An Empirical Examination of Informed Trading in the Option Market

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A thesis submitted to Business School, The University of Adelaide, in fulfillment of the requirements for the degree of Doctor of Philosophy

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SYNOPSIS

Despite a growing research interest in option trading and its impact on the pricing of the underlying asset, the role of options as a vehicle for informed trading remains an important economic question which has not yet been fully explored. In fact, even though academics have often argued that informed traders may prefer to trade in the option market rather than the equity market[1], the question of whether (and to what extent) such a proposition would hold in practice has not been systematically addressed in the literature.

This overarching research problem forms the foundation of this doctoral research project, leading to two important research questions. First, if investors do in fact use options to trade on information about underlying stock prices in practice, what implications does this have for the option (stock) pricing and forecasting? Second, what are the key factors driving traders' decisionsto trade on new information in one market over another? These two issues correspond to the two gaps found in the extant literature on option trading, and also in the strand of empirical studies focusing on the role of options as a mechanism for trading on information about the underlying asset. To explore these research questions, three interrelated projects have been undertaken, each with a unique contribution to informing the research topic.

These closely related investigations jointly provide consolidated answers to the two research questions raised previously. In response to the first research question, we pursue two strands of empirical investigation to examine the presence of informed trading in the option market. Firstly, we investigate the extent to which the information content extracted from options trading can be used to enhance predictions of the future

[1] Mainly due to higher financial leverages, reduced transactions costs and wider trading opportunities (eg speculation on volatility) (Black, 1975).

volatility realised by underlying stocks. Secondly, we examine the price impact of information trading activities within the option market, focusing especially on the way in which the level of trading activities can explain and predict the future dynamics of the option implied volatility smile. Both of these strands yield evidence in support of information trading activities existing in the option market. Regarding the second research question, our collective evidence indicates that the allocation of informed traders between option and stock markets depends on the trade-off of transactioncosts and trading opportunities existing in two related markets. This finding has consistently been corroborated by separate evidence emerging from our independent investigations. We found that the degree of information trading in the option market varies across different stocks, corresponding to variations in the level of individual stock liquidity. It has also been found that the degree of information asymmetry of option trades changed in response to changes in trading costs driven by regulatory changes observed during the 2008 short-sale ban.

This research makes a valuable contribution to the field of option research. From the theoretical perspective, it addresses significant gaps in the existing literature and extends our understanding of informed trading activities in the option market. In particular, it contributes to the body of knowledge on the economic value of derivatives by investigating the critical role they have played in the process of incorporating new information into the market. From the practical perspective, it proposes a simple-yet-effective technique which employs trading volume to improve forecasts of the underlying stock volatility and of the option implied volatility (price) respectively. Since volatility plays such a central role in the practice of derivatives trading, risk analysis and portfolio management, better forecasts of these quantities are clearly important and highly regarded by practitioners.

DECLARATION

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CHAPTER 1

INTRODUCTION

1.1. BACKGROUND TO THE THESIS

The last several decades have witnessed a phenomenal growth of option trading activities in derivatives in major financial markets around the world, highlighting the increasing importance of options in the modern finance construct and, in particular their economic value. While financial theory traditionally emphasised the role of options as a risk management tool, whether options can also be seen as a vehicle of informed trading in practice has quickly emerged as an important economic question.

In a perfect capital market, one could argue that options are redundant securities and that options trading should convey no new information to market participants. In the absence of market completeness, however, the option market could be regarded as the ideal venue for informed trading, because of the achievement of high leverage and wider trading opportunity, accompanied by lower transaction costs and a built-in downside protection (Black 1975). Further, some proportion of informed trading in the option market may also arise from the fact that options are uniquely suited to investors who have private information about the volatility of the underlying stock price. For the reasons stated, informed traders may prefer to trade in the option market instead of the stock market, which also means that the option trading process is not redundant. Although numerous empirical studies have endeavoured to examine the extent of the informed trading activities existing in the option market and the different implications this may have for option and stock pricing, there are a number of important aspects which have not been systematically addressed in the literature.

Firstly, while past research offers some evidence of the existence of informed trading in the option market[2] , it is still unclear what factors determine the allocation of informed traders between the stock and option markets and particularly the implications this has for the linkage between these related markets. In the existing literature, a number of authors have pointed to the importance of leverage, trading volume and spread in the investor's decision to trade in the option market (Easley, O'Hara et al., 1998; Chakravarty, Gulen et al. 2004 and Pan and Poteshman, 2006). One issue that has not been previously analysed, however, is the relative sensitivity of informed versus uninformed traders to changes in trading costs and/or trading restrictions imposed by regulations. This issue is of practical importance because the difference in the responses of informed and uninformed traders may change the trader composition and ultimately influence the price formation process in related markets.

Secondly, there has been little investigation of how informed trading activities in the option market affect option (stock) pricing and forecasting. Past research which investigated the informational linkage between the stock and option markets was pursued for the sole purpose of determining which market plays the greater role in discovering information relevant to the future dynamics of the underlying stock (Anthony, 1988; Stephan and Whaley, 1990; Easley, O'Hara et al., 1998; Chan, Chung et al., 2002; Chakravarty, Gulen et al., 2004). While this strand of research offers support to a notion that option trades have some predictive power concerning the stock return (volatility), as found in Easley, O'Hara et al. (1998), Chan, Chung et al. (2002), Pan and Poteshman (2006) and Ni, Pan et al. (2008), there have been limited studies to date attempting to make links between the informativeness of option trading volume

[2] Some indirect evidence of informed trading in the option market can be found in Anthony (1988), Easley, O'Hara et al. (1998) and Ni, Pan et al. (2008), which look into the lead-lag relationship between option volume and stock return and other studies which examine changes in option trading level in response to changes in margin requirements (Mayhew, Sarin et al., 1995) or to take-over announcements (Cao, Griffin et al., 2005). Examination of the informed trading via more direct measures has also been undertaken in Chakravarty, Gulen et al. (2004) and Ni, Pan et al. (2008).

and the forecasting applications. Another independent inquiry that has recently emerged in the literature also suggests that the option demand pressure reflected in trading transactions has some impact on option pricing, evidenced by its effect on the changing shape of the smile and/or the time-varying level of implied volatility (Bollen and Whaley 2004; Chan, Cheng et al. 2004; Ni, Pan et al. 2008; Gârleanu, Pedersen et al. 2009). Despite this knowledge, there has been no previous attempt to carry out an investigation of the predictive power of option trading volume in forecasting the future movement of option implied volatility (price).

This overarching research problem forms the foundation of this research project, leading to two important research questions which will be discussed in detail in the next section.

1.2. RESEARCH QUESTIONS

As previously discussed, we have been able to identify two major gaps in the extant literature on option trading, particularly in the strand of empirical studies focusing on the role of options as a mechanism for trading on information about the underlying asset. This leads to the development of two important research questions which this thesis aims to address.

1. If investors do in fact use options to trade on information about underlying stock prices in practice, what implications does this have for the option (stock) pricing and particularly forecasting?

This question involves examining the information content reflected by option trading activities, particularly in terms of the predictive power of option trading volume in forecasting stock volatility and option price (implied volatility smile). There are a number of advantages of this line of inquiry. Firstly, an examination into the predictive power of option volume will help shed light on both the following questions: whether informed traders participate in the option market and what is the information content reflected by option trades. In examining these issues empirically, our research also contributes to the body of knowledge on the economic value of derivatives by investigating the critical role they play in the process of incorporating new information into the market. Secondly, our predictive analysis expands the empirical literature on the informational linkage between the option and stock markets by providing unambiguous evidence of the informativeness of option trades. In fact, a lead-lag relation between option volume and stock volatility, if it exists, clearly suggests that volatility-related information should have been disseminated into the market through option trading activities. Further, our paper also relates to the strand of the option literature which examines the information content of option implied volatility, as found in the work of Christensen and Prabhala (1998) and Mayhew and Stivers (2003). It is chiefly argued that option implied volatility incorporates information about future volatility dynamics through the trading process by which new information is impounded to option prices. Hence, by using volume information in addition to the option implied volatility (price) information, our predictive analysis complements this literature by providing more insight into the process by which new information is incorporated into the option market. Lastly, given that volatility serves as a critical input in most financial asset pricing models, the issue of volatility forecasting is clearly of great practical importance. It naturally follows that it is worth investigating further the question of whether better forecasts can be achieved by using the additional set of information extracted from trading volume.

2. What are the factors driving traders' decisions to trade on new information in one market over another?

This question seeks to explore the key determinants of traders' preference for a specific trading venue. Establishing how traders behave and what factors drive their decision to trade in one market rather than another is clearly important, because their trading activities directly influence the price formation process in the related markets. Hence, our empirical findings will contribute to the existing literature which aims to address the fundamental economic question of how the flow of new information is disseminated to the market via different channels (options versus stocks trading). In particular, we are motivated to empirically examine how informed traders respond to shifts in trading costs and/or trading restrictions imposed by regulatory changes, and what implications this would have for the linkage between the stock and option markets. Our analysis will shed light on the relative sensitivity of informed versus uninformed traders to variations in trading costs. Further, it will demonstrate how regulatory changes which target one specific market may have an impact on the informational linkage between related markets, an issue that has rarely been examined in the existing literature.

1.3. RESEARCH AGENDA

1.3.1. An Overview of the Research Design

The two research questions discussed previously pointed to various interrelated research issues in relation to the role of options as a vehicle of information trading, which require further investigation. Hence, it is believed that conducting a single research project following the traditional thesis style, which often places the research focus on a single issue, appears to be insufficient to address all the related research enquiries satisfactorily. Because of the comprehensiveness and complexity of the current research topic, this thesis has been structured to encompass a selection of separate projects which undertake independent investigations into the different issues previously discussed. Though each project has its own unique focus on the main research topic, they have been designed to collectively contribute to addressing the two major research questions put forward earlier.

In response to the first research question, we pursue two strands of empirical investigation to examine the presence of informed trading in the option market. Firstly, we investigate the extent to which the information content extracted from options trading can be used to improve forecasts of future stock volatility. Secondly, we examine the price impact of information trading activities within the option market, focusing especially on how the level of trading activities can explain and predict the future dynamics of the option implied volatility smile. Evidence emerging from these two strands of investigation will offer some insight as to whether information trading activities exist in the option market. Regarding the second research question, we undertake the traditional approach found in the literature and examine how the informational linkage between option and stock markets vary across different stocks. In addition, we take advantage of the fact that regulatory changes, such as the short-sale ban implemented in the US market in 2008 at the peak of the global financial crisis, have a significant impact on increasing the transaction costs and/or trading restrictions for traders who wish to undertake short-sales activities in the stock market. Hence, one of our research projects has been framed around the period of this regulatory impediment so as to investigate how traders react to these changes.

Therefore three interrelated projects have been undertaken, each with a unique contribution to informing the research topic. Not only is this approach to constructing the thesis considered to be suitable for the achievement of our research objectives, it is also felt that the practical implications which arise from the existence of informed traders in the option market and their trading behaviours will be examined in more depth, through a series of questions and investigations undertaken in different settings.

1.3.2. An Outline of Major Research Components

This thesis comprises three interrelated projects whose details are presented in Chapters 2 to 4. Each of them constitutes an independent academic paper, which has been either published in a refereed academic journal or presented (or will be presented) at refereed academic conferences. They collectively inform the topic of this thesis and jointly provide consolidated answers to the two questions which this research aims to address. This section is devoted to a brief description of the individual research components, with some treatment of their respective contributions to the research problems discussed previously.

The first project, titled “The Role of Trading Volume in Volatility Forecasting”, attempts to examine the predictive power of option trading volume in forecasting stock return volatility. While the project itself takes a broader perspective than solely focusing on the informational role of option trading, its key emphasis is to shed light on the first research question, namely whether informed traders participate in the option market. In fact, the predictive analysis undertaken in this project seeks to provide unambiguous evidence of the informativeness of option trades so as to ascertain the role of options as a mechanism for informed trading. In particular, it is expected to enlighten readers about whether a proportion of trades have been motivated primarily by information in relation to the future stock volatility, by investigating whether the specific information set impounded in option trades can be used to improve volatility forecasts. This research also encompasses some analysis pertaining to the second research question about the factors influencing the allocation of informed traders, by simultaneously assessing how the predictive power of trading volume varies across individual stocks with different degrees of liquidity.

The second project, titled "The Role of Trading Volume in Forecasting the Option Implied Volatility Smile", seeks to examine the predictive power of option trading volume in forecasting the time-series dynamics of the implied volatility smile, a power which can be used simultaneously to derive forecasts of option implied volatility (prices). This work complements the previous analysis and expands the empirical literature which focuses on the role of options in discovering information. Not only does it offer some indirect evidence showing that a proportion of informed trading has been initiated in the option market, it further informs the first research question with reference to the information dissemination process into the market, by suggesting that the predictive power of volume reflects the slow diffusion of information into the market. In addition, the improvement in understanding the forecasts achieved in these two projects guides readers to perhaps consider other practical implications which can be derived from using the information impounded in option trades.

