7.34	9.14	7.84

This table shows the descriptives for the daily logreturns of all the market indices for the entire sample period. These returns were calculated using equation 3.1.

Table 3.1 shows the descriptives for the daily log returns of the market indices. The time-series summarized in this table were obtained using formula 3.1 generating a time-series of the log returns. All of the return series are highly leptokurtic distributions whilst most days the return of the general stock index is close to the mean value approximating zero. All of the return series look roughly the same, with the exception of a slightly lower standard deviation in the return series of the FTSE 100.

Table 3.2: Descriptive Statistics on the Realized Volatility

	Level RV Series				Log RV Series			
Stats	*AEX*	*DAX*	*FTSE*	*CAC*	*AEX*	*DAX*	*FTSE*	*CAC*
Min	0.06	0.06	0.06	0.06	-2.88	-2.77	-2.89	-2.74
Max	0.85	0.75	0.74	0.79	-0.16	-0.28	-0.30	-0.23
Mean	0.20	0.21	0.17	0.21	-1.75	-1.64	-1.90	-1.66
σ (%)	11.79	11.05	9.30	10.59	48.91	44.84	46.38	43.79
Skewness	2.15	1.74	2.24	1.87	0.65	0.46	0.55	0.44
Kurtosis	8.80	6.58	10.71	7.89	3.14	2.97	3.07	3.00

This table shows the descriptives of the annualized realized volatility for the different market indices. The level volatility series give the descriptives of the rolling standard deviation obtained using formula 3.2. The log volatility series were obtained by creating new variables using the natural logarithm of the level time-series.

The 30-day realized volatility descriptives as shown in Table 3.2 were obtained using formula 3.2. The values obtained by this formula had to be annualized and thus be multiplied by the square root of the number of trading days in one year. To obtain the average number of trading days per stock exchange per year for the sample the total number of observations was divided by the number of years included in the sample. The level series in table 3.2 show that the realized volatility data is highly skewed and leptokurtic. To account for this and make the series usable for OLS-regression purposes the natural logarithm of these series were taken. The natural logarithm series, in the table denoted as the log volatility series show lower levels of skewness and a kurtosis of around 3 approximating a normal distribution. Furthermore no exceptional differences between the realized volatility variables can be observed.

Table 3.3: Descriptive Statistics on the Implied Volatility Indices

	Level IV Series				Log IV Series			
Stats	*AEX*	*DAX*	*FTSE*	*CAC*	*AEX*	*DAX*	*FTSE*	*CAC*
Min	0.06	0.11	0.06	0.00	-2.85	-2.20	-2.78	-5.45
Max	0.81	0.83	0.76	0.78	-0.20	-0.18	-0.28	-0.25
Mean	0.23	0.24	0.20	0.23	-1.55	-1.49	-1.69	-1.52
σ (%)	10.44	9.74	8.63	8.86	38.53	34.70	37.60	34.46
Skewness	1.82	1.79	1.85	1.68	0.73	0.75	0.61	0.13
Kurtosis	6.84	6.90	8.00	7.01	3.21	3.33	3.11	7.23

Descriptives for the level and log implied volatility series. The level series in this table are the implied volatility tickers that were obtained from Datastream denoting the annualized implied volatility for the coming 30 trading days. The log IV series show the statistics for the natural logarithm of the level IV series.

Table 3.3 shows the descriptives on the level and log implied volatility series. The natural logarithm was taken for the same reason as for the realized volatility. The log implied volatility series are less skewed and have a kurtosis of around 3. Noticeable however is the log IV series for the CAC40, which has a value close to zero regarding the skewness but is however highly leptokurtic. The different market indices and tables above will be further compared in chapter four together with the regression analyses.

3.1.3 Stationarity Testing

The next thing to do is test the log implied and log realized volatility variables for stationarity as was done in (Szakmary et al., 2003) since both are time-series variables. To do so the Augmented Dickey-Fuller (ADF) test was used, if the test statistic is significant we can reject the null hypothesis. To determine the right number of lags we use the method devised by (Schwert, 1989). With regard to this study and the fact that Monte Carlo experiments suggest that is is better to have too many lags than too few, the number of lags is set at 31.

