Evaluating the forecasting ability of implied volatility: a study of FTSE 100 index options

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1 Introduction

The subsequent content offers brief and accessible explanations of the relevant financial theory for this topic area, specifically a description of what an option is and how it functions, how they are priced and what the implied volatility value means.

Research into this topic is important as implied volatility is widely referenced by practitioners and the financial press as a fear gauge for upcoming market conditions, whilst also high-quality volatility forecasts are imperative for effective risk management. Hence, an assessment of implied volatility's forecasting ability and how it compares to other forecasting models, such as ARCH models and its extensions or stochastic volatility based models is meaningful.

Discovering the source of a poor forecast can be used to make systematic improvements to the option pricing models used by investors to which, considering its extensive use, any improvements are valuable.

1.1 Options

An option is a contract that entitles the right, but not the obligation, to buy or sell the asset it is written upon for a fixed price, called the strike price. A call option is the right to buy the underlying asset and a put option is the right to sell it. An American style option is one where the investor can exercise the option at any time, whereas European style options can only be exercised on the specified maturity date.

At maturity, the difference between the price of the underlying asset and the pre-specified strike price determines the 'moneyness' of the option". If the underlying price is higher than the strike price, the option is described as being 'in the money' whereas if the underlying price is below the strike price the option is 'out of the money'. As such, no rational investor would exercise an option that is out of the money as it is cheaper to buy the underlying asset at the current market price.

The underlying asset of the options under investigation here is the FTSE 100 index. This stands for the Financial Times Stock Exchange 100 index and represents the hundred largest companies floated on the London Stock Exchange by market capitalization. These options [1] have the characteristics of being cash-settled, European style options, with an expiration day of the 3rd Friday of the 3rd month of its maturity length.

To the best of our knowledge, studies investigating the forecasting ability of implied volatility for this particular underlying asset and market are severely limited and outdated, with the most recent paper being Buckle (1999). In contrast, the wealth of studies on index options within other markets, especially the United States, offer a sound basis to extend and update the research for the implied volatility forecasts of the UK index options market.

1.2 Black-Scholes option pricing model

The pricing of an option is subject to an array of different models, yet the Black-Scholes option pricing model (BSPOM) proposed by Fisher Black, Robert Merton and Myron Scholes (1973) is used in this research due to its popularity and widespread use by investors. This model involves the assumption that the underlying asset follows a Geometric Brownian motion, volatility is constant, options are European and no dividends are paid.

[1] The option specification sheet can be found in the Appendix

The pricing formula for a call option is shown in Equation (1).

$$C = N(d_1)S_t - N(d_2)Ke^{-rt} \tag{1}$$

where $d_1 = \frac{ln\frac{S_t}{K}+(r+\frac{\sigma^2}{2}t)}{\sigma\sqrt{t}}$ and $d_2 = d_1 - \sigma\sqrt{t}$.

and

C = rrice of a call
S_t = price of underlying asset
r = risk free rate
σ = constant volatility of underlying asset

1.3 Implied volatility

All the inputs for the BSOPM are directly observable except for the volatility of the underlying asset parameter. As the output price is also observable, theoretically a rearrangement of this pricing formula can back out the volatility parameter which, conditional on correct option pricing model specification and efficient option markets, will have a strong ability to forecast future realized volatility.

This value is implied volatility and represents a consensus of the market's prediction for the expected volatility of the underlying asset, which is reflected in the price of the option. This value provides an estimate for the expected volatility for the underlying asset for the duration of the option and hence can be used by market participants as a forecast. The core of this paper is therefore to assess how well this forecast predicts the actual realized volatility (RV) the underlying asset experiences.

The ability of a volatility forecast depends on the extent to which informational content regarding future realized volatility is contained within it. As implied volatility is extracted from the peripheral options market rather than the market of the underlying asset, it is expected that it should contain at least the amount of informational content available in historical volatility. This is because historical volatility is readily available, public information and as such implied volatility should subsume this information content. As options are traded by mostly institutional investors, there is an opportunity for their private information and expectations to give rise to additional informational content to be internalized into implied volatility. Therefore, the better implied volatility is as a forecast, the more information content it contains.

The aim of this paper is therefore to evaluate the forecasting ability of implied volatility by measuring how much information content it contains, and then compare this value to options on different underlying assets and also with the amount found in historical volatility.

2 Literature Review

2.1 Introduction

This literature review analyzes the different approaches used to answer the question of the forecast ability of implied volatility, starting with an evaluation of both the methods used to calculate the required variables and then the common methodological approaches the variables are used within.

This is followed by a review of the most prominent issues faced by studies within this literature; the use of non-overlapping data and bias present in the implied volatility forecast. The latter is a subject matter that is heavily concentrated on by the studies, to which this literature review revealed the two most discussed sources of the bias are errors in variables (EIV) or systematic errors arising from the instrumental features[2] involved with the implied volatility forecast.

The process of evaluating the forecast ability of implied volatility occurs through three key stages. Firstly, studies within the literature repeatedly use a set of ordinary least square (OLS) regressions containing the dependent variable of ex-post realized volatility and the independent variables of ex-ante implied volatility and ex-ante historical volatility.

The results from these regressions are then typically assessed using basic econometric evaluations, primarily tests for statistical significance of regression coefficients and measurements of bias and efficiency. A review of the literature revealed only two studies that look at the same options and market as this paper, Gemmil (1986), and Buckle (1999). The methodology used in these studies are vastly different to the common approach employed by more recent studies hence, the overall procedure described prior forms the base approach for this paper.

[2]This term is not found in the literature but is frequently used in this paper to collectively reference the features that decide the forecasting ability that is; efficient option markets, correct specification of option pricing model and correct use of option pricing model by investors.

2.2 Calculation of The Required Variables

The literature focuses on three theoretical features that have a causal relationship to the forecasting ability of implied volatility: option market efficiency, correct use of a correctly specified option pricing model by investors.

These can be viewed as the instrumental features required for the highest quality implied volatility forecast, that is in an efficient market where investors correctly use a correctly specified option pricing model, the backed-out value of implied volatility will be of the highest quality (Merton 1973). However, these instrumental features are not directly observable therefore there is paramount importance in ensuring the most accurate possible calculation of the observable market features is employed.

The observable markets features described here include the variables of implied volatility, realized volatility and historical volatility required; all of which are required for assessing the forecasting ability of implied volatility. This is due to the fact that even if the three instrumental features deliver the best possible implied volatility forecast, faulty calculation of the required variables will lead to incorrect conclusions about the forecasting ability. With this considered, a careful selection of methods used by studies in the literature to calculate these variables is required.

2.2.1 Realised Volatility Variable

With the importance of accurate variable calculation established, more recent studies within the literature have investigated how the frequency used to construct the realized volatility variable affects the assessment of forecasting ability.

For example, Shu and Zhang (2003) examine how four different realized volatility measures affect the relationship between implied volatility and realized volatility. They conclude that "In particular, the forecast ability can be improved by constructing a more accurate measurement of realized volatility, with the realized volatility constructed from intraday 5-minute returns being the most predictable.".

Similarly, Poteshman (2000) concluded that "approximately half of the forecasting bias in the S&P 500 index (SPX) options market is eliminated by constructing measures of realized volatility from five minute observations on SPX futures rather than from daily closing SPX levels". The theory behind this is that the forecast from implied volatility may be unbiased, efficient and contain high levels of informational content, yet if this ex-ante value is measured against an ex-post realized volatility series that is an inaccurate measure of the true volatility value, incorrect inferences regarding implied volatility forecasting ability will be made.

Despite variations in the frequency of the returns data used to construct the realized volatility series, the actual calculation of the annualized standard deviation of the log returns of the index is approximately the same throughout the studies and will be replicated in this paper.

2.2.2 Implied Volatility Variable

There is a range of methods used within the studies of the literature to calculate the implied volatility value, not through different pricing models, but due to the different ways implied volatility values from options with different strike prices may be aggregated. These methods are commonly referred to as weighting schemes and this was a popular topic of earlier research, an example of which can be seen in Flemming (1995).