The third project, titled“The Allocation of Informed Trading across Related Markets: An Analysis of The Impact of The 2008 Short-Sale Ban”, continues to address the second research question by examining how traders respond to the increasing transaction costs and trading restrictions induced by the implementation of short-sale restrictions by the SEC in 2008. This project will not only provide some insights into the allocation of informed traders across the related markets but will also shed light on the factors influencing their trading decisions. It clarifies the questions both of how informed traders react differently to uninformed traders, and how this consequently affects the trader composition in both related markets. Further, it offers some important evidence illustrating how the information linkage between related markets is ultimately affected by regulatory changes. By documenting significant findings of the effects of the short sale ban, this project tends to make readers reflect on some key practical implications of policy decisions on the informational linkage between related markets.

1.3.3. Some Highlights of the Research Methodology

While details of the methodological design corresponding to each project will be discussed in greater detail in the relevant chaptersthis section aims to highlight some of the main themes underlying the research design and especially the way in which these projects have facilitated the addressing of the research questions of interest discussed earlier.

Firstly, it is important to point out that the reader will find a variety of different statistical models employed across projects, since they have been structured differently to address the distinct research questions, as pointed out earlier. In fact, these models have been carefully selected, depending on the variable of interest and the research question that needs to be addressed in each project. While details of the quantitative modelling and statistical analysis vary across different projects, generally they can be categorised into two distinct themes of research. The focus of the first is on the evaluation of the forecast improvement achieved from the employment of trading volume in the first two projects. The second aims at empirically investigating changes in the market microstructure and the informational linkage between the option and stock markets during and after the implementation of the 2008 short-sale restrictions.

More specifically, the model forecast performance in the first two projects will be assessed in terms of the in-sample fit, as well as the out-of-sample forecasts in a horse race with other alternative forecast approaches. The assessment will be grounded on two sets of criteria, including the statistical loss functions which measure the forecast errors, and the trading simulation which evaluates the economic significance of the forecast improvement, if any. While the latter offers additional insights on the practical benefits of the forecast performance achieved in each project, the former places a greater emphasis on informing the main research questions in relation to the information content of option volume, and ultimately to the existence of informed trading in the option market. In order to examine the effect of the ban on the microstructure in the option and stock markets in the third project, we use various measures of liquidity, such as the trading volume and spread, as well as measures which capture changes in the trader composition and their impact on asset pricing, such as the speed of stock price adjustments and the probability of informed traders (PIN) measure proposed in Easley, Kiefer et al. (1996). In addition, changes in the informational linkage between two markets are also demonstrated, by analysing the effect of variations in the information share of option trades on the price discovery of the underlying stock and the lead-lag relationship between them.

Lastly, it is also noteworthy that, in the first two projects, different modelling techniques have been employed to reflect the distinct time-series dynamics of the variables of interest whose relationship with option volumes will be analysed for forecasting purposes. In particular, the EGARCH model and the VAR model will be utilised to model the stock volatility dynamics and the option implied volatility smile respectively. These choices are optimal, as suggested by the preliminary statistical analysis conducted at the beginning of each project. In sum, the information content of option volumes has been assessed thoroughly via a range of different modelling techniques and data sets employed in these studies.

1.4. THESIS OUTLINE

Before providing the details of the three research projects undertaken, this small section offers a brief description of the overall structure of this thesis. This thesis is organised into five chapters. Chapter 1offers an overview of the research background, followed by the key research questions with an emphasis on how they fit in the existing literature, and finally, by some details of the research agenda employed to address these questions. Details of the three interrelated projects will be provided in Chapters 2 to 4 respectively. While each chapter will be presented in the form of a separate and complete paper in itself, a small section will be devoted to offer some explanation of the relationship of the chapter to the whole thesis. In addition, the key findings of these projects will be reiterated at the end of the thesis in Chapter 5, complemented by an explanation of how they contribute to informing the research topic. The key contributions of this thesis as a whole will also be discussed both in terms of theory and practice. Chapter 5 concludes by stating the limitations associated with the whole research project and making suggestions for future research directions.

CHAPTER 2

THE ROLE OF TRADING VOLUME IN FORECASTING VOLATILITY

Paper published on the *Journal of International Financial Markets, Institutions and Money* (December 2010) and presented at the *29th International Symposium on Forecasting*, June 2009, Hong Kong.

STATEMENT OF AUTHORSHIP

THE ROLE OF TRADING VOLUME IN FORECASTING VOLATILITY

Journal Article

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For this paper (chapter), Van Le developed the theoretical framework and hypothesis, performed the data analysis, wrote the manuscript and acted as the corresponding author. Prof Ralf Zurbrugg assisted in guiding the theory development, supervised the development of work and provided evaluation and feedbacks.

The majority of the work and the primary authorship have been undertaken by Van Le.

Van Le (Candidate)

I hereby certify that the statement of contribution is accurate.

Signed__________________________________Date: 17/05/2012

Prof Ralf Zurbrugg (Principal Supervisor)

I hereby certify that the statement of contribution is accurate and I give permission for the inclusion of the paper in the thesis.

Signed__________________________________Date: 17/05/2012

THE RELATIONSHIP OF THIS CHAPTER TO THE THESIS

This chapter attempts to address the first research question as to whether informed traders participate in the option market through an examination of the predictive power of option trading volume in forecasting the stock return volatility. In fact, the predictive analysis undertaken in this project seeks to provide unambiguous evidence of the informativeness of option trades to validate the existence of informed trading in the option market. As the key focus of this paper has been placed on volatility forecasting, the evidence found in this paper not only ascertains the role options as a mechanism for information trading but also suggests that volatility traders in particular play a major role in the price discovery process in the option market. Lastly, since the predictive power of trading volume has been evaluated simultaneously across individual stocks with different degrees of liquidity, the second research question concerning the factors influencing the allocation of informed traders has also been partially addressed in this project.

Abstract

Current models of volatility generally either use historical returns or option implied volatility to generate forecasts. Motivated by recent findings in the strand of literature focusing on volume-return (price) volatility relationships, this paper proposes the introduction of trading volume into various ARCH frameworks to improve forecasts. In particular, ex-ante evidence indicates that the incorporation of option implied volatility and trading volume into an EGARCH model leads to outperformance over other alternate forecast approaches. Noticeably, abnormal returns obtained from trading simulation underscores the improvement in forecast accuracy to be economically significant. These results remain robust to different measures of volatility and volume and offers scope for investors to more accurately predict volatility in the future.

2.1. INTRODUCTION

Forecasting volatility has been the subject of much investigation by academics and practitioners in recent years, due to the increasing recognition of its great practical importance in derivatives pricing, risk analysis, and portfolio management. Given that volatility serves as a critical input in most financial asset pricing models, the question of whether its dynamics can be forecasted falls within the vast literature on the predictability of asset prices and market efficiency.

Despite the extensive literature in developing sophisticated models to forecast volatility dynamics [refer to Poon and Granger (2003) for a review], little investigation exists on whether a synthesis between the research that focuses on option implied volatility and that of price-volume relationships can lead to an improved time series model for volatility forecasting. Our line of inquiry emerges from recent developments in two strands of studies independently existing in the literature which may give potential to improving forecasts. One investigates the dynamics of volatility driven by the market trading process to incorporate new information reflected in trading volume, while another seeks to capture the market expectation subsumed by option implied volatility. While independent forecasts can be estimated from single-factor models which are structured to extract the information content of each factor, anecdotal evidence gives higher merit to combining forecasts (Clemen 1989; Becker 2008). Besides, the appropriate incorporation of multiple factors may potentially offer an advanced forecasting model. It is documented in Poon and Granger's (2003) review that singular-factor time series models have some limitations which few empirical studies have attempted to overcome.

In this paper, the information content of option implied volatility and trading volume in forecasting the return volatility of individual stocks and the S&P 500 index in the US market will be tested for the period from 2 January 2003 to 30 June 2008. This study is necessary due to conflicting evidence surrounding whether additional information can be gleaned from option implied volatility. Work by authors such as Lamoureux and Lastrapes (1993), Mayhew and Stivers (2003) and Donaldson and Kamstra (2005) have shown mixed, if no improvement at all, in using option implied volatility over historical volatility in forecasting volatility.

In addition, the investigation into the information content of trading volume will provide further insight into three competing hypotheses currently upheld in the literature regarding the nature of the volume-volatility relation. The mixture of distribution hypothesis (MDH), proposed by Clark (1973), implies that the volume-volatility relation is simultaneous since they inherit a joint dependence on an underlying latent event and information flow variable. Hence, past volume does not contain any additional useful information on the future dynamics of volatility. Though the empirical confirmation of the hypothesis shows inconsistent results, its stance in the literature has firmly been established through the development of many influential theoretical models (Tauchen and Pitts 1983; Andersen 1996). In contrast, the sequential information arrival hypothesis (SIH) [see Copeland, 1976] and the noise trading hypothesis (Brock and LeBaron 1996; Iori 2002; Milton and Raviv 1993) both suggest a lead-lag (causal) relation exists, and can be exploited for forecasting purposes.

Results from our study can further elucidate the efficacy of the above models given that we intend on incorporating volume into the forecasting model. It will be interesting to therefore determine the importance of any lag relationships that may exist. This line of research has not yet been pursued vigorously in the past, either because of the conflicting evidence surrounding the nature of the volume-volatility relation (Lamoureux and Lastrapes 1990a; Wagner and Marsh 2005; Abu Hassan Shaari Mohd and Chin Wen 2007) or due to discouraging results found in the earliest examinations of the role of volume in forecasting volatility (Brooks 1998). Only recently, Donaldson and Kamstra (2005) discovered the switching role of stock trading volume between the relative informativeness of ARCH and option implied volatility.

Unlike these previous studies, our results suggest the information content on future stock volatility is shared between option implied volatility, actual option trading volume, and stock trading volume when we interact these factors in an augmented ARCH model. Our results show, that at the very least, stock and option trading volume can improve the forecast quality. This would provide support to research that has examined the role of trading activity in the option market in alleviating the information assimilation process in the underlying market (see Easley, O'Hara et al. 1998; Chakravarty, Gulen et al. 2004; Pan and Poteshman 2006). Our findings suggest its nature is important to explain the varying pattern of the volume- volatility dynamics across different stocks and markets reported in previous studies.

The remaining of the paper will be structured as follows. The next section describes the nature of the data set and variable construction. It is followed by the methodology section which outlines the forecast evaluation procedure where multiple alternate assessment criteria (statistical functions of loss versus trading simulation) are appraised in direct comparison to other forecasting techniques. The information content of implied volatility and trading volume is then discussed in the empirical results, while the final section provides concluding remarks and outlines some directions for future research.

2.2. DATA AND VARIABLE COMPUTATION

The primary data set employed in this study focuses on a period between 2 January 2003 and 30 June 2008. Of this sample, the first period up until 21 November 2007 is used for in-sample hypothesis testing and model construction, while the remaining data is utilised for out-of-sample evaluation. The time frame provides an interesting mix of bull and bear market trends, therefore incorporating an environment containing various market dynamics.

Table 2.1

List of equities and index				
Exchange Ticker (CBOE)	Company Name	Industry Classification	Stock Volume ('000) Total 2003- mid 2008	Option Volume Total 2003- mid 2008
AIG	AMERICAN INTL.GP.INCO.	Financials	13,938,876.7	32,397,760
IBM	INTL.BUS.MCHS.CORP.	Technology	9,283,961.7	38,022,632
GM	GENERAL MOTORS	Industrials	14,774,256.1	48,046,712
GE	GENERAL ELECTRIC CO.	Industrials	38,434,988.3	84,263,186
WMT	WAL MART STORES INCO.	Consumer Services	18,505,915.0	44,983,968
HPQ	HEWLETT-PACKARD CO.	Technology	18,295,916.0	32,934,816
TXN	TEXAS INSTS.INCO.	Technology	19,366,638.6	32,500,162
JNJ	JOHNSON & JOHNSON	Healthcare	12,351,670.3	19,059,264
XRX	XEROX CORP.	Technology	6,373,009.7	4,667,630
SPX	S&P500 INDEX	N/A	3,033,027,318.0	293,644,820

Apart from the S&P500 index, nine individual shares were chosen and are listed in Table 2.1. The selection was based on identifying stocks that had the most liquid, in terms of daily trading volume, options written on the underlying equity traded on the Chicago Board Options Exchange (CBOE). Daily option contract information, price and volume data for all active options on each of the underlying stocks were obtained from the data provider Stricknet Ltd. All remaining data relating to the underlying was collected from DataStream International. This included closing prices and daily trading volume for both the index and shares, dividend yield of the S&P500 index, the discrete cash dividends paid on the equities and the 30-day T-bill yield which we utilize as the risk-free rate.