Table 3.4: Augmented Dickey-Fuller on Log Realized Volatility Series

	RV_{AEX}	RV_{DAX30}	$RV_{FTSE100}$	RV_{CAC40}
Z(t)	-3.37	-3.39	-3.60	-3.39
P-Value	0.01	0.01	0.01	0.01

This table shows the results of the Augmented Dickey-Fuller test on the log realized volatility series. The 1% critical value of the test statistics lies at -3.43. If the z-value found for the series is smaller than this value the null hypothesis can be rejected at the 1% level.

Table 3.4 shows the results of the ADF-tests for the log realized volatility. The test shows that there is no unit root to be found in the FTSE100 on the 1% confidence level. For the AEX, the DAX30 and the CAC40, the null hypothesis of unit root can be rejected on the 5% confidence level, yet it can not be rejected on the 1% level. Even though the Z-values for these two series are not smaller than the 1% critical value of -3.43 it is enough to assume them to be non-stationary as well.

Table 3.5: Augmented Dickey-Fuller on Log Implied Volatility Series

	IV_{AEX}	IV_{DAX30}	$IV_{FTSE100}$	IV_{CAC40}
Z(t)	-3.27	-3.55	-3.58	-3.59
P-Value	0.02	0.01	0.01	0.01

This table shows the results of the Augmented Dickey-Fuller test on the log implied volatility. As with table 3.4, the 1% critical value of the test statistics lies at -3.43. If the z-value found for the series is smaller than this value the null hypothesis can be rejected at the 1% level.

Table 3.5 shows that the log implied volatility series of all market indices except for the AEX show no signs of unit root on the highest confidence level. For the AEX however the null hypothesis can be rejected at the 5% level. The P-values for the rest of the indices are 0.01 for the tested log-IV series. Yet, this is due to the rounding of numbers. The null hypothesis can be rejected for all of the IV-indices. The implied volatility time-series and the realized volatility series were both expected to be stationary since they are most likely to be mean-reverting processes. There is still the possibility that volatility might have undergone structural breaks in the researched time period, yet this is very hard to discover and the ADF-test is unlikely to provide evidence supporting this theory.

3.2 Experimental Setup

To provide an answer to the research questions the ordinary least squares (OLS) regressions below will be tested on the provided data. These regressions were previously used in research by (Canina and Figlewski, 1993; Christensen and Prabhala, 1998; Li and Yang, 2008; Szakmary et al., 2003) and have been combined for this study. For all of the regressions, the independent and dependent variables are the log-series of the respective variable.

$$RV_t = \alpha_0 + \alpha_1 RV_{t-1} + \varepsilon_t \tag{3.3}$$

Equation 3.3 is the first OLS regression measuring solely the forecasting value of historical realized volatility on the future realized volatility without taking into account the implied volatility.

$$RV_t = \alpha_0 + \alpha_1 IV_t + \varepsilon_t \tag{3.4}$$

Equation 3.4 is the second OLS regression measuring the forecasting value of implied volatility on the realized volatility in the coming month. This regression does not account for the predictive value held by historical volatility.

$$RV_t = \alpha_0 + \alpha_1 IV_t + \alpha_2 RV_{t-1} + \varepsilon_t \tag{3.5}$$

The last equation measures both the forecasting value of the implied volatility as well as the forecasting value of historical volatility making it the most important regression of this study. The historical volatility is denoted here as the realized volatility of the previous period. For all of the regressions α_0 measures the size and direction of the bias of the prediction. If there is no bias the α_0 should be zero or insignificant. The α_1 measures the predictive value, or the efficiency, of the implied volatility in regressions 3.4 and 3.5, if these are significant and most likely positive meaning the implied volatility holds predictive power over the realized volatility. The α_1 from regression