The rationale behind the aggregation is that the overall information content is spread across near the money options, with the at the money (ATM) options at the centre. Weighting schemes therefore aggregate the available information content whilst the averaging function acts as a way to eliminate noise.

When considering if an explicit weighting scheme should be used in this research, a retrospective look through the literature reveals that no weighting scheme approach proved to be significantly superior in practice, potentially since pricing error remains despite the averaging attempts involved in weighting schemes (Granger and Poon, 2003). There is some degree of consensus that the actual final impact it has on the forecasting ability of implied volatility is relatively insignificant and other aspects of the methodology should be focused on (Ederington and Guan, 2002).

The alternative is therefore to calculate implied volatility simply from the ATM options. The rationale here is that the effects of measurement errors and BSOPM misspecification on implied volatility should be minimized to an insignificant level if calculated from ATM rather than a weighting scheme. Additionally, the observed volatility smirk and smiles as evidence of BSOPM misspecification is absent when looking only at ATM options.

Similarly, since ATM options typically have the largest trading volume, the implied volatility calculated from these options should contain the largest amount of informational content, resulting in a strong representation of the market's volatility prediction for the underlying asset. (Beckers, 1981).

There is a further benefit of using ATM options highlighted by the literature; the implied volatility value also approximates stochastic volatility models (Christensen and Prabhala, 1989). This would be valuable to the quality of the implied volatility forecast as it greatly improves the correct pricing model specification component of the instrumental features. However, this is challenged by Poteshman (2000) who argues that the index price level and its volatility are negatively correlated which is opposite to the uncorrelated assumption required for the ATM Black-Scholes implied volatility to approximate stochastic volatility models.

With all this considered, the resulting recommendation is that this paper uses the implied volatility value calculated from ATM options. There is the possibility that this approach will have the parallel benefit of minimizing BSOPM misspecification, yet the primary reason is due to the lack of evidence that the use of a weighting scheme provides visible benefits.

2.3 Common Regressions

There is a set of recurring OLS regressions consistently used across the timeline of studies and as such, replicating these regressions for the FTSE100 index options is valuable as it allows for direct comparisons to the results from other studies. To the best of our knowledge, no other study has done this yet.

Almost all studies in the literature commence with the use of the 'rationality test' regression, first introduced by Canina and Figlewski (1993) and remains the core regression across in most other studies.

The regression is appropriately named since implied volatility theoretically internalizes the rational forecasts of investors, therefore impounding some degree of informational content regarding the future realized volatility. This regression acts as the primary one for evaluating the forecast ability of Implied volatility as if no significant relation was found between Implied volatility and future realized volatility, there would be little use for implied volatility as a forecast. Similarly, the assessment of bias and efficiency outputted by the 'rationality test' regression provides further opportunity for evaluation and comparison.

The second most common regression is called the 'encompassing regression', and is essentially an extension of the 'rationality test'. Here, as part of the assessment of the forecasting ability of implied volatility, studies in the literature test the informational efficiency[3] of the option market under study. This is

[3]Not to be confused with option market efficiency or econometric efficiency.

performed using the encompassing regression to test to what extent implied volatility is informational content efficient, relative to historical volatility.

The expectation held throughout the literature is that implied volatility should be informationally efficient since it subsumes the information content contained in the historical volatility (Granger and Poon, 2003).

The consistent use of the rationality test and encompassing regression within the literature allows for comparison against other studies, and how different methodological approaches may have induced any differences in results. Investigating these discrepancies proves to be particularly formative for this research as it can distinguish the source of the most important issue in the implied volatility, the expected bias in the forecast.

2.4 Findings From The Literature

The results of the existing literature can be grouped by congruent findings on the two most popular econometric based gauges of the forecasting ability of implied volatility; forecast bias and econometric efficiency.

The first group of results include the studies of Day and Lewis (1992) and Lamoureux and Lastrapes (1993) who both conclude that implied volatility is an upward bias, weak predictor of future realised volatility and contains the same amount, or less, information content than that found in historical volatility. It is important to note that whilst Day and Lewis (1992) study S&P100 index options, the asset type of Lamoureux and Lastrapes (1993) are individual equities, not equity indexes as used in this paper.

The second group are more recent studies that improved upon the research design and data handling flaws of the previous group, allowing for implied volatility to be classed as an unbiased and efficient estimator. The higher quality methodology introduced by the seminal work of Christensen and Prabhala (1998) has been adopted by many subsequent studies such as Christensen and Hansen (2002), Kumar (2008) and Shu and Zhang (2003). All of these studies conclude that implied volatility forecasts, for their respective index options, are both unbiased and efficient. This cohort of studies all include the same underlying asset type as this paper, however, the markets range from the Indian market in Kumar (2008) to the Australian market of li and Yang (2009).

Reviewing the findings of the literature, there is no clear consensus[4] on the forecasting ability of implied volatility in terms of the bias present and efficiency characteristics, whilst a partial consensus has formed that implied volatility

[4]This lack of consensus applies equally to studies with the same option and underlying asset.

subsumes the informational content of historical volatility and is a better predictor of future volatility as a result.

2.5 Overlapping Data and The Maturity Mismatch Effect

The difference between the two groups of findings is due to how data sampling methods give rise to overlapping data. Christensen and Prabhala (1998) was the first to suggest that when investigating the forecasting ability of implied volatility, it is crucial that the sampling procedure for implied and realised volatility data "results in nonoverlapping data, as time periods covered by successive options exhibit no overlap whatsoever".

Therefore, when assessing ex-ante implied volatility forecasting ability, it is crucial to ensure that the value of ex-post realised volatility it is compared against is for the same time period. This ensures that sampling windows are completely independent and prevents the 'maturity mismatch' problem.

To emphasize the importance of this sampling procedure issue, Christensen and Prabhala (1998) rerun the previously used regressions but with purposefully overlapping data, resembling that used by Canina and Figlewski (1993). This was done to illustrate the impact overlapping data has on the conclusions from the rationality test and the encompassing regression.

This was later investigated by Hansen et al (2002) in "The Telescoping Overlap Problem in Options Data" who revealed that the use of overlapping periods was causing serial correlation issues. Here, the future realised volatility series will contain some of the historical volatility series consequently meaning the explanatory power of historical volatility is overstated. This explains the conclusions of the earlier studies that there was no additional information content found in implied volatility relative to historical volatility, for example, Day and Lewis (1992) which suffers from the maturity mismatch issue.

2.6 Impact of Error in Variables On Implied Volatility

Another imperative concept found in the literature is the consideration of errors in variables (EIV), before concluding the forecasting ability of implied volatility. This is the idea that when calculating a value for implied volatility, inaccuracies in measurement and calculation will introduce an element of error into the explanatory variable. With the consequence of EIV making the implied volatility coefficient downward bias (source), this affects the statistical inference used to draw conclusions about the implied volatility forecast.

Despite investigating the forecasting ability of implied volatility of a different asset class, Jorion (1995) was the first to suggest that the bias and inefficiency displayed in the forecasts of implied volatility may be due to EIV issues caused by measurement errors.

Granger and Poon (2003) identified one measurement error that arises from the bid ask spread with "since transactions may take place at bid or ask prices, transaction prices of option and the underlying assets are subject to bid-ask bounce making the implied volatility estimation unstable." There are other errors in market variable observations referenced by studies in the literature such as the asynchronous prices between the option market and underlying asset closing or infrequent trading effects.

With the assessment of the forecasting ability of implied volatility relying heavily on the accurate calculation of both implied volatility and realised volatility, EIV issues skew the implied volatility value used. The consequence of this resembles that of an inaccurate realised volatility series mentioned previously; there may be an exaggeration or dampening effect on the implied volatility value.