The option implied volatility is also required for our analysis and for the S&P500 index we utilise the CBOE's implied volatility index (VIX) also obtained from DataStream. Its construction is designed to represent the implied volatility of an at-the-money (ATM) option with 22 days to maturity, by taking the weighted average of four calls and four puts nearest to the money at the two nearest expiration dates. While it is intended to mitigate pricing bias and measurement error caused by staleness by using a wide band of the most liquid call and put options, this measurement inherits many other beneficial attributes, including consistency, efficiency and vega-maximizing. Due to these preferable features, the weighting scheme used to compute the VIX index of the CBOE is re-applied in this study to produce a single estimate of implied volatility of all traded options on each of the stocks we analyse. Consequently, on every trading day, eight nearest-to-the-money calls and puts from two nearby option expiration dates are chosen. Their implied volatilities are calculated from the observed trading prices using the binomial tree that explicitly account for early exercise and discrete dividends. We follow the procedure outlined in Harvey and Whaley (1992), conducted in Matlab. Despite the computational expense, its application ensures a precise estimation of implied volatilities. These eight estimates are then aggregated using the VIX weighting procedure, whose exact algorithm can be found in Fleming, Ostdiek et al. (1995), and Corrado and Miller (2005).

Finally, this paper focuses on using realized volatility (RV) as the instrument that is to be forecasted. Daily stock returns are computed from closing prices, ie $r_t = \ln(S_t) - \ln(S_{t-1})$, and then utilized to calculate our proxy for the latent integrated volatility process, where $RV_{t,\tau} = \frac{1}{\tau}\sum_{i=t+1}^{T} r_i^2$ with τ being the frequency of observations. For the in-sample tests we only utilize daily data. However, for the out-of-sample test period we examine a number of alternate proxies including realized volatility from 5-minute intra-day price data obtained from CQG Ltd.

Descriptive statistics

Descriptive statistics for the return and daily volatility series reported in Table 2.2 suggest that all series do not conform to having a normal distribution[3]. The Box-Pierce statistic also rejects the null hypothesis of independence for each series which shows a high auto-correlation up to the 10th lag. In particular, the pervasive evidence of volatility persistence in both the equity and options markets can be highlighted by the extremely high Qs(10) statistics found in the volatility series, consistent with previous studies (see Ding, Granger et al. 1993; Brailsford and Faff 1996; also refer to Gospodinov, Gavala et al. 2006 for a discussion of possible explanations for volatility persistence). All series are also stationary, plus none of the volatility series show signs of significant persistence / long memory effects[4].

[3] Both series tend to have leptokurtic distribution, with volatility series being considerably right-skewed. Departures from normality are further illustrated by the Jarque-Bera statistic strongly rejecting the null hypothesis of normality at the 5% level of significance in all cases.

[4] The differencing long memory parameter d of the volatility process is estimated from the Geweke and Hudak (1983) (GPH) regression with a bandwidth parameter equals to $T^{0.6}$, similar to Seungmook and Wohar (1992). Also to differentiate between long memory dependence and the presence of structural break, we repeat it for different temporal aggregates of data [using daily, weekly and biweekly frequencies as proposed by Gospodinov, et al (2006) in the spirit of Andersen et al. (2001), also refer to Lamoureux and Lastrapes (1990b) and Diebold and Inoue (2001) for a discussion] and find unstable estimates of d. Finally,

Table 2.2

Descriptive Statistics of the daily return series (%) and the daily volatility series (%) for the period from 2 January 2003 to 30 June 2008

Panel A:daily return series (%)

	AIG	IBM	GM	GE	WMT	HPQ	TXN	JNJ	XRX	SPX
Mean	-0.057	0.031	-0.084	0.007	0.008	0.068	0.045	0.013	0.038	0.026
Std.Devn (%)	1.725	1.204	2.381	1.223	1.184	1.859	2.065	0.939	1.770	0.888
Skewness	-0.633	-0.268	0.193	-0.788	0.226	-0.659	0.335	0.236	0.787	-0.104
Excess Kurtosis	7.115	3.789	4.725	12.643	1.594	10.155	2.655	2.288	7.124	1.987
Minimum	-12.466	-8.662	-15.045	-13.684	-5.224	-16.790	-8.651	-3.922	-8.922	-3.569
Maximum	9.279	5.246	16.647	5.756	5.938	12.367	12.330	4.102	16.034	4.132
J-B	721	363	517	1499	95	1193	200	169	624	143
ARCH (10)	13.429	5.912	4.876	1.406	3.941	0.427	2.296	5.699	2.674	17.465
Q(10)	9.190***	9.680***	11.750***	9.490***	7.940***	12.470***	10.420***	10.960***	23.820***	21.350***
Qs(10)	242.190***	92.220***	43.130***	16.050***	46.460***	4.770***	28.790***	94.510***	29.540***	308.530***
ADF test	-35.790***	-37.500***	-35.050***	-38.370***	-38.000***	-38.430***	-37.240***	-39.280***	-41.830***	-41.450***

Panel B: daily volatility series (%)

	AIG	IBM	GM	GE	WMT	HPQ	TXN	JNJ	XRX	SPX
Mean	0.030	0.031	-0.084	0.007	0.008	0.068	0.045	0.013	0.038	0.026
Std.Devn (%)	0.090	0.035	0.147	0.057	0.027	0.120	0.092	0.018	0.095	0.016
Skewness	8.363	9.663	9.169	25.360	5.137	14.894	6.734	4.448	16.004	4.529
Excess Kurtosis	99.057	159.540	130.370	803.030	40.300	285.550	70.915	24.587	380.760	27.141
Minimum	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	1.554	0.750	2.771	1.873	0.353	2.819	1.520	0.168	2.571	0.171
J-B	23825	16948	21390	327470	7227	102170	11406	9512	73645	8356
Q(10)	242.190***	92.220***	43.130***	16.050***	46.460***	4.770***	28.790***	94.510***	29.540***	308.530***
ADF test	-32.500***	-35.060***	-33.820***	-36.240***	-35.570***	-36.530***	-35.290***	-37.130***	-32.540***	-35.580***

Notes: JB statistic measures the difference of the skewness and kurtosis of the series with those of the normal distribution . Under the null hypothesis of a normal distribution, the JB statistic follows a Chi^2 distribution with 2 degrees of freedom. The F-stat of the test of autoregressive conditional heteroskedasticity(ARCH) in the residuals for up to 10th-order serial correlation is also reported. The Q(10) and Qs(10) are the Box-Pierce test statistics for the return (volatility) series and the squared return series for up to the 10th-order serial correlation, respectively . Under the null hypothesis of independence, the test statistic is distributed asymtotically as a Chi-square distribution with 10 degrees of freedom.

The t-stat of the ADF test is reported. Null hypothesis is the time series contains a unit root I(1) process.

*** indicates rejection at the 1% significance level.

---

the test of the consistency of GPH estimates proposed by Ohanissian (2001) rejects the null hypothesis of a true long memory for all stocks.

2.3. METHODOLOGY

In this paper we use the lowest order EGARCH (1,1) model which, from preliminary tests[5], removes satisfactorily the residual autocorrelation, ARCH and sign-ARCH effects noted in Table 2.2 from the underlying data series. Hence, the specification of the augmented-ARCH model we employ to test the information content of option implied volatility and of trading volume is as follows:

$$r_t = \mu + \varepsilon_t$$
$$\varepsilon_t = \sqrt{h_t}\, z_t$$
$$z_t \sim N(0,1)$$

$$\ln(h_t) = \alpha_0 + \alpha_1 |z_{t-1}| + \alpha_2 z_{t-1} + \alpha_3 \ln h_{t-1} + \alpha_4 IVI_{t-1} + \alpha_5 AOV_{t-1} + \alpha_6 ASV_{t-1} \quad (1)$$

where r_t is the daily arithmetic stock return from close on day t-1 to close on day t; h_t is the conditional variance generated from the model based on past information; ε_t is the residual from the mean equation representing news about volatility; z_{t-1} is ε_{t-1} standardized on past volatility, which represents the leverage effect; IVI_{t-1} is the option implied volatility at the close on day t-1; AOV_{t-1} and ASV_{t-1} are the lagged option and stock abnormal volume amounts, respectively[6]. We define abnormal trading volume as the unexpected above-average trading volume after filtering for stochastic trends, similar to Wagner and Marsh (2005). In order to remove a stochastic trend in volume series a standard moving average filtering method is applied[7]. These procedures yield

[5] Unreported results show that the EGARCH (1,1) model passes all the standard specification tests at the conventional 5% level of significance, including the Engle's (1982) ARCH test and Box Pierce's test on the autocorrelation of squared residuals. Also, the presence of asymmetric responses of conditional volatility to positive and negative news, consistent to the leverage effect theory, and the mean reversion were found in most stocks and the index.

[6] Both volume series have been rescaled to be out of 1,000,000 and of 1,000,000,000 for normal stocks and the index respectively.

[7] A non-centred 5 day moving average is utilised in this paper, though in-sample analysis shows no significant qualitative difference would have occured if the 20-day or 50-day moving average was used instead. As an alternative, we also considered the filtering method of Hodrick and Prescott (1997), but found the results did not change significantly. They also had a very high correlation with the moving average technique.

series of normalised volume, conditional on available information at any point in time, V_t. Abnormal volume is then computed as the de-trended volume series by taking the difference between the actual and normalised volume series.

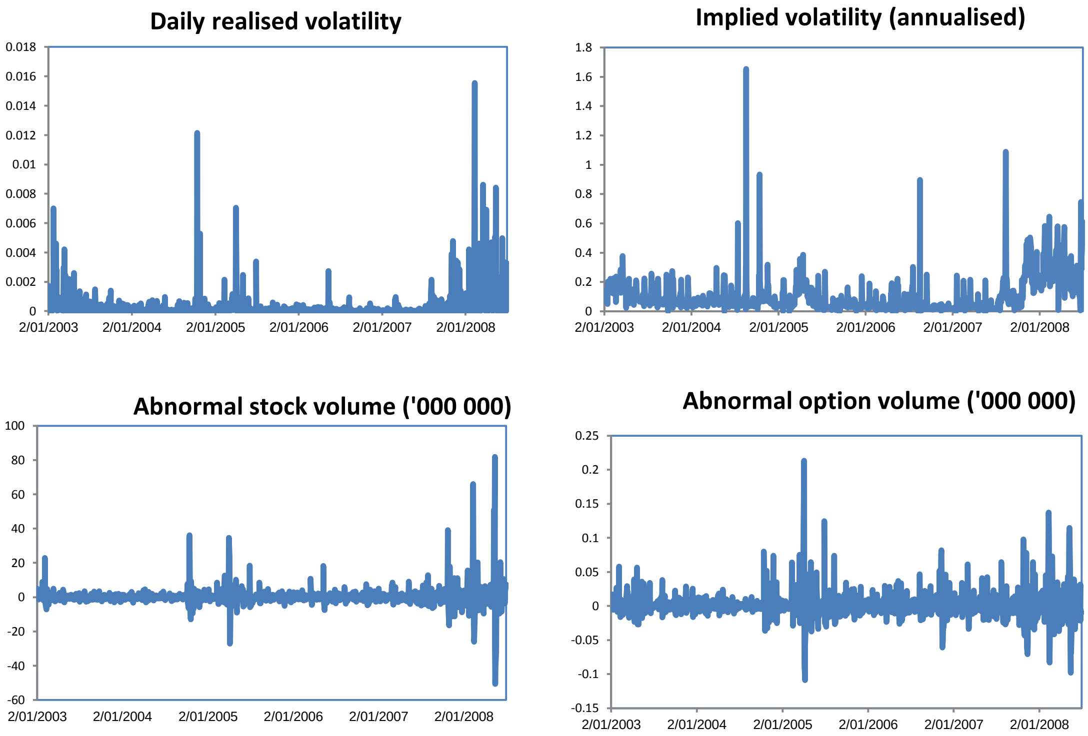

Figure 2.1

The realized volatility series, the implied volatility series, the abnormal stock volume series and the abnormal option volume series of the stock AIG being plotted for the period from 2 January 2003 to 30 June 2008

For the purpose of this study, IVI_{t-1}, AOV_{t-1} and ASV_{t-1} are designed to assess whether option implied volatility and trading volume contain any useful information of the future dynamics of stock return volatility, beyond what has been incorporated in past movements of the stock return. A graphical illustration of the intuitive relation between these factors and the return volatility can be found in Figure 2.1 when comparing plots of these different series for the whole sample period.