3.3 and the α_2 from regression 3.5 measure the predictive power of historical volatility on future realized volatility. The historical volatility is expected to be of more importance in regression 3.3 and thus have a lower value in regression 3.5. For all of the regressions tested and market indices researched the R-squared will also be analyzed to see which model and which market provides the best future volatility forecast. This study uses overlapping data as was done by (Canina and Figlewski, 1993), this was criticized in the study by (Christensen and Prabhala, 1998) since they claim the autocorrelation in the error term makes their findings incorrect. To control for this error all regressions will be done with Newey-West standard errors with 30 lags as the volatility measures are done over a 30-day period. To provide an answer to the first research question the following hypothesis has to be tested;

Hypothesis 1: Implied volatility has a higher forecasting value than historical volatility when predicting future volatility.

All three regressions above will be tested on the four different market indices for the entire sample period to determine whether hypothesis 1 should be rejected or accepted. This hypothesis was based on previous findings in research by (Christensen and Prabhala, 1998) and (Li and Yang, 2008) mainly, but also on the summarizing paper by (Poon and Granger, 2003) who found the IV to be superior in 76 percent of the examined studies. The α_1 coefficient from regressions 3.3 and 3.4 can be indirectly compared to see which one generates the highest forecasting value in terms of size and significance. Regression 3.5 generates a direct comparison between realized and implied volatility. The α_1 and α_2 from regression 3.5 directly show which one of the two has a higher coefficient value and whether these coefficients are still significant when put together in the same equation.

For the second and third research question the data has to be split into groups depending on the market index returns of the previous or the following month. To obtain an answer to the second research question we have to find whether IV gives a better or worse volatility forecast following a month of positive or negative returns. To check the outcome of this question the data has to be split into two new groups. One with the implied volatility after a month of positive returns, hereafter known as group A, and one with the implied volatility after a month of negative returns, hereafter known as group B. For these groups regressions 3.4 will be tested and compared using the same method as previously described comparing coefficients and significance levels.

The third research question is very similar to the second question, yet it takes into account market return differences in the month following the IV_t instead of the month prior to the IV_t. To answer this question hypothesis 2 was created;

Hypothesis 2: The prediction of future volatility is more accurate previously to months with positive index returns.

To reject or accept this hypothesis a similar procedure will be used as for research question 2. Hypothesis 2 is based on previous research by (Sornette et al., 2017) who researched asset bubbles and found that implied volatility is a bad predictor of future large bearish movements. The period before such 'storms' showed low volatility levels in most of the cases. These low levels were of course not shown by the realized volatility in the following period. The only change in methodology between answering research question 2 and 3 is a different split in the same dataset. Again two groups will be formed, one with the IV_t before a month with positive average market index returns and one with the IV_t before a month with negative average market returns. These groups will hereafter be known as group C and group D.

The last research question will be answered by means of hypothesis number three. This research question is meant to chart how well the implied volatility works as a predicting variable in an international context. Hypothesis four is formulated as follows;

Hypothesis 3: Since all IV indices are computed in approximately the same way over the same time period, there will be no significant difference in the relationship between IV and RV for the different markets.

To test this hypothesis and answer the fourth research question, the answers to the previous three research questions will be used. This hypothesis was based on the study performed by (Szakmary et al., 2003) who researched 35 futures option markets on eight different exchanges. For most of the researched markets they found no large differences between the forecasting values of implied volatility. A comparison between markets will be made on the basis of coefficient size, significance levels and the size of the determination coefficient. The combined analysis of the regressions on the different markets will be used to come to a coherent conclusion about the forecast value of the IV indices in an international perspective.

Chapter 4

Results

Using the methodology as described in the previous chapter, this chapter will discuss and display the results of the regression analyses and look at the findings in a wider behavioral perspective. Emphasis will lie on analyzing the regression coefficients and hence provide data to answer the research questions and hypotheses. Chapter 3 already showed some descriptive statistics and the Augmented Dickey-Fuller tests to check for unit root in the volatility series. Since we rejected the null hypothesis of unit root for all tested time series we can run the regressions as specified.