2.6.1 Detecting errors in variables

Following Christensen and Prabhala (1998), the subsequent literature became very cautious of how EIV may affect their studies, as if the effects are large enough in magnitude, this can lead to the wrong conclusions about the forecasting ability of implied volatility being made. For example, after implied volatility failed the rationality test and encompassing regressions, Li and Yang (2009) showed that it was the severity of the impact of error in variables that almost made them reach an incorrect conclusion. Suspicious of EIV significantly affecting the regression results, they formally test for the presence of EIV using an auxiliary regression in the form of the Hausman test.

Using a test to detect EIV issues is especially rare in the literature as many studies resort to applying EIV correction schemes using an instrumental variable technique (Christensen and Prabhala (1998). The absence of such a test before correcting for the EIV can lead to speculative judgements regarding whether or not the EIV correction scheme actually corrected for the resultant bias, or if it was due to the transformation of variables. For example, Poteshman (2000) argues it was taking the log of the variables in Christensen and Prabhala's study (1998) that removed the bias as opposed to the instrumental variable technique.

After the Hausman test detected EIV presence for the implied volatility of the call series in Li and Yang (2009), this signaled the requirement for an IVT intervention before assessing forecasting ability. The usefulness of such a test means it will be incorporated into this research's method, the results of which will help in further distinguishing the source of bias which remains undecided in the literature.

2.7 Common methods used to correct biased forecast

EIV correction schemes are commonly found in the literature (Christensen and Prabhala, 1998) (Ederington and Guan, 2002) (Li and Yang, 2009) and can take two forms.

2.7.1 Instrumental Variable Technique

Firstly, is an IVT which has the underlying rationale that the error in the variables are orthogonal to true investor volatility predictions. These errors therefore should not be correlated with explanatory variables across time and hence the inclusion of a lagged value of implied volatility in the regression should theoretically eliminate this error noise. As such, the most common instrument variable used in the studies is generated from a one period lagged value of implied volatility.

However, there is some disagreement in the literature on the extent that measurement errors can be blamed for introducing biasdness into implied volatility. For example Jorion (1995) argues that the magnitude of the EIV effect on implied volatility doesn't explain away enough of the bias that is present in the forecast. Similarly, Poteshman (2000) argues that just because the use of instrumental variable technique reduces forecast bias, this is not convincing enough to draw the conclusion that EIV introduced the biasdness into the relationship. Alternatively, the bias could be caused by non orthogonal, systematic error introduced from the structural issues in the instrumental features, for example Black-Scholes model misspecification or option market inefficiency as opposed to EIV measurement error.

This all considered, the impact of EIV on implied volatility is debated in the literature and the use of instrumental variable techniques to correct for this is also the subject of disagreement. To remedy this, the inclusion of a EIV detection test is incredibly useful to distinguish the source of bias, hence the approach taken by Li and Yang (2009) provides a suitable base for the inclusion of this test in the methodology of this paper.

2.7.2 Coefficient Based

An alternative approach to bias correction was used by Ederington and Guan (2002). By assuming that the bias is persistent across the time series, a correction can be calculated based on the historical data to give a bias corrected implied volatility value.

Following the success of this scheme, a possible interpretation is that bias introduced into the implied volatility from a different sources rather than the errors in variables. Instead, this bias correction scheme seems to be aimed at correcting the systematic non-orthogonal error due to the inefficiencies in the three instrumental features, in line with Poteshman's (2000) argument. However, due to the use of this scheme being apparently limited to only the study by Ederington and Guan (2002), this proposed theory surrounding its use is more speculative.

As such, with the primary reason of this study being to apply the implied volatility forecasting assessment to the UK options market, there is an embedded micro study to attempt to distinguish the source of the expected forecast bias, either from EIV or non-orthogonal systematic error within the instrumental features.

2.8 Consequences of Black-Scholes Option Pricing Model Misspecification

The most frequently discussed component of the three instrumental features in the literature is BSOPM misspecification and the consequential impact this may have on the forecasting ability of implied volatility with Poteshman (2000) arguing "It is well known that the Black-Scholes formula significantly misprices options".

The theory underlying this is that the forecast quality will be reduced following error introduced into it by systematic over or under-pricing caused by pricing model misspecification, consequently resulting in a biased value of implied volatility. This reasoning was adopted by Canina and Figlewski (1993) to explain their results of biasdness and inefficiency. Here, they argue that although there is information content regarding future realized volatility available in the options market, it is not correctly impounded into option prices, despite correct use by market participants, due to BSOPM misspecification. Specifically, Canina and Figlewski (1993) argue that the void assumption of constant volatility created the misspecification that introduced the bias, a point that is frequented within the literature.

As such, naturally one would look to amend the BSOPM with one that models the dynamics of the underlying asset more accurately. With the limitations of the BSOPM assumption of constant volatility recognised, more complex models involving stochastic volatility are alternatively used to reduce the pricing misspecification that effects implied volatility values, for example the Hull-White model was used by Lamoureux and Lastrapes (1993).

However, Christensen and Prabhala (1998) argue that "Black-Scholes implied volatility is approximately equal to expected future return volatility for at-the-money options even when returns follow the (non-Black-Scholes) stochastic volatility model of Hull and White". This therefore provides the justification for the implied volatility values given by ATM options of the BSOPM, but with its limitations from potential misspecification limitations duly considered.

2.9 Consequences Of Inefficient Markets and Investor Pricing Misspecification

Following pricing model misspecification, the remaining instrumental features are efficient options markets and correct investor price specification. Flemming (1998) was one of the first to consider that the value of implied volatility calculated may diverge from its true value due to investor specification error where market participants price the option differently to that predicted by the BSOPM. This consideration remains apparently undiscussed in the literature and instead appears to take the form of a robust assumption; investors adhere to the pricing model and the implied volatility value is not impacted by divergent pricing behaviour. As such, this research will adopt the assumption that the three instrumental features will be assumed to function correctly and efficiently.

2.10 Further Research

More recently, studies have experimented by replacing specific pricing models with model free approaches. This is seen in Jiang and Tian (2005) who further add to the existing literature by investigating the information content of model free implied volatility. Clearly this is a more powerful method as it removes the joint hypothesis issue of the prior research of option market efficiency and correct pricing model. However, considering this relatively better method replaces the Black-Scholes option pricing model with a significantly more complex no-arbitrage condition model, this is outside the scope of this paper.

As some studies show that Model Free approaches do not outperform Black-Scholes in forecasting ability (Taylor et al., 2010), there still remains value in using the traditional Black-Scholes implied volatility approach. The theoretical suggestion that implied volatility derived from ATM optionsis the best forecast of future realized volatility is attractive, but widespread contradictory findings across the literature, and across the decades this topic has been researched, results in the absence of consensus.

With the already surprising lack of research into the implied volatility forecasting ability for FTSE 100 index option market, this research can be instrumental in bringing studies on FTSE 100 index options up to date before more modern and complex methods, like that used by Jiang and Tian (2005), are applied.

3 Methodology

With the literature review complete, it is possible to extract a selection of research hypothesis's that can be investigated with econometric tests in order to evaluate the forecasting ability of implied volatility from FTSE 100 index options. The hypotheses are given in the null, or counterfactual form and are investigated in turn following the format of first a brief provision of the underlying theory, the statistical test, test result interpretation and then a comparison to existing literature.

Research questions in null hypothesis form [5]:

i. Implied volatility has no information content about future realized volatility
ii. Historical volatility has no information content about future realized volatility.
iii. Implied volatility is no better than historical volatility as a predictor.
iv. Implied volatility subsumes the information content available in past realized volatility.
v. Implied volatility is an efficient estimator of future realized volatility.
vi. Implied volatility is an unbiased estimator of future realized volatility.
vii. Implied volatility suffers from error in variables.
viii. Implied volatility suffers from systematic error from the instrumental features.

Firstly to test the hypothesis the data must be collected, appropriately transformed, and then used to construct the required variable series using the sampling procedure recommended by findings of the literature review.