In order to determine the performance of the model from adding option implied volatility and trading volume, we compare results in the empirical section when just one of the two additional variables are added, a combined forecast from both, plus when both are included at the same time in the model. Also, as a benchmark for an alternative to ARCH-type forecasting models, we check performance relative to three alternate specifications, that being an autoregressive moving average model (ARMA(1,1)), a non-parametric principle component model (PCA) and a stochastic volatility model (SVM). The PCA (see Anderson and Vahid 2007; Konstantinidi, Skiadopoulos et al. 2008 for examples of this approach) specifies the volatility dynamics as a composition of a number of common factors

$$\Delta V_t = c_1 + \sum_{i=1}^{7} \phi_i PC_{t-1,i} + \varepsilon_t \; with \;\; \varepsilon_t \;\sim N(0,1). \tag{2}$$

where ΔV_t is the change in volatility; $PC_i \;\; with \;\; i = 1,...,7$ are the common factors; and $\phi_{i,} i = 1,...,7$ are coefficients to be estimated. Based on in-sample results of the statistical significance of parameter estimates and the explanatory power of the model measured by the adj-R^2, only the first seven PCs are retained. For the SVM, we specify it as:

$$\begin{aligned} r_t &= \sigma \sqrt{V_t}\varepsilon_t \;\; with \;\; \varepsilon_t \;\sim N(0,1) \\ \ln(V_t) &= \lambda \ln(V_{t-1}) + \sigma_v \xi_t \;\; with \;\; \xi_t \;\sim N(0,1) \end{aligned} \tag{3}$$

where r_t is the daily stock return as similar to equation (1), V_t the "unobservable" stochastic volatility. The deterministic terms λ and σ_v measure the volatility persistence and the volatility of volatility respectively[8].

Forecast accuracy can be assessed with reference to statistical loss functions, namely mean absolute error (MAE), mean absolute logarithmic error (MALE), mean absolute percent error (MAPE), and a linear exponential function (LINEX)[9]. The major challenge is the choice of appropriate criterion because these measurements of error entail different implications on the forecast inaccuracy. The complication of this task is mainly due to the non-normality of the distribution of volatility which can either lead to the possibility of finding a significant difference between alternate forecast methods or to conflicting verdicts derived from different evaluation measures (Poon and Granger 2003). Despite this matter, these statistics have often been used in the literature due to their simplicity for calculation and interpretation purposes.

We also employ the mean correct prediction (MCP) of the direction of change in volatility which is defined as the percentage of observations for which the model predicts a change of the same sign as the realized change in volatility. Its appraisal can be found in many papers (see Gonçalves and Guidolin 2006; Konstantinidi, Skiadopoulos et al. 2008) and is based on the perception that correct direction forecasts provide investors with profit opportunities through option trading. The key theme employed in our study however will be the orthogonality test which has proven to be a more powerful technique in comparing between forecasts, with its application being found in Day and Lewis (1992), Day (1993) and Donaldson and Kamstra (2005).

[8] Similar to Gospodinov, Gavala et al. (2006), we apply the MCMC method to estimate the model parameters and generate forecasts recursively.
[9] Refer to Gospodinov, Gavala et al. (2006) for the algorithm and interpretation of these metrics.

Specifically, the verification of forecasting power is based on the regression of the "actual" volatility on multiple forecasts generated from different models (Mincer-Zarnowitz regression), ie $\sigma_t^2 = \alpha + \sum_{i=1}^{n} \beta_i \hat{\sigma}_{ti}^2 + e_t$, where σ_t^2 is the ex-post volatility, and $\hat{\sigma}_{ti}^2$ is the forecasted volatility. The criteria of assessment include the t-statistic and the R^2 (adj-R^2) of the regression.

The accuracy of the generated out of sample forecasts are also evaluated in an economic setting, using trading simulation to determine if profit arises from volatility forecasts. It is noted this evaluation approach is currently under active investigation in the literature (see, for example, Engle, Hong et al. 1993; West, Edison et al. 1993; Konstantinidi, Skiadopoulos et al. 2008). While volatility is not a direct tradable asset for stocks (and most indices), volatility trading can still be achieved by establishing synthetic positions in options and their underlying assets. Similar to Guo (2000), "dynamic" trading on ATM straddles is simulated in this study by simultaneously going long (short) on a call and a put of nearest-to-the-money and nearest-time-to-maturity available when the return volatility of the underlying asset is expected to increase (decrease). Dynamic trading requires closing the position on the next trading day. Whilst also taking into account transaction costs, the economic significance of these trading strategies over the long run will be evaluated using traditional measurements of portfolio performance, namely the Sharpe ratio and the Leland (1999)'s modified alpha to account for non-normality[10], along with their 95% bootstrapped confidence interval.

[10] Refer to Leland (1999) for the algorithm the argument of why these metrics are more appropriate to measure the performance of portfolios containing options or assets with non-linear payoffs.

2.4. EMPIRICAL RESULTS

2.4.1. In sample testing

To assess whether lagged implied volatility and trading volume help to improve forecasting stock return volatility, we examine the regression results of the augmented-EGARCH (1,1) model specified in equation (1). Table 2.3 shows joint significance for both factors has been found in six of the stocks. In particular, it is observed that the estimate of volatility persistence (α_3) drops remarkably after the introduction of option implied volatility and trading volume into the conditional variance equation. An intuitive explanation, similar to Wagner and Marsh's (2005) suggestion, would be that the benchmark EGARCH (1,1) model is likely to be restrictive in explaining volatility persistence. Moving across the table, IVI_{t-1} takes the expected sign for all stocks and the index, and indicates a positive relationship between the market expectation of future stock volatility reflected in option price and the realized volatility. Except for one stock (GE), a positive relationship between lagged trading volume and future stock volatility is also evident in cases where volume is statistically significant at the conventional 5% level of significance. This provides early indicative support to the sequential information hypothesis which predicts that future stock volatility is positively correlated to the abnormal volume generated from trading activities revealing news into the market.

Considering the construction of two volume variables is meant to capture the informed trading component in each market, the testing results would address whether each proxy of the arrival of news has any additional information content beyond what has been captured by the other (refer to Chordia et al (2009) for a similar approach in the context of testing different proxies of liquidity). Our finding, being option trading volume stays significant at the presence of stock trading volume in the same regression, suggests that the incorporation of information would have been initiated through the speculative trading activities of informed traders in the option market. Our conjecture builds on Black's (1975) argument that informed traders may prefer to trade in the options market due to the high financial leverage, reduced transactions costs and wider trading opportunities (eg speculation on volatility). Indirect evidence of informed trading in the options market has been highlighted through numerous testing methods, including the causality test (Easley et al. 1998; Anthony 1988), and the "information share" approach (Chakravarty et al. 2004). Intriguingly, the insignificance of the abnormal stock trading volume suggests that the rejection of the sequential information hypothesis in earlier studies into the stock market (Brooks 1998; Wagner and Marsh 2005) may arise from the omission of option trading activities.

In addition, the statistical significance of IVI_{t-1} and AOV_{t-1} suggests each factor possesses a separate information set of the future dynamics of the return volatility of the underlying asset. The caveat of the above analysis is that the implied volatility derived from the prevailing option price would not capture the impact of trading activities attributable to the heterogeneity of traders at the arrival of new information. This aspect is re-examined in later analyses (viz., Table 2.4 onwards). The forecasting quality of both factors is further confirmed by the enhanced model fit, as illustrated by an improvement in the AIC, the Schwartz criteria and the log likelihood statistic of the augmented-model relative to the benchmark EGARCH (1,1) across the sample. At the same time, results of the ARCH and the Box-Pierce tests on the squared residual listed at the bottom of the table indicate that volatility clustering in the residuals remains insignificant.

Table 2.3

Results of in-sample hypothesis testing

The specification of the model underlying the results reported is as follows

$$r_t = \mu + \varepsilon_t$$
$$\varepsilon_t = \sqrt{h_t}\, z_t$$
$$z_t \sim N(0,1)$$
$$\ln(h_t) = \alpha_0 + \alpha_1 |z_{t-1}| + \alpha_2 z_{t-1} + \alpha_3 \ln h_{t-1} + \beta_{IVI} IVI_{t-1} + \beta_{AOV} AOV_{t-1} + \beta_{ASV} ASV_{t-1}$$

Within the model construction, r_t is the daily return from close on day t-1 to close on day t, ϵ_t is the disturbance term, z_t is the standardized residual of stock return ,h_t is the stock return variance conditional on the infromation set at time t, IVI_{t-1} is one lag weighted implied volatility generated from eight options nearest to the money and nearest time to maturity using settlement price at close on day t-1. AOV_{t-1} and ASV_{t-1} are measurements of the abnormal trading volume on day t-1 relative to its one-week lagged moving average of stocks and options respectively.

	AIG	GE	GM	HPQ	IBM	TXN	JNJ	WMT	XRX	SPX
µ1	-0.0001	0.0003	-0.0001	0.0010	0.0004	0.0005	0.0002	-0.0001	0.0005	0.0002
	(0.0003)	(0.0003)	(0.0005)	(0.0005)**	(0.0003)	(0.0005)	(0.0002)	(0.0003)	(0.0004)	(0.0002)
µ2	0.050	-0.009	0.077	-0.032	-0.019	0.016	-0.038	-0.012	-0.138	-0.055
	(0.031)**	(0.032)	(0.030)***	(0.030)	(0.029)	(0.026)	(0.032)	(0.032)	(0.032)***	(0.026)**
α0	-2.18	-0.89	-5.76	-2.97	-2.44	-1.26	-0.21	-6.57	-1.95	-3.74
	(0.98)**	(0.30)***	(1.78)***	(0.70)***	(0.68)***	(0.39)***	(0.05)***	(2.94)**	(0.57)***	(0.81)***
α1	0.10	0.08	0.06	0.11	0.06	-0.03	-0.02	0.17	0.19	-0.13
	(0.045)**	(0.039)**	(0.079)	(0.066)**	(0.051)	(0.036)	(0.015)*	(0.076)**	(0.068)***	(0.080)**
α2	-0.07	-0.03	0.07	-0.03	-0.10	-0.02	-0.02	0.04	-0.05	-0.24
	(0.045)*	(0.024)	(0.062)	(0.062)	(0.043)***	(0.026)	(0.014)*	(0.046)	(0.040)	(0.039)***
α3	0.81	0.93	0.41	0.70	0.78	0.87	0.98	0.33	0.80	0.67
	(0.088)***	(0.027)***	(0.188)**	(0.074)***	(0.062)***	(0.041)***	(0.005)***	(0.321)	(0.060)***	(0.072)***
β_IVI	1.77	0.65	2.76	1.33	1.60	0.67	0.24	1.81	0.57	0.04
	(0.837)**	(0.229)***	(0.801)***	(0.358)***	(0.493)***	(0.188)***	(0.067)***	(0.632)***	(0.202)***	(0.009)***
β_AOV	11.52	1.61	-2.30	7.27	3.60	7.69	1.49	0.26	-6.40	-0.62
	(4.906)***	(0.576)***	(1.020)**	(4.797)*	(1.821)**	(3.573)**	(5.094)	(2.312)	(6.965)	(0.617)
β_ASV	-0.02	0.00	0.01	-0.02	0.03	-0.01	0.02	0.00	0.03	0.00
	(0.030)	(0.005)	(0.012)	(0.013)*	(0.025)*	(0.008)	(0.016)*	(0.012)	(0.016)**	(0.145)
LLH	3602.1	3736.2	2926.1	3146.8	3717.9	2979.2	3900.1	3616.5	3204.9	4149.1
AIC	-6.12	-6.34	-4.97	-5.34	-6.31	-5.06	-6.62	-6.15	-5.44	-7.05
Schwart	-6.08	-6.31	-4.93	-5.30	-6.27	-5.02	-6.58	-6.12	-5.40	-7.01
Q (10)	3.84	4.40	5.30	14.93	7.40	10.23	3.19	13.40	9.45	9.95
ARCH	0.65	0.66	0.18	0.21	1.01	0.83	0.93	0.57	0.63	1.13

Notes: Standard errors are in the parentheses below corresponding to the parameter estimates. LLH is the value of maximised Gaussian log likelihood. AIC (Akaike information criteria) and Schwartz are two information criteria which indicate the model fit . The Q(10) is the Box-Pierce test statistics at lag 10th for the standardized residual of the estimated model. Under the null hypothesis of no autocorrelation, the test statistic is distributed asymtotically as Chi-square distribution with 10 degrees of freedom. The statistics of the Engle (1982)'s LM ARCH test is also reported. It also follows Chi-square distribution under the null hypothesis of no ARCH effects. The model has been estimated for the period from 2 January 2003 to 21 November 2007.