4.1 Running the Regressions

In this section the results of the three regression equations will be analyzed. All of the equations will be treated in a different subsection. The tables show the coefficients as well as their respective T-values and the adjusted R-squared showing what percentage of the dependent variable can be explained by means of the independent variables. The three regressions that were used for the different stock markets without splitting the data on the basis of past or future market returns had Newey-West standard errors with 30 lags. The ideal scenario for the first two regressions (3.3 and 3.4) predicting future realized volatility would be an intercept of zero that is significant and values as close to 1.00 as possible for the independent variable. Those results would mean the independent variable is unbiased and efficient. The last regression (3.5) without creating subgroups in the data will show which one of the independent variables has the highest forecasting value whilst being significant.

4.1.1 Historical Volatility

The results of running regression 3.3 on the four different markets are displayed in table 4.1. For all of the markets the intercepts as well as the independent variables are found to be significant at the 1% level. All of the markets display a negative intercept of around -0.50 meaning the historical volatility is a biased forecast of future realized volatility. The coefficents of the historical volatility for all of the markets lies around 0.70 with meaning it is a fairly reasonable predictor of realized volatility. All of the stock indices display roughly the same forecast values for the historical volatility. Yet, the adjusted R-squared of the indices is slightly different. The AEX has the highest R-squared with 51%, this means 51% of the variation in realized volatility of the AEX index is explained by the historical volatility of the respective index. The CAC40 however shows a lower value of 46%. Even though these differences are not that large it still means the historical volatility of the AEX has the highest forecasting value over realized volatility and the CAC40 the lowest.

Table 4.1: Newey West regression estimates of equation 3.3

Dependent	Intercept	RV_{t-1}	Adjusted R^2
$RVAEX_t$	-0.51^{**}	0.71^{**}	51%
	(-6.25)	(16.90)	
$RVDAX_t$	-0.50^{**}	0.70^{**}	48%
	(-6.76)	(16.47)	
$RVFTSE_t$	-0.59^{**}	0.69^{**}	47%
	(-6.53)	(15.47)	
$RVCAC_t$	-0.53^{**}	0.68^{**}	46%
	(-6.63)	(15.23)	

Displays the results of regression equation 3.3 using Newey West standard errors with 30 lags. The RV_{t-1} displays the natural log series of the historical volatility of the previous 30 trading days. The realized volatility series displayed as the dependent variable also actually denotes the natural log series of the corresponding realized volatility at time t.
* and ** represent 5% and 1% significance levels, respectively.

4.1.2 Implied Volatility

In table 4.2 the results of regression 3.4 are displayed. For the relationship between implied volatility and realized volatility without considering historical volatility. All of the coefficients are found to be significant at the 1% level as well just like the coefficients from regression 3.3. The intercepts are all slightly negative, which means the implied volatility is biased as well in forecasting future volatility. The intercepts however are closer to zero than those of the historical volatility meaning the implied volatility is less biased when regressed as the single independent variable against realized volatility.

The implied volatility also shows coefficients that lie around 0.25 higher than those of the historical volatility. This can be interpreted as the implied volatility being a more efficient forecast than historical volatility. The coefficients show high levels of forecast precision as 1.00 would be the ideal scenario. This is in compliance with the research by (Christensen and Prabhala, 1998) who found approximately the same values in the post crash period from 1987 to 1995 in the S&P 100 index options. The coefficients found in this study are slightly higher but since the sample used in this study runs from 4-1-2000 until 4-8-2017 it can be assumed the option market has grown more efficient over the years. This is consistent with the aforementioned research

Table 4.2: Newey West regression estimates of equation 3.4

Dependent	Intercept	IV_t	Adjusted R^2
$RVAEX_t$	-0.24^{**}	0.98^{**}	59%
	(−3.27)	(21.42)	
$RVDAX_t$	-0.17^{**}	0.99^{**}	59%
	(−2.67)	(23.33)	
$RVFTSE_t$	-0.31^{**}	0.94^{**}	58%
	(−3.86)	(20.45)	
$RVCAC_t$	-0.25^{**}	0.93^{**}	53%
	(−2.79)	(16.25)	

Displays the results of regression equation 3.4 using Newey West standard errors with 30 lags. The IV_t displays the natural log series of the implied volatility for the coming 30 trading days. The realized volatility series displayed as the dependent variable denotes the natural log series of the corresponding realized volatility at time t.