3.1 Data Collection

When choosing the data collection period, the primary consideration is the effect of potential disturbances caused by the period's proximity to a financial

[5] The last two hypotheses regarding forecast bias sources were added after the results from hypothesis 6 revealed that the implied volatility from FTSE 100 index options of this study is a biased forecast.

crisis. The rationale for a data collection period excluding periods of high market volatility is that this research has the objective of determining the extent of the presence of potential option pricing misspecification, investor misspecification or inefficient option markets. As such, periods of relative market calm are required to draw valid inferences about the condition of these three instrumental features affecting implied volatility forecast ability.

For this research, the financial crisis of 2007/2008 and the impact of Covid-19 pandemic are intuitively recognised to severely impact the volatility of the UK FTSE 100 index options market meaning the sampling period will instead fall between the end of the 2009 aftermath and before the start of the market reaction to the pandemic in January 2020. Data is provided by Wharton Research Data Services (WDRS) through the IVY DB Europe database from the OptionMetrics data vendor. The last available date of the data is the last day of December 2019 which conveniently falls just prior to the start of the pandemic, hence deciding the end of the time series.

In terms of the start date, Chirstensen and prabhala (1989) do utilize a pre-post crisis methodology for the 1987 crash, however there is an absence of an explanation of the method used to decide the date for when the post crisis eras commences. With the vast majority of the literature being published around or before 2008, rationale for choosing a sampling period that avoids the impacts of the financial crisis has to alternatively be derived intuitively.

Here, volatility is assumed to have fallen back to pre-crisis level when the value of volatility reaches the peak of the pre-crisis level. According to the data collected and displayed in Figure 1, the pre-crisis peak volatility [6]reached a level of 0.283 and as such, the post crisis volatility fell back to this value on the 5th January 2009 hence marking the start of the total time period for this paper.

3.2 Sampling Periods

In line with the recommendations arising from the literature review, this methodology will specifically use implied volatility values from sATM options and a sampling periods that carefully ensures non-overlapping samples. This occurs by having an ATM option held with a time left to maturity of a fixed

[6]Volatility of the FTSE 100 Index calculated with a 91 day period

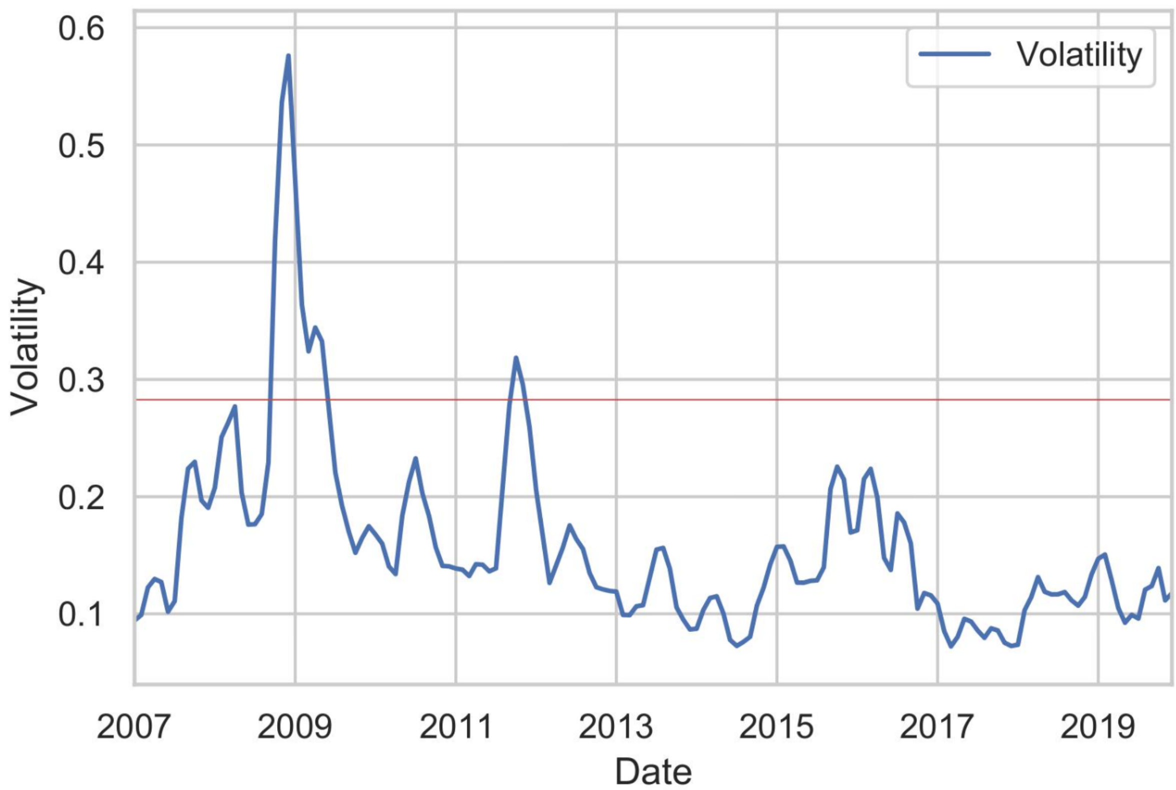

Figure 1: A line graph showing the realized volatility of the FTSE 100 index.

N number of days, this marks time t with time to maturity being T. The value of implied volatility at time t is the ex-ante forecast for the volatility of the underlying asset for the next N number of days and is recorded at the start of the period.At time T, N days later, there will be an ex-post realized volatility value calculated retrospectively on the last day of the period. Hence this prevents the two series from suffer from the telescoping data problem avoiding any exaggeration of the explanatory power of past realized volatility whilst mitigating the security mismatch which studies like Day and lewis (1992) suffered from. A diagram from Okumu (2013) is included in Figure 2 to aid in visualising this sampling period process.

With the quarterly expiry cycle of the FTSE 100 index options, the sampling procedure almost identically resembles that of Li and Yang (2009) where their index options for the Australian market share the same expiry cycle months as the options of this research: March, June, September, December. However, unlike Li and Yang (20090, the FTSE 100 index option expires on the last figures/series2.png

Figure 2: Sampling period construction technique. Taken from Okumu (2013).

Friday in the month meaning the sampling period will start on the next trading day following expiry date, Monday.

This creates a period length of 91 calendar days, excluding the day of Friday, a marginal error considering the 91 day long period. However, with the options expiring on the Friday, this shortens the length of each period to 89 calendar days. Naturally this creates a gap between the length of days used to calculate the volatility series(91), and the number of days per sample period (89). However, considering the gap is the same for the two series, and the sample period values are annualized too, it is assumed that this discrepancy will not have a significant impact when used in the subsequent regressions.

3.3 Variable Construction

3.3.1 Realized and Historical volatility

Unlike the seminal papers of the literature, modern developments in data sources allow for the provision of direct variables that require little further transformation. As such, the realized volatility data given by the WDRS HistoricalVolatitly file is pre-calculated from the previous 91 days, "using a simple standard deviation calculation on the logarithm of the close-to-close daily total return". (quote the website pdf page)

This calculation of realized volatility is the same one used in the vast majority of the literature and is replicated in this methodology. Considering implied volatility is calculated in annualized form, the only preliminary transformation required for the realized volatility data is for it to be annualized according to the equation (2) below. The data for realized volatility is for a 91 calendar day period to which there are 61 trading days, 252 is the number of trading days in a year and R_i is the return on day i.

$$\sigma_{RV,t} = \sqrt{252/61 \sum_{i=1}^{61} r_i^2} \tag{2}$$

σ_{RV} = Realised volatility for period t
r_i = return on day i

Historical volatility is not directly related to implied volatility, but is instead used as an independent variable to test hypothesis 3 and 4, and is constructed using a lagged period of realized volatility for period t-1.

3.3.2 Implied Volatility

Also reflecting advancements in pre-calculated variables available from modern data sources, WDRS provides a pre-calculated, BSOPM implied volatility values for ATM options, a calculation that otherwise is manually done through the Newton-Raphson method.