* indicates rejection at the 10% significance level

** indicates rejection at the 5% significance level

*** indicates rejection at the 1% significance level

In our next step, a progression of different model specifications has been examined empirically in order (1) to understand better the information content of option implied volatility and trading volume and (2) to provide justification on competing hypotheses regarding the volume-volatility relation. We report in Table 2.4 statistics of the

Table 2.4

In sample testing for different specifications of the conditional variance equation

The specification of models underlying the results reported is as follows

$$r_t = \mu + \varepsilon_t$$
$$\varepsilon_t = \sqrt{h_t} z_t$$
$$z_t \sim N(0,1)$$
$$(1) \ln(h_t) = \alpha_0 + \alpha_1 |z_{t-1}| + \alpha_2 z_{t-1} + \alpha_3 \ln h_{t-1}$$
$$(2) \ln(h_t) = \alpha_0 + \alpha_1 |z_{t-1}| + \alpha_2 z_{t-1} + \alpha_3 \ln h_{t-1} + \beta_{IVI} IVI_{t-1}$$
$$(3) \ln(h_t) = \alpha_0 + \alpha_1 |z_{t-1}| + \alpha_2 z_{t-1} + \alpha_3 \ln h_{t-1} + \beta_{AOV} AOV_{t-1}$$
$$(4) \ln(h_t) = \alpha_0 + \alpha_1 |z_{t-1}| + \alpha_2 z_{t-1} + \alpha_3 \ln h_{t-1} + \beta_{ASV} ASV_{t-1}$$
$$(5) \ln(h_t) = \alpha_0 + \alpha_1 |z_{t-1}| + \alpha_2 z_{t-1} + \alpha_3 \ln h_{t-1} + \beta_{AOV} AOV_{t-1} + \beta_{ASV} ASV_{t-1}$$
$$(6) \ln(h_t) = \alpha_0 + \alpha_1 |z_{t-1}| + \alpha_2 z_{t-1} + \alpha_3 \ln h_{t-1} + \beta_{IVI} IVI_{t-1} + \beta_{AOV} AOV_{t-1}$$
$$(7) \ln(h_t) = \alpha_0 + \alpha_1 |z_{t-1}| + \alpha_2 z_{t-1} + \alpha_3 \ln h_{t-1} + \beta_{IVI} IVI_{t-1} + \beta_{AOV} AOV_{t-1}^{ATM}$$
$$(8) \ln(h_t) = \alpha_0 + \alpha_1 |z_{t-1}| + \alpha_2 z_{t-1} + \alpha_3 \ln h_{t-1} + \beta_{IVI} IVI_{t-1} + \beta_{AOV} AOV_{t-1} + \beta_{ASV} ASV_{t-1}$$

where IVI_{t-1} is one lag weighted implied volatility generated from eight options nearest to the money and nearest time to maturity using settlement price at close on day t-1. AOV_{t-1} and ASV_{t-1} are measurements of the abnormal trading volume on day t-1 relative to its one-week lagged moving average of stocks and options respectively.

	AIG	GM	GE	HPQ	IBM	TXN	JNJ	WMT	XRX	SPX
Panel A: Akaike information criterion										
(1)	-6.082	-6.327	-4.957	-5.286	-6.244	-5.000	-6.602	-6.142	-5.422	-6.988
(2)	-6.102	-6.339	-4.966^	-5.334	-6.306	-5.047	-6.620	-6.144	-5.439	-7.047
(3)	-6.100	-6.331	-4.960	-5.307	-6.278	-4.969	-6.605	-6.142	-5.423	-6.990
(4)	-6.093	-6.329	-4.943	-5.293	-6.281	-5.002	-6.606	-6.140	-5.436	-6.986
(5)	-6.098	-6.330	-4.960	-5.334	-6.283	-5.025	-6.605	-6.140	-5.431	-6.988
(6)	-6.117^	-6.346^	-4.966^	-5.340	-6.312	-5.057^	-6.621	-6.142	-5.438	-7.049^
(7)	-6.103	-6.341	-4.965	-5.333	-6.307	-5.045	-6.620	-6.146^	-5.437	-7.047
(8)	-6.116	-6.344	-4.965	-5.341^	-6.313^	-5.056	-6.623^	-6.145	-5.440^	-7.047
Panel B: Schwarz information criterion										
	AIG	GM	GE	HPQ	IBM	TXN	JNJ	WMT	XRX	SPX
(1)	-6.056	-6.301	-4.931	-5.260	-6.218	-4.974	-6.576	-6.116	-5.397	-6.962
(2)	-6.072	-6.309	-4.936^	-5.303	-6.276	-5.017	-6.590^	-6.114	-5.409^	-7.017^
(3)	-6.069	-6.301	-4.929	-5.277	-6.247	-4.939	-6.575	-6.112	-5.393	-6.959
(4)	-6.063	-6.299	-4.913	-5.263	-6.251	-4.971	-6.575	-6.110	-5.405	-6.956
(5)	-6.064	-6.296	-4.926	-5.299	-6.249	-4.990	-6.571	-6.106	-5.397	-6.953
(6)	-6.082^	-6.311^	-4.932	-5.305^	-6.278^	-5.022^	-6.587	-6.108	-5.403	-7.014
(7)	-6.068	-6.307	-4.930	-5.298	-6.273	-5.011	-6.585	-6.111	-5.403	-7.012
(8)	-6.077	-6.305	-4.926	-5.302	-6.274	-5.017	-6.584	-6.117^	-5.401	-7.008

Notes: The Akaike information criterion is defined as the obtained maximum log-likelihood, penalised for the number of coeffients in the model $AIC = -2l/T + 2k/T$ where l is log-likelihood, k is the number of parameters and T is the number of observations. The Schwarz criterion is an alternative to AIC which imposes a larger penalty for additional coefficient (s). The results are reported for the period from 2 January 2003 to 21 November 2007. The hat sign (^) highlights the model of best fit.

empirical fit which would help to address the question of how to best model the conditional variance of stock return. While the AIC criterion in panel A provides an overwhelming evidence supporting a nested model of the implied volatility and trading volume (being specified as either an integrated IVI-AOV-EGARCH (1,1) model in row 6 or an integrated IVI-AOV-ASV-EGARCH (1,1) model in row 8), a greater penalty on additional coefficients imposed by the Schwarz criterion means that the former seems to provide the most suitable specification overall. This verdict is broadly consistent with the insignificant evidence of any additional information content of stock trading volume found previously.

Table 2.5

Statistics of the in-sample performance

with daily squared return being used as the realised volatility

The specification of models underlying the results reported is as follows

$$r_t = \mu_1 + \mu_2 r_{t-1} + \varepsilon_t$$

$$\varepsilon_t = \sqrt{h_t}\, z_t$$

$$z_t \sim N(0,1)$$

$$(1)\ \ln(h_t) = \alpha_0 + \alpha_1 |z_{t-1}| + \alpha_2 z_{t-1} + \alpha_3 \ln h_{t-1}$$

$$(2)\ \ln(h_t) = \alpha_0 + \alpha_1 |z_{t-1}| + \alpha_2 z_{t-1} + \alpha_3 \ln h_{t-1} + \beta_{IVI} IVI_{t-1} + \beta_{Aov} AOV_{t-1} + \beta_{ASV} ASV_{t-1}$$

$$(3)\ \ln(h_t) = \alpha_0 + \alpha_1 |z_{t-1}| + \alpha_2 z_{t-1} + \alpha_3 \ln h_{t-1} + \beta_{IVI} IVI_{t-1}$$

$$(4)\ \ln(h_t) = \alpha_0 + \alpha_1 |z_{t-1}| + \alpha_2 z_{t-1} + \alpha_3 \ln h_{t-1} + \beta_{Aov} AOV_{t-1}$$

$$(5)\ \hat{\sigma}_t^2 = \alpha_0 + \mu_1 (\hat{h}_{IVI-egarch})_t + \mu_2 (\hat{h}_{AOV-egarch})_t$$

$$(6)\ \hat{\sigma}_t^2 = \alpha_0 + \mu_1 (\hat{IVI})_t + \mu_2 (\hat{h}_{AOV-egarch})_t$$

where IVI $_{t-1}$ is one lag weighted implied volatility generated from eight options nearest to the money and nearest time to maturity using settlement price at close on day t-1. AOV $_{t-1}$ and ASV $_{t-1}$ are measurements of the abnormal trading volume on day t-1 relative to its one-week lagged moving average of stocks and options respectively.

		AIG	GE	GM	HPQ	IBM	TXN	JNJ	WMT	XRX	SPX
Panel A EGARCH (1,1)	MAE	0.0468	0.0417	0.1220	0.0834	0.0464	0.1048	0.0468	0.0474	0.0637	0.0230
	MAPE	120.444	58.082	112.293	45.383	194.833	43.158	202.897	120.069	12.577	7547.419
	MALE	1.8504	1.7942	1.8156	1.6597	1.9711	1.6589	2.2289	1.8381	1.5199	2.2615
	LINEX	0.0008	0.0014	0.0022	0.0014	0.0023	0.0036	0.0035	0.0027	0.0002	0.0003
Panel B: IVI-EGARCH (1,1)	MAE	0.0493	0.0288^	0.1395	0.0943	0.0327^	0.1118	0.0235^	0.0342^	0.0749	0.0159^
	MAPE	116.024^	46.470^	121.198	69.110	131.045^	57.789	93.852^	79.521^	29.999	4409.740^
	MALE	1.8388^	1.6542^	1.9494	1.8653	1.8067^	1.7589	1.8644^	1.7935^	1.7134	1.8540^
	LINEX	0.0014	0.0003^	0.0067	0.0026	0.0003^	0.0045	0.0002^	0.0003^	0.0015	0.0001^
Panel C: AOV-EGARCH (1,1)	MAE	0.0522	0.0296^	0.1396	0.0938	0.0327^	0.1094	0.0235^	0.0342^	0.0750	0.0160^
	MAPE	210.828	57.788^	121.149	70.845	133.868^	59.206	93.287^	79.905^	29.895	4655.127^
	MALE	1.8292^	1.6519^	1.9486	1.8598	1.8019^	1.7479	1.8602^	1.7935^	1.7142	1.8526^
	LINEX	0.0036	0.0004^	0.0067	0.0025	0.0003^	0.0037	0.0002^	0.0003^	0.0015	0.0001^
Panel D IVI-AOV-EGARCH (1,1)	MAE	0.0516	0.0294^	0.1399	0.0931*	0.0329^	0.1092*	0.0237^	0.0342^	0.0762	0.0160^
	MAPE	173.312	55.011^	121.106*	70.548	134.262^	59.840	94.636^	79.586^	30.381	4655.039^
	MALE	1.8306^*	1.6522^*	1.9468*	1.8534*	1.8024^*	1.7482*	1.8609^*	1.7937^	1.7154	1.8526^*
	LINEX	0.0027	0.0003^	0.0069	0.0024*	0.0003^	0.0037*	0.0002^	0.0003^	0.0018	0.0001^*
Panel E: COMB(IVI-EGARCH(1,1),AOV-EGARCH(1,1))	MAE	0.0482*	0.0289^	0.1360*	0.0939*	0.0324^*	0.1103*	0.0234^*	0.0341^*	0.0754	0.0155^*
	MAPE	120.491	45.481^*	114.395*	58.147*	130.303^*	61.274	92.017^*	84.277^	30.673	4706.712^
	MALE	1.9562	1.6407^*	1.9724	1.8278*	1.8052^*	1.7655	1.8639^*	1.7826^*	1.7249	1.8840^
	LINEX	0.0007^*	0.0003^	0.0047*	0.0028	0.0003^*	0.0033^*	0.0002^*	0.0003^	0.0015	0.0001^*
Panel F: COMB (AOV-EGARCH (1,1), IVI)	MAE	0.0495	0.0300^	0.1358*	0.0943*	0.0327^	0.1109*	0.0235^	0.0340^*	0.0771	0.0157^*
	MAPE	131.506	54.103^	121.214	55.791*	128.420^*	59.630	86.285^*	85.881^	34.387	5290.427^
	MALE	1.9298	1.6949^	1.9503	1.8195*	1.7795^*	1.7580*	1.8756^	1.7813^*	1.7720	1.8745^
	LINEX	0.0007^*	0.0002^*	0.0048*	0.0028	0.0003^	0.0034^*	0.0001^*	0.0003^	0.0013*	0.0001^*

Note: This table represents the in-sample fitting performance in term of different statistical loss functions, including the mean absolute error (MAE), the mean absolute percentage error (MAPE), the mean absolute logarithmic error (MALE) and the linear exponential function (LINEX), using annualised measurement of volatility and its forecasts. Details of the calculation and interpretation of these metrics can be referred to in Gospodinov et al (2001) . The results are reported for the period from 2 January 2003 to 21 November 2007. Statistics with the hat sign(^) and the asterisk sign (*) show better performance relative to the benchmark EGARCH (1,1) model and the integrated IVI-EGARCH (1,1) model respectively.

To provide further insight into the impact of incorporating both factors into the ARCH framework, Table 2.5 sets out four common statistics of the in-sample performance, namely the MAE, MAPE, MALE and LINEX. Considering the insignificance of stock trading volume in the evidence at this stage, the set of models of our interest encompasses different forms of integrating the option implied volatility (IVI) and the abnormal option volume (AOV) into the EGARCH (1,1) specification in panel B through to D, and two combined forecasts in panel E and F.