* and ** represent 5% and 1% significance levels, respectively.

where the pre-crash period from 1983 to 1987 showed much lower coefficients for the same relationship.

The adjusted R-squared values are approximately the same for the AEX, the DAX30 and the FTSE100 at around 59%. The CAC40 however, again shows the lowest value with 53%, hence the implied volatility explains the future volatility the worst for this index. Noticeable is nonetheless that for the regression analyses displayed in table 4.2 the lowest adjusted R-squared is still higher than highest the adjusted R-squared from table 4.1. This implies the implied volatility has higher forecasting value than historical volatility. To check whether this assumption is true regression 3.5 is used combining both the historical and implied volatility into one regression.

4.1.3 Combining HV and IV

The results of regression 3.5, the most important regression of this study, are displayed in table 4.3. Here the implied and historical volatility forecast values can be directly compared as they are both regressed simultaneously against the realized volatility. The table immediately shows a few remarkable things. The intercepts as well as the adjusted R-squared for all of the markets show approximately the same values as the regression coefficients from table 4.2. Furthermore the historical volatility suddenly becomes either

Table 4.3: Newey West regression estimates of equation 3.5

Dependent	Intercept	IV_t	RV_{t-1}	Adjusted R^2
$RVAEX_t$	-0.24^{**}	0.84^{**}	0.11	59%
	(−3.28)	(8.42)	(1.49)	
$RVDAX_t$	-0.17^{**}	0.93^{**}	0.06	59%
	(−2.68)	(9.56)	(0.79)	
$RVFTSE_t$	-0.31^{**}	0.84^{**}	0.09	58%
	(−3.74)	(8.87)	(1.22)	
$RVCAC_t$	-0.25^{**}	0.70^{**}	0.02^{*}	54%
	(−3.03)	(5.43)	(2.19)	

This table shows the estimates of regression equation 3.5 using Newey West standard errors with 30 lags. The implied volatility, historical realized volatility and realized volatility used in the regression are actually the natural log series of the aforementioned variables.

* and ** represent 5% and 1% significance levels, respectively.

insignificant (for the AEX, the DAX30 and the FTSE100), or significant on the lower 5% level (for the CAC40). Also the coefficients corresponding to the historical volatility have much lower values than those found with regression 3.1. The coefficient of the historical volatility of the CAC40 is, even though it is the only coefficient that is significant to some extent, actually very close to zero with 0.02. This means that however significant, it has almost no forecast value with regard to future realized volatility.

The implied volatility on the other hand is significant in all markets on the 1% level. The coefficients are lower than those found with regression 3.4, yet they still have a high forecasting value. The implied volatility is in comparison with historical volatility, as proven in table 4.3, the most efficient forecasting variable. These findings are in accordance to the results found in previous research by (Christensen and Prabhala, 1998; Li and Yang, 2008; Szakmary et al., 2003). These studies also found the historical volatility not to contain any information that was not already incorporated in the implied volatility forecast. These findings are supported by the regression coefficients of table 4.3.

The evidence provided also leads to the acceptance of hypothesis 1. This in turn answers the first research question of this study showing implied volatility indeed has a higher forecasting value than historical volatility. Even though the forecast is slightly biased, the implied volatility coefficients remain highly efficient throughout.

4.2 Splitting for Average Market Return Values

To obtain an answer to research questions 2 and 3, the data had to be split into different groups based on market returns. To obtain an answer to research question 2, we will first examine the regression results of table 4.4, and in specific, group A and group B. Group A depicts regression 3.4 with the condition of positive market returns in the 30 trading days previous to the date the implied volatility was measured. Group B shows the same regression but with the condition of average negative returns for the underlying market index in the previous 30 trading days. There are a couple of differences that can be observed in the table. The intercepts of group A are noticeably more significant than those of group B. Also, the intercepts coefficients show that the regressions in group A have larger negative values and thus are more biased. The coefficients corresponding to the independent implied volatility variable show that the forecasting efficiency of group A, with positive past returns, are higher than those of group B. The adjusted R-squared is also at least 10% higher for all markets in group A. This means the implied volatility is a better predictor of future realized volatility when the underlying market has had a positive average return in the past 30

Table 4.4: Overview of the Newey West regression estimates of equation 3.4 grouped to postive/negative average market returns in the 30 days after/before the IV estimate was made. For the implied and realized volatility in this regression the natural log series were used.