Additionally, WDRS offers a version of option price data called 'standardized options'. In line with advancements in financial option theory regarding volatility surface, the standardized option implied volatility involves the use of linear interpolation and the forward prices of the underlying asset. As such, standardized implied volatility values of ATM options with 91 days until expirations are used.

3.4 Data Transformation

One methodological consideration which is subject to debate in the literature is if the variables should be transformed into natural log form. Poteshamn (2000) argues that if EIV correction methods are used in the methodology, it is important that series are not transformed to natural log form. This is because the transformation itself may give rise to a degree of implicit EIV correction making the bias corrections from explicit schemes, such as Instrumental variables, hard to distinguish. This occurs as the natural log transformation of variables can artificially change the coefficients of the main regressions to be used in this research.

For example, Poteshman (2000) argues that Christensen and Prabhala (1989) had incorrectly assigned the abscene of bias of the implied volatility forecast to the EIV correction when in fact it was the natural log transformation which was the cause. However, Li and Yang were able to confirm the presence of EIV in natural log transformed variables which refutes Poteshman 2000's criticism of Christensen and Prabhala (1989) use of transformed variables.

This finding, combined with Anderson et al's (2001) recommendation for the use of natural log transformed variables as they match a normal distribution better, provides rationale and support for the transformation of the variables in this research. This log return transformation to be used in realized volatility is shown in equation 2 and 3 below.

$$\sigma_{RV,t} = \sqrt{252/61 \sum_{i=1}^{61} r_i^2} \tag{2}$$

Where

$$ln(r_i) = ln(P_i/P_{i-1}) \tag{3}$$

σ_{RV} = Realised volatility for period t
$ln(r_i)$ = log return on day i

With the variables appropriately constructed, the set of hypotheses provided by the literature review can be tested.

3.5 Hypotheses Testing

3.5.1 (i.) Implied volatility has no information content about future realized volatility

Consistent with the suggestions from the literature review, this research starts with an OLS regression called the rationality test. The reason behind this is to examine how well implied volatility values have internalized the rational volatility forecasts of investors to form useful information content. The greater the information content in the implied volatility value, the more correlated they are to the realized volatility values they attempted to predict and hence the better implied volatility is as a forecast. The theoretical null hypothesis is therefore that implied volatility has no information content about future realized volatility.

$$\boxed{\ln(RV_t) = \beta 0 + \beta 1 \ln(IV_t) + \epsilon_t \qquad (4)}$$

Table 1: OLS Regression output for equation (4)

Dependent variable: Log realised volatility (RV_t)				
Independent variables		Partial R^2	T-value	T-prob
Constant	$Ln(IV_t)$			
0.0164190 (0.2434)		0.0001	0.0675	0.0675
	0.721378 (0.1308)	0.4261	5.52	0.0000
Adj. R^2: 0.412				

Table 2: Statistical test for research hypothesis (i.)

Test type	Students T test
Degrees of Freedom	42
Alpha level	5
Tails	2
Critical Value	2.015
Test Value	5.52
Null hypothesis: $\beta 1 = 0$	
Alternate hypothesis: $\beta 1 \neq 0$	

Following the results of the Students T test of significance for the output of the regression on equation 4, the null hypothesis is rejected and the alternate hypothesis that the coefficient is statistically different from zero is accepted. The T-prob is also less than 0.05 supporting this however the low adjusted R^2 value of 0.412 should be noted. In terms of economic significance, implied volatility from FTSE 100 index options passing the rationality test with a coefficient value of 0.721 signifies that it contains a high amount of information content, making it a reasonably good predictor of future realized volatility.

The most useful value to compare this result to would be another value outputted by the rationality test for the same asset and the same market. Unfortunately, the only study found in the literature review that matches such criteria of FTSE100 Index options are, Buckle (1999) and Gemmill (1986) who, due to the dated methodology, do not include an explicit version of the rationality test.

Alternatively, the next best option is to compare it to the regression results for the most similar asset, but a different market. Additionally, only studies that utilize the same sampling procedure of non-overlapping periods are used when comparing results to ensure valid comparisons with studies that might otherwise be affected by the maturity mismatch issue.

With Christesnen and Prabhala (1998), using the same non- overlapping sampling period and also log transformed data implemented in this paper through equation 3, this provides a very similar study to draw useful and valid comparisons to. As such, their coefficient value for the rationality test was 0.76 with an adjusted R^2 value of 39 percent. This closely resembles the rationality test values of the FTSE100 index options implied volatility of this research, hence implying that the extent to which information content is internalized into implied volatility is similar for both index options for the two different markets.

A second useful comparison is to purposefully compare it to a market which may include different characteristics. With Li and Yang (2009) also using a very similar methodology to this research, investigating the put series of options on the Australian index displayed a statistically significant coefficient value 0.66 therefore suggesting the UK FTSE 100 index options market has more information content internalized into the implied volatility values.

3.5.2 (ii.) Historical volatility has no information content about future realized volatility

When assessing the forecasting ability of implied volatility, it is common for studies in the literature (Kumar, 2008) (Christesnen and Prabhala, 1998) to compare the information content present in implied volatility with that contained in past realized volatility. This is done by replacing implied volatility with historical volatility in the previous regression and then applying the same Students T Test and is also a preliminary step before the more informative encompassing regression.

$$\boxed{\ln(RV_t) = \beta 0 + \beta 1 \ln(HV_t) + \epsilon_t \qquad (5)}$$

Table 3: OLS Regression output for equation (5)

Dependent variable: Log realised volatility (RV_t)

Independent variables		Partial R^2	T-value	T-prob
Constant	$\mathrm{Ln(HV}_t)$			
-0.637732 (0.1601)		0.2790	-3.98	0.0003
	0.521643 (0.1198)	0.3161	4.35	0.0001
Adj. R^2: 0.299454				

Table 4: Statistical test for research hypothesis (ii.)

Test type	Students T test
Degrees of Freedom	42
Alpha level	5
Tails	2
Critical Value	2.015
Test Value	5.52
Null hypothesis: $\beta 1 = 0$	
Alternate hypothesis: $\beta 1 \neq 0$	

The outcome of the test for significance means the null hypothesis is rejected and the alternate hypothesis that the coefficient is statistically different from zero is accepted, an interpretation supported with the T-prob being less than 0.05. Therefore, similar to the rationality test for implied volatility, there is some information content present in past realized volatility however this is less than that found in implied volatility.

Comparing this to the results of Christensen and Prabhala (1989), their result for the information content of historical volatility outputted a coefficient of 0.57 with an adjusted R^2 value of 32 percent. The coefficient value is incredibly similar to the 0.52 for historical volatility of this research signaling the amount of information content is approximately the same.

Compared to another market, the ASX index option of the Australian market studies by Li and Yang (2009) displayed a historical volatility information content coefficient value of 0.48 and a corresponding R^2 value of 18 percent. Kumar (2008), studying options on the indian nifty50 index, also found a past realized information content coefficient value of 0.39 with an R^2 of 0.0847. This therefore suggests the amount of information content available in historical volatility for the FTS100 index options is more than that found for options on other markets. Yet, the amount approximates that found for the SPX options of the American market when compared to the results of Christensen and Prabhala (1989).

3.5.3 (iii.) Implied volatility is no better than historical volatility as a predictor

As done by Christensen and Prabhala (1989), the forecasting ability of implied volatility can be judged econometrically through two approaches; comparing the coefficients of the rationality tests of implied volatility and historical volatility, and also by comparing the R^2 values [7].

$$\ln(RV_t) = \beta 0 + \beta 1 \ln(IV_t) + \epsilon_t \tag{4}$$

$$: \ln(RV_t) = \beta 0 + \beta 1 \ln(HV_t) + \epsilon_t \tag{5}$$

Table 5: OLS Regression output for equation (4) and (5)

Dependent variable: Log realised volatility (RV_t)			
Independent variables			Adjusted R^2
Constant	$\text{Ln}(IV_t)$	$\text{Ln}(HV_t)$	
0.0164190	0.721378		0.4120
(0.2434)	(0.1308)		
-0.637732		0.299554	0.2995
(0.1601)		(0.1198)	

With the implied volatility coefficient value of 0.72 exceeds the coefficient value of 0.52 for historical volatility, this implies that the latter has a greater amount of information content relative to historical volatility and hence greater forecasting power. In terms of the adjusted R^2 values, the rationality test for implied volatility reaches 0.4120 whilst historical volatility obtains a value of 0.2995further supporting the interpretation that implied volatility is a better predictor than historical volatility.