While the integrated models are central in validating the information content of option implied volatility and trading volume in our previous discussion, the practice of combining forecasts introduces a novel way to account for the separate effects of those factors. This paper proposes two alternate models out of many different specifications which are capable of optimally utilizing different information sets possessed by option implied volatility and trading volume to improve forecasts. One employs forecasts generated by each of the augmented IVI-EGARCH (1,1) model and the augmented AOV-EGARCH (1,1) model conditional on past information, while another makes use of naïve forecasts from option implied volatility combined with forecasts of the AOV-EGARCH (1,1) model. Both forms of combined forecasts can be obtained in a joint linear regression defined as follow

$$\hat{\sigma}_t^2 = \alpha_0 + \mu_1(\hat{h}_{IVI-egarch})_t + \mu_2(\hat{h}_{AOV-egarch})_t \tag{4}$$

$$\hat{\sigma}_t^2 = \alpha_0 + \mu_1(IV\hat{I})_t + \mu_2(\hat{h}_{AOV-egarch})_t \tag{5}$$

where $(\hat{h}_{IVI-egarch})_t, (\hat{h}_{AOV-egarch})_t$ are forecasts generated from integrating lagged option implied volatility and lagged abnormal option trading volume respectively into an

EGARCH (1,1) model; $\hat{IVI}_t$ is the naïve forecast derived from the historical implied volatility, which means $\hat{IVI}_t = IVI_{t-1}$ where *IVI* is the implied volatility prevailing in the market at time (t-1). Though the parameter estimates of the combining regressions for the in-sample period are not presented here, it is noticed that the statistical significance of μ_1 and μ_2 suggests that implied volatility and trading volume each possesses different information sets with regards to the future dynamics of volatility. Hence, one's contribution to improve volatility forecast is independent of another.

With daily squared return being used to measure the realized volatility in Table 2.5, it is clearly depicted that the introduction of either option implied volatility or volume or both into the EGARCH (1,1) variance equation in Panel B through F helps to reduce the gap between the model estimate of volatility and the actual volatility. This is illustrated by an improvement across the majority of the sample. While the MAE results show no clear distinction between the relative performances between models on a cross-sectional basis, models of combining forecasts in the last two panels outperform the EGARCH (1,1) model under the LINEX criterion. Of particular interest, while MAPE seems to favour the IVI- EGARCH (1,1) model in panel B, the AOV-EGARCH (1,1) model in panel C is more preferred under the MALE statistic cross-sectionally. Consequently, the integration of both factors into the EGARCH (1,1) model shown in panel D leads to its outperformance over each of the IVI-EGARCH (1,1) model and the AOV-EGARCH (1,1) model under MALE and MAPE respectively. Another interesting observation is that two combined forecasts perform relatively better than the IVI-GARCH (1,1) model for the majority of stocks in the sample. The model which combines forecasts of the IVI-EGARCH (1,1) model and of the AOV-EGARCH (1,1) model in particular provides the best performance, as one observes much lower MAPE across the board relative to the rest of the models.

It is worth noting that the MAPE is relatively high across the table. One possibility is bad proxy being used while another points to a poor forecast performance due to model misspecifications. We re-examine these aspects by (1) comparing the characteristics of different proxies of realized volatility and (2) by re-assessing the performance of these models in a different context in later analyses (viz., Table 2.6 where the sum of intra-day squared returns at 5-minute intervals provides a more appropriate proxy of daily realised volatility, see Poon and Granger (2003)). In sum, the proper inference seems to be that daily squared returns misrepresent the true latent volatility process [11] [refer to Andersen and Bollerslev (1998); Andersen et al. (1999) for a formal scrutiny]. To avoid misleading results inherent from this problem, we therefore use the 22-day-average daily squared returns as an alternative to proxy for daily realized volatility, similar to Gospodinov, Gavala et al. (2006). Results, not being reproduced here, yield a very similar observation of forecast improvement while the MAPE statistic is maintained at a reasonable level of less than 1 at this instance.

Overall, the in-sample evidence thus far demonstrates that the combination of both factors either by way of integrating them in an EGARCH (1,1) variance equation or through the exercise of combining forecasts leads to a better performance than the use of option implied volatility alone.

[11] A possibility of model specifications is also unlikely since we found the performance of all models worsened after applying the ad-hoc intercept-correction proposed by Gospodinov, et al (2006).

2.4.2. Out-of-sample forecast performance

In this section, the out-of-sample forecast performance of six models previously considered is assessed based on the statistical criteria and the economic significance of forecast accuracy obtained through trading simulation, in direct comparison to three other techniques specified in the methodology section. The forecast exercise is performed for the period from 24th October 2007 to 30th June 2008 by repetitively rolling the whole set of data input following the in-sample period. In the other words, the oldest data is dropped whenever a new observation is added.

For our out-of-sample tests we examined a host of alternate proxies to measure the latent realized volatility. We settle on producing in this paper the outcome from using intra-day squared returns, simply because it is a widely practiced method and the results differ little when applying other measures, such as the rolling daily averages used for the in-sample results. Intra-day data does, however, have the advantage of utilizing the most recent information sets available to determine the forecast horizon.

2.4.2.1. Statistics of forecast accuracy

Table 2.6 reports the out-of-sample forecast performance expressing in term of different statistical loss functions analogous to those presented in the in-sample test in Table 2.5. Panel A comprises of three alternate models which we have developed in an attempt to employ a synthesis of option implied volatility and trading volume to derive forecasts, namely the integrated IVI-AOV-EGARCH (1,1) model specified in equation (1) and two combined forecasting models specified in equation (4) and (5). Results of forecasts generated from many different benchmarks, either being drawn from the ARCH approach or other techniques, are summarized in panel B, following the same criteria. These panels address a number of questions of interest, including (1) whether the synthesis of option implied volatility and trading volume (a) helps to improve forecasts generated from the ARCH approach and (b) performs better than each component standing alone within the ARCH framework, and (2) how it performs relative to other forecasting techniques prominent in literature.

To briefly summarise the results presented in Table 2.6, we find some evidence of forecast improvement consistently spanning across different error measures and model specifications considered in Panel A even though the cross-sectional performance of our models does not fare as well as in the sample. Of particular interest, a combination of naïve forecasts of option implied volatility and forecasts generated from the integration of volume into an EGARCH (1,1) model in subpanel A3 clearly dominates all the benchmark models considered in Panel B. Another interesting observation is a significant reduction in the MAPE statistic relative to results reported in the in-sample test, as one would expect. This confirms the use of squared returns to proxy the actual volatility itself leads to the overestimation of MAPE. Diagnostics presented in subpanel A1 to B3 indicate that all models of the EGARCH family perform relatively well. A cross-check on other competing models highlights they uniformly perform better than the PCA and the SVM in subpanel B5 and B6 while two combined forecasts slightly dominate the ARMA (1,1) model in subpanel B4. The robustness of these findings has also been confirmed in other forecasts exercises with longer horizon (such as weekly and monthly forecasting) whose results are available upon request.

Table 2.6

Statistics of the out-of-sample performance

with intra-day squared return being used as the realised volatility

Panel A comprises of different model specifications which incorporate the information sets of both option implied volatility and trading volume within the EGARCH (1,1) framework, including the integrated EGARCH (1,1) model (Panel A1), the combined forecast of the IVI-EGARCH (1,1) and the AOV-EGARCH (1,1) (Panel A2), as well as the combined forecast of the AOV-EGARCH (1,1) and option implied volatility (Panel A3). Their performance will be compared to the benchmark EGARCH (1,1) model (Panel B1), the integrated IVI- EGARCH (1,1) model (Panel B2), the integrated AOV-EGARCH(1,1) model (Panel B3), the ARMA (1,1) model (Panel B4), the Principal Component Analysis model (Panel B5) and the stochastic volatility model (Panel B6). Details of models in panel A1 through to B3 are anologous to those presented in the in-sample test in Table 5, while the specifications of the last three models can be found in equation (3) (4) and (5) in the methodology section.

Panel A : Our models											
		AIG	GE	GM	HPQ	IBM	TXN	JNJ	WMT	XRX	SPX
Panel A1: IVI-AOV-EGARCH (1,1)	MAE	0.2673	0.0983	0.2461*	0.0732^	0.0671	0.0969^*	0.0148^*	0.0434^	0.0656^*	0.0291
	MAPE	1.8976*	1.9368	1.2868*	0.5874^	0.7742*	0.7304^*	0.8436^*	0.6278^*	0.9584*	0.9362
	MALE	0.9362	0.7512	0.7876*	0.5889^	0.6608	0.6797^*	0.6836^*	0.6840^*	0.6131^*	0.6446
	LINEX	0.0401	0.0113	0.0307*	0.0014^	0.0015	0.0019^	0.0001^*	0.0003*	0.0021	0.0006*
Panel A2: COMB(IVI-EGARCH(1,1),AOV-EGARCH(1,1))	MAE	0.1792^*	0.0759	0.2204*	0.0728^*	0.0611*	0.0961^*	0.0154^	0.0437^	0.0679	0.0269*
	MAPE	0.8075^*	1.3401	1.0308^*	0.6311^	0.6158*	0.7331^*	0.9271	0.6299^*	0.9515*	0.8224*
	MALE	0.7380^*	0.7730	0.7255*	0.5925	0.6030*	0.6714^*	0.7022^*	0.6900^	0.6454	0.6068*
	LINEX	0.0064^*	0.0014	0.0194*	0.0016^	0.0010*	0.0018^	0.0001	0.0003^*	0.0020*	0.0005*
Panel A3: COMB (AOV-EGARCH (1,1), IVI)	MAE	0.1785^*	0.0729	0.2227*	0.0744	0.0652*	0.0988	0.0147^*	0.0425^*	0.0643^*	0.0279*
	MAPE	0.9379^*	0.9358^*	1.0471^*	0.6066^	0.7889	0.7445^*	0.8333^*	0.6544^	0.8357^*	0.9068*
	MALE	0.7191^*	0.6810^*	0.7319*	0.6320	0.6405*	0.6979^	0.6691^*	0.6619^*	0.5950^*	0.6308
	LINEX	0.0072^*	0.0028	0.0189*	0.0014^	0.0014	0.0018^	0.0001^*	0.0004	0.0015^*	0.0005*
Panel B: Benchmark models											
		AIG	GE	GM	HPQ	IBM	TXN	JNJ	WMT	XRX	SPX
Panel B1: EGARCH (1,1)	MAE	0.1849	0.0697	0.2101	0.0734	0.0596	0.0985	0.0154	0.0450	0.0676	0.0266
	MAPE	0.9716	1.0623	1.0769	0.7348	0.5089	0.8798	0.9222	0.6884	0.9405	0.6541
	MALE	0.7504	0.7366	0.7049	0.5914	0.5996	0.7009	0.7074	0.7210	0.6418	0.5946
	LINEX	0.0097	0.0008	0.0173	0.0020	0.0007	0.0021	0.0001	0.0003	0.0020	0.0003
Panel B2: IVI-EGARCH (1,1)	MAE	0.2557	0.0685^	0.2551	0.0730^	0.0656	0.0973^	0.0153^	0.0434^	0.0657^	0.0285
	MAPE	1.9638	1.0292^	1.3350	0.5708^	0.7864	0.7543^	0.9257	0.6342^	0.9603	0.9156
	MALE	0.9095	0.7109^	0.8102	0.5844^	0.6531	0.6885^	0.7100	0.6870^	0.6198^	0.6301
	LINEX	0.0379	0.0009	0.0317	0.0012^	0.0014	0.0017^	0.0001^	0.0003	0.0020	0.0006
Panel B3: AOV-EGARCH (1,1)	MAE	0.2198	0.0992	0.1975^	0.0793	0.0634	0.0984^	0.0151^	0.0444^	0.0661^	0.0274
	MAPE	1.2744	1.9383	0.8135^	0.7628	0.5849	0.8889	0.8653^	0.6092^	0.8731^	0.6789
	MALE	0.7975	0.7727	0.6506^	0.6687	0.6610	0.7023	0.6873^	0.7092^	0.6298^	0.6153
	LINEX	0.0232	0.0111	0.0129^	0.0018^	0.0010	0.0024	0.0001	0.0003^	0.0019^	0.0003^
Panel B4: ARMA (1,1)	MAE	0.1959*	0.0773	0.2105*	0.0783	0.0618*	0.1017	0.0146^*	0.0447^	0.0692	0.0328
	MAPE	1.0551*	1.2911	0.8820^*	0.6886^	0.5496*	0.8786^	0.8676^*	0.7078	0.6896^*	1.1065
	MALE	0.8043*	0.7899	0.7100*	0.6527	0.6420*	0.7432	0.6903^*	0.7126^	0.6838	0.7411
	LINEX	0.0106*	0.0015	0.0107^*	0.0012^*	0.0007^*	0.0017^	0.0001^*	0.0004	0.0009^*	0.0005*
Panel B5: PCA	MAE	0.2891	0.1216	0.2852	0.1229	0.1053	0.1575	0.0226	0.0694	0.1255	0.0504
	MAPE	1.8362*	2.1816	1.1185*	1.4757	1.3277	1.6464	1.2352	1.2807	1.5290	1.5860
	MALE	2.3629	1.2373	1.7228	2.7692	2.0239	2.3940	2.6267	1.3865	2.0297	1.5212
	LINEX	0.0358*	0.0178	0.0438	0.0082	0.0053	0.0108	0.0002	0.0026	0.0092	0.0016
Panel B6: SVM	MAE	0.2269*	0.0788	0.6318	0.8441	0.1684	0.1182	0.4321	0.4085	0.4422	0.0361
	MAPE	1.5391*	1.4672	3.3144	15.5947	3.2130	1.3974	35.4781	13.8973	8.6155	1.3625
	MALE	0.8951*	0.8020	1.2628	2.1168	1.0333	0.8462	2.1115	1.7629	1.6781	0.7896
	LINEX	0.0219*	0.0021	0.2266	0.3006	0.0353	0.0046	0.1804	0.1188	0.1219	0.0007