Group A: Positive Past Returns				**Group B: Negative Past Returns**			
Dependent	Intercept	IV_t	Adjusted R^2	Dependent	Intercept	IV_t	Adjusted R^2
$RVAEX_t$	-0.33^{**}	1.00^{**}	74%	$RVAEX_t$	-0.10	0.96^{**}	59%
	(-5.67)	(25.54)			(-0.86)	(14.25)	
$RVDAX_t$	-0.27^{**}	1.00^{**}	70%	$RVDAX_t$	-0.12	0.91^{**}	56%
	(-4.21)	(22.76)			(-1.34)	(15.61)	
$RVFTSE_t$	-0.36^{**}	0.98^{**}	76%	$RVFTSE_t$	-0.22	0.90^{**}	49%
	(-6.53)	(30.75)			(-1.49)	(10.85)	
$RVCAC_t$	-0.38^{**}	0.92^{**}	64%	$RVCAC_t$	-0.11	0.91^{**}	51%
	(-3.26)	(12.02)			(-0.96)	(12.70)	
Group C: Positive Future Returns				**Group D: Negative Future Returns**			
Dependent	Intercept	IV_t	Adjusted R^2	Dependent	Intercept	IV_t	Adjusted R^2
$RVAEX_t$	-0.23^{**}	0.97^{**}	59%	$RVAEX_t$	-0.24^{*}	0.99^{**}	59%
	(-3.19)	(20.36)			(-2.28)	(15.76)	
$RVDAX_t$	-0.17^{*}	1.00^{**}	59%	$RVDAX_t$	-0.17	0.98^{**}	58%
	(-2.51)	(21.07)			(-1.87)	(15.88)	
$RVFTSE_t$	-0.28^{**}	0.95^{**}	57%	$RVFTSE_t$	-0.33^{**}	0.95^{**}	60%
	(-3.09)	(17.86)			(-3.45)	(17.50)	
$RVCAC_t$	-0.26^{**}	0.91^{**}	53%	$RVCAC_t$	-0.23^{*}	0.94^{**}	52%
	(-2.71)	(15.15)			(-2.04)	(13.14)	

* and ** represent 5% and 1% significance levels, respectively.

trading days. Group A shows a higher efficiency even though it has a larger bias than group B, answering the second research question.

For the third research question we have to analyze group C and D for differences in the regression results with the condition of average positive or negative returns in the 30 trading days after the implied volatility measurement was taken. The analysis of groups C and D merely provides retrospective results that can not be used in practice. Group C shows the coefficients for all markets to be significant at the 1% level. The implied volatility estimates all near 1 which is the most efficient level that can be obtained. The intercepts however are slightly negative implying a bias in the predictions. Group D also shows high coefficients for the implied volatility that are approximately the same level as those found in group C. Not all the intercept for the markets in group D are significant on the 5% or 1% level. When groups C and D are directly compared we see the adjusted R-squared is again approximately the same for group C as well as group D with R-squared levels of around 55-60%. Because of this, we have to reject our second hypothesis which says implied volatility provides a better future forecast when the underlying markets show positive average trading returns in the coming 30 days. The R-squared values of the regressions lie too close to each other to really prove there is a significant difference.