Both of these metrics therefore show that implied volatility has information content beyond that contained in historical volatility which is congruent with the findings of studies on other markets and their respective index options. One observation that can be made however is that whilst the relative amount of information content is always greater for implied volatility than historical volatility, the absolute amount appears to change from market to market.

From this, a tentative observation can be made that the information content of both implied and historical volatility for the FTSE100 index of this research

[7] adjusted R^2 values are used in this methodology instead due to the increased accuracy of this measure achieved by adjusting for the number of explanatory terms

ranks higher than the Australian market studied by li and Yang (2009), and the Indian market studied by Kumar (2008), whilst approximates that of the SP100 due the close similarity to the results of Christensen and Prabhalas (1989).

It is worth noting that Li and Yang (2009) were unable to reach the conclusion that implied volatility was a better predictor than historical volatility due to the coefficient of the rationality test regression on the call option series only being statistically significant for historical volatility not implied volatility. Whilst at a surface level this seems to be in significant contrast to the findings of this research, Li and Yang (2009) propose this is due to the presence of EIV affecting the coefficient values with a downward bias towards zero. Applying this concept to the results from this study, observing the high level of statistical significance of the implied volatility coefficient could be an interpreted early sign of the absence of EIV, in contrast to the results of Li and Yang (2009).

3.5.4 (iv.) Implied volatility subsumes the information content available in past realized volatility

The encompassing regression tests the information content of the two series simultaneously which grants insight into the informational efficiency [8] of implied volatility. The expectation is that implied volatility should be informationally efficient due to the fact that it subsumes the information content contained in the historical volatility (Granger and Poon, 2003). The hypothesis that all information content available in past realized volatility is subsumed into implied volatility can be confirmed if the coefficient for historical volatility is not significantly different from zero in the encompassing regression.

$$\boxed{\ln(RV_t) = \beta 0 + \beta 1 \ln(IV_t) + \beta 2 \ln(HV_t) + \epsilon_t \qquad (6)}$$

[8] not to be confused with option market efficiency, or econometric efficiency.

Table 6: OLS Regression output for equation (6)

Dependent variable: Log realised volatility (RV_t)					
Independent variables			Partial R^2	T-value	T-prob
Constant	$Ln(IV_t)$	$Ln(HV_t)$			
0.0841121 (0.2971)			0.0020	0.283	0.7785
	0.828784 (0.2956)		0.1642	2.8	0.0078
		-0.100789 (0.2482)	0.0041	-0.406	0.6868
Adj. R^2: 0.3998545					

Table 7: Statistical test for research hypothesis (iv.)

Test type	Students T test
Degrees of Freedom	42
Alpha level	5
Tails	two
Critical Value	2.015
Test Value	-0.406
Null hypothesis: $\beta 1 = 0$	
Alternate hypothesis: $\beta 1 \neq 0$	

The null hypothesis is accepted that the coefficient of historical volatility is not statistically different from zero and is supported by the T-prob is also higher than 0.05. This result therefore proposes that implied volatility subsumes all information content available in historical volatility and therefore suggests that the option market of the FTSE index 100 is informationally efficient.

Comparing the encompassing regression results from other studies, the same conclusion was reached by Kumar(2008) who found that the coefficient of historical volatility did not remain significant in the encompassing regression, for both the put option series and the call option series, hence implying the implied volatility of the Nifty 50 index option market to be informationally efficient too.

In contrast, both the studies of Christensen and Prabhala (1998) and Li and Yang (2009) show that the coefficient of past realized volatility remained statistically significant despite the inclusion of implied volatility as an explanatory variable in the encompassing regression. This initially implies the FTSE100 index option market is more informationally efficient than its American and Australian counterpart when bias correction schemes have not been implemented.

3.5.5 (v.) Implied volatility is an efficient estimator of future realized volatility

With econometric inefficiency disturbing the associated standard error of an explanatory variable (Okumu, 2008), testing the econometric efficiency of the implied volatility forecasts is primarily done in order for valid conclusions to subsequently be made regarding possible bias present in the forecast. In order for implied volatility to be efficient, the residuals of the rationality test are serially orthogonal to the markets information set (Christensen and Prabhala, 1998) and should be Guassian white noise.

As such, the relevant statistical test to be used is the Durbin-Watson test for autocorrelation. The critical values are determined with 45 observations (rounded up from 43) and the number of explanatory terms in the regression being equal to one. It is important to note that by having a null hypothesis of no autocorrelation, the upper bound critical value is transformed with (4 - CV upper bound) to give CV (upper bound)'before it is used.

$$\boxed{\ln(RV_t) = \beta 0 + \beta 1 \ln(IV_t) + \epsilon_t \qquad (4)}$$

Table 8: Statistical test for research hypothesis (v.)

Test type	Durbin Watson
Number of observations	45
Alpha level	1
K (number of explanatory variables)	1
CV (upper bound)	1.288
CV (lower bound)	1.376
CV (upper bound)'	2.624
DW Test Value	2.05445
Null hypothesis: No autocorrelation	
Alternate hypothesis: Autocorrelation is present	

Decision rule for this test is do not reject the null hypothesis if dw is between CV (lower bound) and CV (upper bound)'. As such, considering the DW test statistic of 2.05445 is between the upper and lower bound critical values, the null hypothesis is accepted hence suggesting that implied volatility is an efficient predictor of future realized volatility. With this result having little economic significance, it is still congruent with similar research (Kumar, 2008) and does allow for more accurate analysis of potential bias present in the implied volatility forecast.

3.5.6 (vi.) Implied volatility is an unbiased estimator of future realized volatility

An important takeaway from the literature review is that the extent of the bias present in the implied volatility forecast is one of the most widely considered metrics and hence will be subject to the same rigor in this research. A test for bias is implemented through a joint hypothesis test on the coefficient results from the rationality test.If implied volatility is unbiased, the constant term should be observed to not be statistically significantly different from zero , whilst simultaneously the coefficient of implied volatility is not significantly different from unity.

$$\ln(RV_t) = \beta 0 + \beta 1 \ln(IV_t) + \epsilon_t \tag{4}$$

Table 9: Statistical test for research hypothesis (vi.)

Test type	Joint Hypothesis F test (Wald Test)
Degrees of freedom	41
Alpha level	5
Null hypothesis: $\beta 0 = 0, \beta 1 = 1$	
Alternate hypothesis: $\beta 0 \neq 0, \beta 1 \neq 1$	

Table 10: Wald test output for equation (4)

Test for linear restrictions (Rb = r)	
R matrix:	
Constant	Ln(IV_t)
0.00000	1.0000
r vector:	
1.0000	
linRes F(1,41)	4.5407 [0.0391*]

Inspecting the output of the statistical test, the F test statistic of 4.5407 is significant at the 5 percent level meaning the joint hypothesis is rejected, and implied volatility is seen to be a biased forecast of realized volatility. The observation of a coefficient value for implied volatility being significantly less than one signifies the potential involvements of EIV or the bias introduced by inefficiencies in the instrumental features

Comparing the findings from similar studies, Christensen and Prabhala (1998) arrived at an F-test statistic of 10.58 which was significant at 1% signaling implied volatility to be a biased forecast too. Yet, with the F test value from a test on the FTSE100 index options being only significant at 5%, the difference in significance levels implies that the bias present in this research is not as strong compared to that present in the implied volatility of S&P100 index options.