Note: This table represents the out-of-sample forecast performance in term of different statistical loss functions, including the mean absolute error (MAE), the mean absolute percentage error (MAPE), the mean absolute logarithmic error (MALE) and the linear exponential function (LINEX) , using annualised measurement of volatility and its forecasts. Details of the calculation and interpretation of these metrics can be referred to in Gospodinov et al (2001) . The results are reported for daily forecasts over the period from 24 November 2007 to 30 June 2008. Statistics with the hat sign(^) and the asterisk sign (*) shows better performance relative to the benchmark EGARCH (1,1) model and the integrated IVI-EGARCH (1,1) model respectively.

Table 2.7

The direction forecast performance for the out of sample period with different alternate measures of realised volatility

Details of models in panel A1 through to B6 are anologous to those presented in Table 6, including the integrated IVI-AOV-EGARCH (1,1) model (Panel A1), the combined forecast of the IVI-EGARCH (1,1) and the AOV-EGARCH (1,1) (Panel A2), the combined forecast of the AOV-EGARCH (1,1) and option implied volatility (Panel A3), the benchmark EGARCH (1,1) model (Panel B1), the integrated IVI- EGARCH (1,1) model (Panel B2), the integrated AOV-EGARCH(1,1) model (Panel B3), the ARMA (1,1) model (Panel B4), the Principal Component Analysis model (Panel B5) and the stochastic volatility model (Panel B6). Three alternative measures have been used to proxy the latent realised volatility, including the daily squared returns, the 22-day-average squared returns and the sum of intra-day squared returns.

		AIG	GE	GM	HPQ	IBM	TXN	JNJ	WMT	XRX	SPX
Panel A : Our models											
Panel A1: IVI-AOV-EGARCH (1,1)	daily	45.26^*	32.85^*	50.36^*	37.23*	35.77^*	55.47^	27.74^	37.23^*	34.31^*	52.55^
	22-day-average	48.91*	43.80^*	49.64	51.82*	51.82^*	50.36	39.42	43.80^*	45.99*	60.58^
	intra-day	56.93^	51.09^*	47.45	49.64*	45.99	53.28^*	46.72	43.80	48.18	46.72
Panel A2: COMB(IVI-EGARCH(1,1),AOV-EGARCH(1,1))	daily	36.50	27.74	49.64^	42.34*	29.93	57.66^	21.17	35.77^	32.12^*	45.99^
	22-day-average	51.82*	38.69	53.28*	51.09*	45.99^	58.39*	41.61	42.34^*	50.36^*	59.12^
	intra-day	48.18^	44.53	49.64^	51.82*	43.07	56.93^*	45.99	42.34	51.09*	47.45
Panel A3: COMB (AOV-EGARCH (1,1), IVI)	daily	46.72^*	35.77^*	52.55^*	42.34*	32.85^*	48.18	29.20^*	40.15^*	41.61^*	50.36^
	22-day-average	53.28*	48.18^*	48.91	51.09*	47.45^*	47.45	39.42	51.09^*	43.07	58.39^
	intra-day	55.47^	49.64*	49.64^	44.53	41.61	47.45	48.18^*	45.26^	51.82^*	45.99
Panel B: Benchmark models											
		AIG	GE	GM	HPQ	IBM	TXN	JNJ	WMT	XRX	SPX
Panel B1: EGARCH (1,1)	daily	37.96	31.39	43.07	46.72	29.93	51.82	21.90	34.31	29.20	37.23
	22-day-average	53.28	40.88	58.39	55.47	43.07	59.85	42.34	37.23	45.99	52.55
	intra-day	46.72	49.64	47.45	51.82	45.99	51.09	46.72	44.53	51.09	50.36
Panel B2: IVI-EGARCH (1,1)	daily	40.15^	29.93	49.64^	35.04	31.39^	57.66^	27.74^	36.50^	29.20	54.74^
	22-day-average	48.18	42.34^	50.36	48.18	45.99^	56.93	43.80^	41.61^	44.53	62.77^
	intra-day	57.66^	46.72	54.01^	47.45	45.99	52.55^	46.72	45.99^	48.91	47.45
Panel B3: AOV-EGARCH (1,1)	daily	40.88^	35.77^	46.72^	49.64^	29.93	45.26	25.55^	37.23^	31.39^	37.96^
	22-day-average	45.99	42.34^	50.36	49.64	38.69	50.36	41.61	48.18^	45.26	54.74^
	intra-day	49.64^	51.09^	45.26	50.36	41.61	48.91	44.53	48.18^	47.45	48.18
Panel B4: ARMA (1,1)	daily	25.55	29.20	27.01	42.34*	33.58^*	52.55^	44.53^*	32.12	34.31^*	24.09
	22-day-average	45.26	41.61^	54.01*	48.18	42.34	40.15	43.07^	36.50	45.99*	43.07
	intra-day	45.99	51.82^*	45.99	45.99	49.64^*	60.58^*	51.82^*	51.09^*	45.26	43.07
Panel B5: PCA	daily	31.39	32.85^*	31.39	33.58	35.04^*	34.31	37.96^*	39.42^*	31.39^*	33.58
	22-day-average	46.72	41.61^	56.93*	40.15	39.42	40.15	39.42	39.42^	43.80	43.07
	intra-day	45.99	46.72	45.99	44.53	45.99	43.80	44.53	43.80	43.80	46.72
Panel B6: SVM	daily	52.55^*	45.99^*	42.34	27.01	48.91^*	45.99	36.50^*	34.31	45.26^*	38.69^
	22-day-average	50.36*	46.72^*	40.15	31.39	59.12^*	51.09	39.42	38.69^	46.72^*	48.18
	intra-day	49.64^	45.26	41.61	30.66	54.74^*	37.96	32.12	38.69	44.53	43.07

Note: This table represents the out-of-sample forecast performance in term of correct forecast of directional changes in volatility. The mean correct prediction statistic presented above can be defined as the percentage of observations for which the model predicts a change of the same sign as the realized change in volatility. The results are reported for daily forecasts over the period from 24 November 2007 to 30 June 2008. Statistics with the hat sign(^) and the asterisk sign (*) shows better performance relative to the benchmark EGARCH (1,1) model and the integrated IVI-EGARCH (1,1) model respectively.

The role of trading volume can be highlighted by a consistent improvement of the direction forecast performance presented in Table 2.7 when different measures of realized volatility are considered. It is found in Panel A that trading volume helps to increase the percentage of correct direction of forecasts of (i) the EGARCH model, (ii) the option implied volatility and (iii) both, no matter whether it is integrated into the EGARCH model or whether the exercise of combining forecasts is applied. The evidence becomes overwhelming in case daily squared returns are used to proxy the realized volatility. Moving across the table, the ARMA (1,1) and the PCA are clearly the worst performers. The SVM, while performing comparably to the benchmark EGARCH (1,1) model in subpanel B1, is surpassed by our proposed models in subpanel A1 and A3. This particular finding further anchors the forecast quality of trading volume. Overall, the combined forecast in subpanel A3 again provides the best performance in a horse race among all models, as one would expect.

To get additional perspective on the forecast performance of a synthesis of option implied volatility and trading volume, we perform the orthogonality test by regressing the realized volatility on one or multiple forecasts of all models being covered thus far. For brevity, we only reported in Table 2.8 statistics of the Mincer-Zarnowitz regression for each model's forecasts of the S&P500 index return volatility. At the first glance, it clearly shows that all models of the EGARCH family fare better than other forecasting techniques when considering the statistical significance and the magnitude of β estimates obtained in columns (1) to (6) in contrast to the rest. The R squared (or the adj-R squared) and the maximum likelihood at the bottom of the table, however, stimulates that daily variations of volatility are best captured by forecasts generated from the integrated IVI-AOV-EGARCH (1,1) model or from the integrated AOV-EGARCH (1,1) model. Furthermore, all those statistics agrees that a combination of forecasts generated from the integrated IVI-EGARCH (1,1) and the integrated AOV-EGARCH (1,1) model dominates the EGARCH (1,1) model.

Table 2.8

The orthogonality test of the volatility forecasts of the S&P500 index returns with intra-day squared return being used as the realised volatility

Details of models (1) to (9) are anologous to those presented in Table 6 & 7, including (1) the integrated IVI-AOV-EGARCH (1,1) model , (2) the combined forecast of the IVI-EGARCH (1,1) and the AOV-EGARCH (1,1), (3) the combined forecast of the AOV-EGARCH (1,1) and option implied volatility, (4) the benchmark EGARCH (1,1) model , (5) the integrated IVI-EGARCH (1,1) model , (6) the integrated AOV-EGARCH(1,1) model, (7) the ARMA (1,1) model, (8) the Principal Component Analysis model and (9) the stochastic volatility model. The results are reported for daily forecasts over the period from 24 November 2007 to 30 June 2008.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
α	0.0001	0.0001	0.0000	0.0000	0.0001	0.0000	0.0002	0.0002	0.0002
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0000)***	(0.0000)***	(0.0000)***
β	0.7486	0.8568	1.1605	1.1768	0.6354	1.4697	0.0262	0.0096	0.1131
	(0.2257)***	(0.2673)***	(0.4116)***	(0.4036)***	(0.2263)***	(0.4356)***	(0.0680)	(0.0358)	(0.1999)
R_2	0.0753	0.0707	0.0556	0.0592	0.0552	0.0778	0.0011	0.0005	0.0024
Adj R_2	0.0685	0.0638	0.0486	0.0523	0.0482	0.0709	-0.0063	-0.0069	-0.0050
Log likelihood	960.25	959.91	958.81	959.07	958.78	960.43	954.96	954.92	955.05

Note: This table represents the statistics of the Mincer-Zarnowitz regression in which the realised volatility is regressed against a constant and the forecasted volatility as follows

$$\sigma_t^2 = \alpha + \beta\hat{\sigma}_t^2 + e_t$$

*** indicates rejection at the 1% significance level.

2.4.2.2. Economic significance

The economic significance of the volatility forecast exercise we have preceded thus far is the next focus of our analysis. Albeit the forecast exercise has been conducted for different forecast horizons, we only report in Table 2.9 simulated results of the ATM-straddle trading strategy based on daily volatility forecasts, being expressed in term of the Sharpe ratio (SR), the Leland's alpha (Ap) and their bootstrapped 95% confidence intervals. While the SR is arguably the most commonly employed criterion of evaluating portfolio performance in the existing literature, the Ap provides a better reference of the profitability of non-linear payoffs by taking into account higher-order moments of the return distributions to accommodate deviations from normality. This problem is especially acute in the context of option trading being investigated in this paper.

Table 2.9

Out of sample trading simulation using daily volatility forecasts

Option straddles have been employed to trade on volatility forecasts generated from alternative forcast models. This trading strategy involves undertaking simultenously long (short) positions on ATM option contracts with the same exercise and time to maturity when future volatility is expected to increase (decrease). Daily volatility forecasts are generated by rolling the sample forward and re-estimating the model's parameters on a daily basis over the period from 24 November 2007 to 30 June 2008.

The strategy is based on daily forecasts obtained from the integrated IVI-AOV-EGARCH (1,1) model (Panel A1), the combined forecast of the IVI-EGARCH (1,1) and the AOV-EGARCH (1,1) (Panel A2), the combined forecast of the AOV-EGARCH (1,1) and option implied volatility (Panel A3), the benchmark EGARCH (1,1) model (Panel B1), the integrated IVI-EGARCH (1,1) model (Panel B2), the integrated AOV-EGARCH(1,1) model (Panel B3), the ARMA (1,1) model (Panel B4), the Principal Component Analysis model (Panel B5) and the stochastic volatility model (Panel B6). In addition, profit is determined for a strategy of purely going long on ATM straddles in Panel B7.