4.3 International Comparison

The final research question of this study dealing with the differences between the implied and realized volatility relationship between the studied market indices can be anwswered by means of analyzing tables 4.2, 4.3 and 4.4. The regression estimates of table 4.2 showing implied volatility as the only independent variable does not hold much clues regarding to differences in the forecasting relationship. The only thing worth noticing is the CAC40 having an R-squared of 53% which is slightly lower than the other indices since those have R-squared values of around 58 to 59%. Table 4.3 in which the implied and historical volatility were both examined simultaneously also shows the same pattern with the CAc40 again showing the least efficient volatility forecast. The rest of the markets do not differ much. Table 4.4 shows approximately the same results, the different market indices do have small differences between them, but the R-squared is never more than 10% apart for all of the studied groups. This leads to believe we can accept the fourth hypothesis of there not being significant differences between the implied volatility relationship for the different markets. This is in accordance with previous research by (Szakmary et al., 2003) who also found slight differences for the relationship in the futures markets but in general found the IV-RV relationship to be roughly the same across markets.

4.4 Behavioral Perspective

This study mostly describes the technical perspective on the results of the regressions focusing merely on the efficiency of the forecasts and comparing independent variables. Yet, in this section we try to look at the results from a behavioral standpoint and focus on possible reasons why this study generated the results it did.

One of the first things to notice is that even though the implied volatility makes a decent prediction in general, there is still a positive bias in the forecast. This means the forecasting value of implied volatility with regard to realized volatility is too high on average. Since the implied volatility is derived from the weighted sum of option prices on the underlying index, rising demand on out-of-the-money puts and calls drives up their price and hence the implied volatility. Especially the demand for puts has a driving effect on implied volatility levels as the put/call-ratio of options on the underlying market index is generally above 1.00 (Russell Rhoads, 2012). This could imply the market participants have an aversion for bearish markets and try to hedge accordingly. Another reason for the implied volatility to be too high on average could be on the seller's side instead of the buyer's side. The options on the underlying market could be priced a bit higher than necessary on purpose generating a higher implied volatility. In a 'the house always wins'-scenario the assumption of higher margins on the sold options could be an explanation for high implied volatility values. Nevertheless this explanation probably will not hold since these are highly liquid markets with lots of sellers.

This study also finds implied volatility to give a better future volatility forecast than historical volatility. An obvious reason for this is the market participants being able to react much faster on unexpected market movements with the implied volatility changing immediately whereas the historical volatility needs some time to catch up. It could also be explained by the ability of market participants to anticipate future market movements due to for example elections, announcements by the financial authorities and quarterly earnings reports.

The last behavioral interpretation of the results concerns the difference in R-squared between the splitted data sample with respect to positive or negative past returns. The implied volatility prediction has a lower goodness-of-fit in the group with the negative past returns. This means that the market participants predict future volatility worse if the market has gone down on average. From a behavioral standpoint one explanation could be that the participants become less rational when the market becomes bearish but then again this argument could be reversed into saying the market becomes less predictive if it is going down.

Chapter 5

Conclusion and Discussion

The next sections will summarize the findings of this study and discuss the answer to the main research question. It will also report the contribution this study makes to the existing literature and the limitations of this study. Furthermore it will discuss some recommendations for further research into the IV-RV relationship.

5.1 Main Findings

In general this study adheres to the findings of (Christensen and Prabhala, 1998) and those from (Li and Yang, 2008) who found the implied volatility to be a better predictor of future realized volatility than historical volatility. However, this study does use overlapping data such as was used in the study by (Canina and Figlewski, 1993) who found historical volatility to have the superior forecast, this means the contradictory findings by (Christensen and Prabhala, 1998) can not be explained by means of the differences in the sampling procedure between the two studies. This study finds historical volatility to be a fairly decent predictor of realized volatility when it is the only independent variable used in the regression. Nevertheless implied volatility as the sole predictor of realized volatility scores higher coefficients and lower biases all round. When both the historical and the implied volatility independent variables are combined into one regression the implied volatility remains a decent predictor of realized volatility, but the historical volatility in general becomes insignificant with low regression coefficients. This implicates all the information contained in the historical volatility is already incorporated in the implied volatility variable. Because the implied volatility variable remains significant it apparently contains the information that was included in the historical volatility, but also contains some extra information about future volatility levels as well.