Whilst the same result of bias was found for li and Yang (2009), this in contrast to Kumar (2008) who concluded no bias was present in the implied volatility forecast. A possible explanation for this is either the absence of bias introduced by EIV or that the instrumental features are efficient enough for the Indian market that no detectable bias is introduced

3.5.7 (vii.) Implied volatility suffers from error in variables.

With bias detected in the implied volatility forecast, the usual remedy applied by studies in the literature is an instrumental variable technique (IVT) to correct for the bias. However, the literature review revealed that the use of an EIV detection technique prior to this has the value of distinguishing the source of bias; EIV or the instrumental features. As such, the next step of the methodology closely resembles that of Li and Yang (2009) who carry out the Hausman Test.

Firstly, the instrumental variable, which can be subsequently used to reduce the bias present in the implied volatility through the IVT, must be first specified and constructed. Historical volatility and past realized volatility are selected as the exogenous variables to be used as the instruments, as in line with the literature (Christensen and Prabhala, 1989), (li and yang, 200). The justification for this choice is that past implied volatility "is quite plausibly unrelated to the measurement error associated with the implied volatility sampled one month later".Similarly, historical volatility should be orthogonal to the errors yet correlated with current period implied volatility.

Following this, lagged implied volatility and historical volatility are regressed against the ex-ante implied volatility value to create the instrumental variable as shown in equation (7). The resultant residuals are saved and subsequently placed into the main encompassing regression and tested for significance through a standard T test, as in line with the Hausman test.

$$\boxed{InstVar = \beta 0 + \beta 1 \ln(IV_{t-1}) + \beta 2 \ln(HV_t) + \epsilon_t \qquad (7)}$$

Table 11: OLS Regression output for equation (7)

Dependent variable: Log realised volatility (RV_t)

Independent variables				Partial R^2	T-value	T-prob
Constant	$Ln(IV_t)$	$Ln(HV_t)$	InstVarResid			
-0.184125 (0.9184)				0.0011	-0.200	0.8422
	0.570446 (0.9912)			0.086	0.576	0.5683
		0.063099 (0.7268)		0.002	0.0868	0.9313
			0.253738 (1.043)	0.016	0.243	0.8090
Adj. R^2: 0.316239						

Table 12: Statistical test for research hypothesis (vii.)

test Type	Hausman Test
Degrees of freedom	41
Alpha level	5
Tails	2
Critical Value	2.21
Test Value	0.243
Null hypothesis: $\beta 2 = 0$	
Alternate hypothesis: $\beta 2 \neq 0$	

The results from the regression of equation (7) provide the coefficient value for the independent variable of ‘ instrumental variable residuals’ which is then tested for statistical significance.

The critical value is given according to a standard T test with degrees of freedom of 41 and a two tail distribution. As the test statistic is smaller than the critical value, the null hypothesis that the instrumental variable residuals are not statistically significant is accepted.

Therefore the Hausman test to detect for EIV has failed and the instrumental variable approach to correct for forecast bias can not be used. This result is in contrast to Li and Yang (2009) where the Hausman test detected EIV presence in the implied volatility series. With the studies within the literature typically implementing the instrumental variable approach after recognising forecast bias, there are no other studies to compare the Hausman test results against.

The conclusion of this statistical test suggest that EIV is not causing the bias present in implied volatility, hence reverts attention to the instrumental features of implied volatility as the source in line with the suggestions of Poteshman (2000).

3.5.8 (viii.) Implied volatility suffers from systematic error from the instrumental features

Ederington (2002) uses a bias correction scheme that involves running the rationality test to obtain numerical values for estimator coefficients and the intercept terms to which are used according to equation (8) to produce bias corrected implied volatility. Following this, whilst Ederington's (2002) study then goes on to using these values to investigate optimal weighting schemes, this paper instead intends to run the Wald joint hypothesis test previously used to measure the new level of bias.

$$\boxed{ln(IV_t^*) = \alpha 0 + \alpha 1 Ln(IV_T) \qquad (8)}$$

$$\boxed{\ln(RV_t) = \beta 0 + \beta 1 \ln(IV_t*) + \epsilon_t \qquad (9)}$$

Table 13: OLS Regression output for equation (4) using Ln(IV_t*)

Dependent variable: Log realised volatility (RV_t)

Independent variables		Partial R^2	T-value	T-prob
Constant	Ln(IV_t*)			
-4.30949e⁻08 (0.2405)		0.0000	0.00	1
	1 (0.1813)	0.4261	5.52	0.4261
Adj. R^2: 0.412				

Before the bias corrected implied volatility values are investigated using the Wald test, the rationality test is rerun with the new values. Running this bias correction procedure produces a coefficient value for the bias corrected implied volatility of perfectly 1 with a statistically significant T probability and an intercept value of -19.6886. After examining the values, it is possible to argue this bias correction scheme has produced invalid coefficient and intercept values. Studies using this approach are seemingly limited to Ederington (2000) and as such, there is no opportunity for validation or modification of this attempted bias correction scheme attempted. This research leaving Hypothesis 8 inconclusive.

4 Discussion of results

Summarizing the results from the methodology, it can be concluded that implied volatility contains a high degree of informational content regarding the future realized volatility of the underlying asset for the remaining time to maturity of the option. The amount of informational content internalized appears to be greater than other markets yet approximates that occurring for the implied volatility of SPX options of the American market. Similarly, Historical volatility also has some information content, yet this is lower than that found in implied volatility and is subsumed into the latter due to the high level of informational efficiency. The difference in information content between historical and implied volatility also is approximately the same in magnitude as the SPX options.

Further reinforcing the findings from the test of hypothesis 4, it can be informative to examine the change in the coefficient value from the rationality test regression to the encompassing regression. Here, the coefficient of historical volatility reduces from a value of 0.52 in the rationality test to -0.10 in the encompassing regression, further supporting the claim that implied volatility has subsumed all the information content of historical volatility.

The studies compared to in-situ during all of the methodology were chosen as they met the criteria of using the same robust sampling procedure and log transformed variables suggested from the literature review. In contrast, a comparison to studies that fail to implement non-overlapping sampling periods display a clear divergence of results.

For example, after implementing the same encompassing regression, Canina and Figlewski (1993) reached the conclusion that implied volatility was not informationally efficient which is in stark contrast to the findings of this research. Considering the difference can be explained with the fact the data used by Canina and Figlewski (1993) suffered from the maturity mismatch problem, this displays the importance of exclusively comparing results to studies who also utilized the non-overlapping sampling period.

With implied volatility established as an efficient estimator, in line with most other studies it was found to be a biased forecast. Error in variables as a source of this bias was refuted as the use of a Hausman test to detect for it was failed meaning that the bias could instead be introduced by inefficiencies in the instrumental features. Supporting the results of the Hausman test for EIV, the fact that the bias present in the implied volatility of this research was only detectable at a lower level of significance of 5% compared to other studies (Christensen and Prabhala, 1989) could be interpreted as an early sign of the absence of EIV.

With asynchronous prices arguably one of the most heavily considered source of errors in variables, the absence of such EIV suggests that there is not a detectable level of EIV introduced by asynchronous prices. A possible reason for this is that external price asynchronization was significantly reduced by the synchronization introduced into the implied volatility value due to calculation used in the WDRS data.

One possible explanation for the absence of error in variables is due to the reduction of error arising from asynchronous prices. The data provided by WDRS reduces the size of asynchronous prices because WDRS uses a seemingly thorough method to synchronize the underlying price with options price when calculating the implied volatility value. This is achieved by setting the underlying security price of the option through a rule based approach that uses either an average of the underlying bid/ask prices, or the last price depending on the closing time of the separate markets. [9].

Looking at similar studies to draw inferences on this possibility, Okumu (2013) also uses interpolation across options with different strike prices and maturities. With bias detected in their forecast, the use instrumental variable technique was not able to correct the bias implying that, as with this paper, the bias is introduced by inefficiencies in the instrumental features. Assuming this is the cause, a possible interpretation is that the interpolation remedied the EIV of asynchronous prices.