Regarding the split in the data based on whether the underlying market had positive or negative returns in the month previous to the implied volatility measurement this study found significant differences in the forecast values between the different groups. The implied volatility shows to have higher bias combined with higher efficiency when the underlying market has had positive returns in the previous 30 trading days. Since these implied volatility tickers are known to measure fear in the markets but no one can really tell how much worth should be attached to these fear measurements these findings could shed some light on the reliability of these measurements. The findings in this study show that when the markets have been going up on average in the past 30 trading days the implied volatility is a more reliable predictor of future realized volatility. When looking at the regressions with the data split using the underlying market returns of the period following the implied volatility measurements as a moderating variable, this study finds almost no dissimilarities. The R-squared values are almost identical, as well as the coefficients and intercepts.

Furthermore no real differences could be found between the markets except for the CAC40, which turned out to have the least predictive implied volatility ticker in nearly all of the regressions. The implied volatility turned out to be the best forecasting variable when compared to historical volatility for all of the market indices. This is in line with the expected outcome as most studies comparing historical and implied volatility find implied volatility to have the highest forecasting value (Poon and Granger, 2003).

5.2 Limitations

There are a few limitations to this study. First of all, this study does not split the data into different time periods, hence the findings of this study are an average of the 17 years and 8 months included in the sample. This means the current state of forecasting reliability could be better or worse than found in this study depending on differences in the relationship with regard to different time periods. If the data had been split into time periods of for example 5 years each, evidence of differences between these periods or proof of increasing efficiency in the forecasting predictions could be found. Another limitation to this study was the lack of data in the Datastream database concerning the implied volatility tickers of Spain and Italy. These southern European countries would have been included in this study if the information was available. Their economies are among the largest in Europe, hence it would have been interesting to include these into this research as well.

5.3 Contribution to the Existing Literature

This study contributes to the existing literature in several different ways. First of all most studies done on the subject of volatility forecasting focus on the American markets, with the S&P 500 in special. This study researches the forecasting values of implied and historical volatility in four European markets, the CAC40 and AEX in special have never been subject to volatility research before. This study provides proof that some findings in US markets such as found by (Christensen and Prabhala, 1998) can be extended to at least some of the European markets. This study also reaffirms earlier studies. Since most of the studies into the IV-RV relationship were performed around or before the year 2000, the findings of these papers could use some reaffirmation of their validity on a more recent data sample.

Another way this paper contributes to the existing literature is the use of previous and future returns of the underlying markets as a moderating variable in the regressions. Most of the existing studies that put some effort into describing the relationship of implied volatility with market returns focused on the implied volatility predicting future returns instead of looking at the market returns as a variable influencing the forecasting relationship. Since this had not been done before these findings contribute to the existing body of literature. This study refutes one of the explanations of (Christensen and Prabhala, 1998) on why (Canina and Figlewski, 1993) found the historical volatility to be the superior forecasting method compared to implied volatility. Since this study also uses overlapping data as was used in the study by (Canina and Figlewski, 1993) instead of the non-overlapping data that was used by (Christensen and Prabhala, 1998), but does find implied volatility to be the superior predictor, the difference in data usage can not be used to explain the different outcomes of these studies.

5.4 Recommendations for Future Research

Further research into the subject of forecasting future volatility or researching the relationship between implied an realized volatility should focus on the possible existence of structural breaks in volatility levels and the implications on the forecast reliability. This study has of course shown differences in forecast reliability depending on average market returns previous to the forecast. New research should focus on trying to find specific time periods for which the volatility forecasting relationship changes and on whether there have been structural differences in forecasting reliability of the IV tickers in the past years. A good place to start would be the research by (Giot, 2005), but instead look for the influence of stock returns on the reliability of IV as a forecasting variable.

Another recommendation for further research would be to use the level of implied volatility as a moderating variable on the predictive relationship between IV and RV. This means instead of using the market returns as a moderator, like this study does, using the level of the implied volatility as a moderating variable. It would be interesting to see whether high or low implied volatility levels have any influence on the forecasting value of implied volatility on realized volatility.

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