However, this a speculative comment to which can only be validated if Okumu (2013) had used an Hausman test to confirm the bias was indeed from the instrumental features rather than EIV. Furthermore, this comparison is also limited in the respect that whilst the standardized options provided by WDRS also involve interpolation across strikes and maturities like Okumu (2013), there

[9] to which details can be found (here - manual)

is an additional element in the calculation used by WDRS's that uses the prices of a forward contract on the underlying asset, and as such, creates a limitation in this comparison to distinguish the remedying effects of interpolation on asynchronous prices.

Recognizing the sources of the absence of EIV is particularly important. This is because it needs to be decided if there is actual absence of EIV due to favorable market characteristics, or apparent absence of EIV arising from data collection and transformation. This is because it is harder to amend the option pricing models used by investors to include market imperfections, such as bid ask spread, that cause the EIV.

The remaining possible source of bias is that introduced by the inefficiencies in the instrumental features of implied volatility. Therefore, a tentative hypothesis was tested that if a bias correction scheme could correct the bias, this may suggest inefficiencies in the instrumental features. Yet with the invalid output from the scheme , this remains inconclusive. Our suggestion for why this scheme failed is due to significant differences in methodological approaches. Ederington's (2000) study used a range of options with varying strike prices for both a call and put series, and used the historical data to correct the forecast bias. This in contrast to to this study who used only one set of options for one series; ATM call options, therefore possibly giving rise to an incompatibility with this bias correction scheme,

Despite this, a ranking of the instrumental features in terms of the extent to which they cause the bias present in the forecast can be suggested, however it is important to recognise that the instrumental features themselves are significant topics with a large wealth of separate studies investigating the features exclusively.

5 Conclusion

5.1 Instrumental features as the source of Bias analysis

Firsty, briefly evaluating the extent of BSOPM misspecification present, it is possible to argue that this is the instrumental feature that is most likely to cause the bias present in the forecast as the literature review revealed that the required assumptions of the BSOPM may constrain the forecasting ability of implied volatility.

Subsequent studies amended this issue with the use of BSOPM extension models. For example, Poteshman (2000) uses the Heston stochastic volatility model to amend the BSOPM assumption of constant volatility of the underlying asset. The non-zero market price of volatility risk that this approach adds to the option pricing model was found to remove the bias present in the forecasting. This has important implications for this research as it strongly suggests that BSOPM misspecification is the instrumental feature that causes the bias present in the implied volatility forecast.

A step further than extending the BSOPM is to replace it with a model free approach, which also includes elements that overcome some of the main limitations of this research. Firstly, a model free approach "aggregates information across options with different strike prices and should be informationally more efficient" Yiang and Tian (2005)

Whilst this research uses the implied volatility exclusively from ATM options, the calculation performed by WDRS in arriving at this value involves interpolation across different strike prices and maturities. As a result, this may have increased the informational efficiency of the implied volatility in this research, similarly to if a model free approach was implemented yet not to the same extent.

Another benefit of the use of a model free approach is that it overcomes the joint hypothesis issue of correct option pricing model and option market efficiency. As such, this would especially increase the accuracy when testing hypothesis relating to the information content and informational efficiency of implied volatility.

Both these aspects combined together explain the results of Jiang and Tian (2005) who find that "the model free implied volatility subsumes all information contained in the Black–Scholes (B–S) implied volatility and past realized volatility and is a more efficient forecast for future realized volatility". With this considered, results from the studies of the peripheral literature strongly suggest that the bias in the forecast is caused by BSOPM misspecification. As such, further comments regarding the two remaining instrumental features, correct use of pricing model by investors and an option market efficiency are excluded from this conclusion and remain topics of potential further research

5.2 Statistical and empirical Evaluation

The literature review was crucial in providing the required data sampling approaches needed to accurately evaluate the forecasting ability of implied volatility. Most notably, the suggestion of the use of non-overlapping sampling periods prevented the impacts of the maturity mismatch issue on this research. This was crucial for when hypothesis (iv.) was investigated as when comparisons between the information content of implied volatility and historical volatility was done, non-overlapping sampling periods ensured the explanatory power of historical volatility was not overstated. Additionally, with the maturity cycles of the FTSE 100 index options matching exactly the SPZ index options of li and yang (2009) making the resultant sampling period procedure almost identical providing validity when regression results were compared.

Despite these findings, it is important to recognize the limitations of this research. The first limitation involves the potentially low number of observations used in this study, a limit imposed by the strict non-overlapping sampling procedure. With 43 observations used, this is a fairly low amount relative to the literature, for example Christensen and Prabhala (1998) used 139 observations. The consequences of this is that it could be the source of the bias detected in the implied volatility forecast and this reasoning was adopted by Okumu (2013) after the use of IVT failed to correct this bias present in the forecast. Yet, looking at other studies with a similar amount of observations, for example kumar with 55 observations, no bias was detected in the implied volatility forecast. This therefore refutes the idea that the bias is due to a low number of observations and as such, other potential sources of bias should be inspected.

Another limitation is the frequency of realized volatility observations used to construct the series. As mentioned in the literature review, the findings from studies examining the effect of intraday data to construct realized volatility show its importance for non-biased implied volatility forecasts. As daily closing prices were use in this paper to create an interday style series, it is possible this introduced the bias, especially considering Poteshman (2000) was able to remove half the bias using high frequency, 5 minute intraday realized volatility data;

Therefore a possible extension of this research would be to use intraday prices in the calculation of realized volatility in order to examine to what extent an increase in the accuracy of the realized volatility series will reduce the bias present in the forecast. This extension is further qualified by the fact it shouldn't affect the conclusions of other hypotheses, specifically hypothesis 1 regarding information content. The reason for this is that the use of intraday returns does not impact the amount of information content detected in implied volatility (Blair et al, 2000)

Another limitation of this research is the use of comparing R^2 values of the rationality test regressions to compare the information content of implied volatility with that of historical volatility. As noted by Kumar (2008), the use of R^2 for comparing the forecast ability, based of the information content, of the two series may lead to incorrect conclusions due to the absence of consideration of the statistical significance of the intercept and coefficient terms. Whilst the comparison method used in this research is also done in other studies, for example Okumu (20013), a more thorough approach is therefore to use the Root Mean Square Error(RMSE) method.

5.3 Concluding remarks and Areas of further research

This research only investigated data exclusively for call options rather than both call and puts and li and Yang (2009) showed that substantially different results can arise for the two different series, for example before the use of the instrumental variable technique, only the put series displayed a significant coefficient for the rationality test coefficient. As such, the conclusions drawn from this research only applies for the call series of FTSE 100 index options and an opportunity for further research would be to look at both series, as done in Kumar (2008), in order to see if different conclusions are reached between the two.

A possible area of further research would be to formally compare how the information content of implied volatility varies between options on different markets. This is because in the process of comparing the implied volatility information content of this research with other studies, there was large variation between information content values, for example the call series in li and yang (2009) only had a coefficient value of 0.45 with an R^2 of 7%. Analyzing how the level of information content varies between the implied volatility from options written on a range of market indexes, and the cause of the differences between them will add depth to the comparisons made in this research.

A study similar to this suggestion was done by Szakmary (2003) who investigated the predictive power of implied volatility across 35 option markets using the same regressions implemented in this research. However, this study investigated futures options and the only equity index included was the S&P500 as Szakmary (2003) mainly looked at currencies and commodities. This is especially important as "bias tends to be most severe for options written on equity indexes." Poteshman (2000) and as such, a similar study to Szakmary 2003 but exclusively for equity index options is recommended.

Another extension to the research of this paper is to inspect how the forecasting ability of implied volatility changes during and around financial crisis's. This was done by Christensen and Prabhala (1998) in relation to the crash of 1987 and considering this research proactively excluded these market conditions during the data sampling stage, gives rise to an area of further research.

6 Declaration

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7 Bibliography

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8 Appendix

8.1 FTSE 100 index options specification sheet

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