Panel A : Our models

		AIG	GE	GM	HPQ	IBM	TXN	JNJ	WMT	XRX	SPX
Panel A1: IVI-AOV-EGARCH (1,1)	Sharpe Ratio	0.261**	-0.104	0.010	-0.017	0.061	0.019	0.151**	-0.111	0.113	-0.050
	95% CI	(0.154)	-(0.228)	-(0.134)	-(0.137)	-(0.077)	-(0.138)	(0.014)	-(0.237)	-(0.026)	-(0.190)
		(0.367)	(0.012)	(0.137)	(0.126)	(0.211)	(0.160)	(0.272)	(0.009)	(0.262)	(0.100)
	Ap	0.117**	-0.072	0.005	-0.009	0.030	0.012	0.056**	-0.050	0.052	-0.018
	95% CI	(0.059)	-(0.162)	-(0.067)	-(0.062)	-(0.039)	-(0.053)	(0.003)	-(0.125)	-(0.015)	-(0.072)
		(0.183)	(0.012)	(0.069)	(0.061)	(0.109)	(0.062)	(0.104)	(0.011)	(0.124)	(0.036)
Panel A2: COMB(IVI-EGARCH(1,1),AOV-EGARCH(1,1))	Sharpe Ratio	-0.036	-0.011	-0.002	-0.002	0.017	0.028	0.071	-0.110	0.100	-0.079
	95% CI	-(0.199)	-(0.152)	-(0.127)	-(0.138)	-(0.116)	-(0.129)	-(0.074)	-(0.225)	-(0.031)	-(0.220)
		(0.104)	(0.127)	(0.148)	(0.159)	(0.146)	(0.173)	(0.213)	(0.034)	(0.269)	(0.055)
	Ap	-0.018	-0.004	-0.001	-0.002	0.009	0.016	0.031	-0.049	0.046	-0.028
	95% CI	-(0.092)	-(0.104)	-(0.064)	-(0.058)	-(0.053)	-(0.051)	-(0.025)	-(0.113)	-(0.012)	-(0.084)
		(0.050)	(0.091)	(0.079)	(0.073)	(0.070)	(0.068)	(0.074)	(0.019)	(0.117)	(0.022)
Panel A3: COMB (AOV-EGARCH (1,1), IVI)	Sharpe Ratio	-0.052	-0.071	0.005	0.006	0.084	0.001	0.054	-0.136**	0.098	-0.073
	95% CI	-(0.207)	-(0.219)	-(0.148)	-(0.153)	-(0.060)	-(0.137)	-(0.084)	-(0.247)	-(0.041)	-(0.216)
		(0.080)	(0.067)	(0.127)	(0.148)	(0.219)	(0.121)	(0.209)	-(0.006)	(0.237)	(0.060)
	Ap	-0.025	-0.047	0.002	0.003	0.041	0.006	0.024	-0.062	0.045	-0.027
	95% CI	-(0.093)	-(0.145)	-(0.073)	-(0.064)	-(0.029)	-(0.055)	-(0.033)	-(0.127)	-(0.019)	-(0.083)
		(0.036)	(0.047)	(0.065)	(0.068)	(0.109)	(0.050)	(0.078)	(0.001)	(0.108)	(0.023)

Panel B: Benchmark models

		AIG	GE	GM	HPQ	IBM	TXN	JNJ	WMT	XRX	SPX
Panel B1: EGARCH (1,1)	Sharpe Ratio	-0.001	-0.079	0.066	0.100	0.010	0.064	0.063	-0.111	0.080	-0.098
	95% CI	-(0.160)	-(0.231)	-(0.066)	-(0.030)	-(0.143)	-(0.074)	-(0.060)	-(0.252)	-(0.065)	-(0.240)
		(0.171)	(0.050)	(0.191)	(0.225)	(0.155)	(0.214)	(0.200)	(0.041)	(0.233)	(0.038)
	Ap	-0.001	-0.053	0.030	0.044	0.005	0.031	0.028	-0.050	0.036	-0.036
	95% CI	-(0.073)	-(0.166)	-(0.033)	-(0.016)	-(0.068)	-(0.030)	-(0.022)	-(0.130)	-(0.031)	-(0.093)
		(0.080)	(0.037)	(0.098)	(0.103)	(0.078)	(0.086)	(0.073)	(0.020)	(0.108)	(0.016)
Panel B2: IVI-EGARCH (1,1)	Sharpe Ratio	0.158**	-0.078	0.008	-0.022	0.013	0.030	0.155**	-0.121	0.122	-0.041
	95% CI	(0.029)	-(0.217)	-(0.152)	-(0.162)	-(0.111)	-(0.139)	(0.019)	-(0.230)	-(0.010)	-(0.161)
		(0.289)	(0.066)	(0.164)	(0.117)	(0.145)	(0.174)	(0.294)	(0.012)	(0.248)	(0.099)
	Ap	0.071**	-0.053	0.004	-0.012	0.006	0.018	0.057**	-0.055	0.056	-0.015
	95% CI	(0.011)	-(0.156)	-(0.075)	-(0.069)	-(0.052)	-(0.054)	(0.003)	-(0.116)	-(0.006)	-(0.062)
		(0.139)	(0.051)	(0.086)	(0.053)	(0.072)	(0.068)	(0.113)	(0.010)	(0.116)	(0.037)
Panel B3: AOV-EGARCH (1,1)	Sharpe Ratio	0.014	-0.115**	-0.092	0.148**	-0.027	0.077	0.060	-0.123	0.051	-0.071
	95% CI	-(0.127)	-(0.261)	-(0.227)	(0.007)	-(0.167)	-(0.079)	-(0.065)	-(0.238)	-(0.098)	-(0.210)
		(0.171)	-(0.002)	(0.058)	-0.274	(0.126)	(0.227)	(0.194)	(0.028)	(0.179)	(0.083)
	Ap	0.004	-0.079	-0.046	0.066**	-0.013	0.036	0.027	-0.055	0.023	-0.024
	95% CI	-(0.059)	-(0.189)	-(0.115)	(0.000)	-(0.079)	-(0.030)	-(0.023)	-(0.121)	-(0.045)	-(0.081)
		(0.083)	(0.003)	(0.031)	(0.127)	(0.063)	(0.089)	(0.070)	(0.017)	(0.082)	(0.031)
Panel B4: ARMA (1,1)	Sharpe Ratio	-0.024	-0.091	0.054	0.030	-0.051	0.044	0.157**	-0.124	-0.066	-0.160**
	95% CI	-(0.179)	-(0.245)	-(0.070)	-(0.103)	-(0.181)	-(0.107)	(0.038)	-(0.256)	-(0.205)	-(0.292)
		(0.106)	(0.041)	(0.196)	(0.131)	(0.099)	(0.187)	(0.279)	(0.016)	(0.081)	-(0.017)
	Ap	-0.012	-0.063	0.026	0.012	-0.023	0.023	0.059**	-0.056	-0.031	-0.057**
	95% CI	-(0.083)	-(0.174)	-(0.036)	-(0.045)	-(0.083)	-(0.043)	(0.012)	-(0.128)	-(0.095)	-(0.114)
		(0.050)	(0.033)	(0.103)	(0.061)	(0.046)	(0.074)	(0.103)	(0.012)	(0.039)	-(0.003)
Panel B5: PCA	Sharpe Ratio	-0.134	0.098	0.022	-0.070	-0.013	-0.107	-0.138**	-0.075	-0.069	-0.017
	95% CI	-(0.262)	-(0.048)	-(0.104)	-(0.182)	-(0.172)	-(0.235)	-(0.268)	-(0.216)	-(0.207)	-(0.157)
		(0.008)	(0.227)	(0.157)	(0.066)	(0.123)	(0.022)	-(0.006)	(0.061)	(0.060)	(0.119)
	Ap	-0.064	0.064	0.012	-0.026	-0.010	-0.042	-0.049**	-0.036	-0.031	-0.005
	95% CI	-(0.126)	-(0.036)	-(0.054)	-(0.085)	-(0.078)	-(0.095)	-(0.101)	-(0.105)	-(0.096)	-(0.059)
		(0.006)	(0.165)	(0.081)	(0.030)	(0.061)	(0.010)	-(0.001)	(0.030)	(0.027)	(0.044)
Panel B6: SVM	Sharpe Ratio	-0.035	0.023	0.205**	0.156**	0.205**	-0.003	0.129	0.144**	0.106	-0.134
	95% CI	-(0.172)	-(0.097)	(0.053)	(0.019)	(0.079)	-(0.163)	-(0.011)	(0.023)	-(0.012)	-(0.267)
		(0.091)	(0.157)	(0.346)	(0.325)	(0.326)	(0.136)	(0.276)	(0.284)	(0.236)	(0.011)
	Ap	-0.015	0.011	0.102**	0.072**	0.091**	0.003	0.045	0.068**	0.054	-0.050
	95% CI	-(0.080)	-(0.067)	(0.021)	(0.010)	(0.027)	-(0.063)	-(0.006)	(0.008)	-(0.008)	-(0.103)
		(0.044)	(0.110)	(0.182)	(0.137)	(0.160)	(0.053)	(0.103)	(0.139)	(0.111)	(0.006)
Panel B7: Long position	Sharpe Ratio	0.310**	0.267**	0.303**	0.342**	0.319**	0.150**	0.267**	0.106	0.138**	0.155**
	95% CI	(0.210)	(0.161)	(0.185)	(0.245)	(0.210)	(0.007)	(0.153)	-(0.043)	(0.019)	(0.021)
		(0.418)	(0.378)	(0.406)	(0.442)	(0.424)	(0.271)	(0.375)	(0.249)	(0.277)	(0.314)
	Ap	0.138**	0.182**	0.147**	0.141**	0.143**	0.057**	0.092**	0.051	0.067**	0.052**
	95% CI	(0.080)	(0.084)	(0.075)	(0.085)	(0.084)	(0.001)	(0.046)	-(0.023)	(0.007)	(0.005)
		(0.203)	(0.278)	(0.210)	(0.210)	(0.203)	(0.109)	(0.144)	(0.124)	(0.128)	(0.117)

Note: The forecast performace can be evaluated based on the Sharpe ration and Leland's Alpha (Ap) and their respective bootstrapped 95% condifidence interval (CI). Two asterisks (**) denote the rejection of the null hypothesis of a zero Sharpe ratio (Ap) at a 5% level of significance

Without transaction costs being considered, the performance of models of the EGARCH family covered in subpanel A1 to B3 is very encouraging with positive abnormal return being obtained for a majority of the sample, even when the non-normality of the empirical distribution of trading profits are taken into account. In some occasions, the magnitude of abnormal returns well exceeds a transaction cost of around 1-2% reasonably expected for option trading, which any investor would see as a dramatic increase in wealth on a daily basis. These results, while hardly being seen in the equity market, are reasonably expected for option trading due to high leverage and stay consistent with previous findings in the literature (Guo 2000).

However, what of more interest is whether these models significantly yield abnormal returns. This being found for the integrated IVI-AOV-EGARCH (1,1) model in subpanel A1, the IVI-EGARCH (1,1) model and the AOV-EGARCH (1,1) model in subpanels B2 and B3 respectively, clearly demonstrates their outperformance over the EGARCH (1,1) model. These statistically significant returns are also associated with significantly large values of the Sharpe ratio, suggesting that their performance is truly abnormal. The dominance of the integrated IVI-AOV-EGARCH (1,1) model is of particular interest, since the results thus far show only slight differences in performance of models, which combine the information sets of both option implied volatility and trading volume, proposed in Panel A. This model also compares favourably with other two benchmarks, namely the ARMA (1,1) model and the PCA model, on a cross-sectional basis.

Nevertheless, the performance of the SVM in subpanel B6 is striking, as illustrated by findings of a statistically significant positive Leland's alpha (Shape ratio) in four cases. This result is so contrary that it induces us to re-examine the forecast quality of the

SVM to provide justification(s) of the source of abnormal returns. Given the substantial value of MAPEs being found in subpanel B6 of Table 2.6, a proper inference seems to be that abnormal returns actually stem from a persistent overestimation of forecasts for those particular stocks. Considering the fact that the SVM leads to the decision to buy for 75% to 91% of the times, this line of reasoning is further confirmed in subpanel B7 in Table 2.9 showing that abnormal returns would have been obtained in most cases (except for WMT stock) by simply going long on ATM straddles for the entire out-of-sample period.

Hence, an overall conclusion from this analysis is that the integration of option implied volatility and trading volume into the EGARCH (1,1) specification leads to outperformance relative to other competing forecasting techniques. Essentially, unreported results show that these findings are robust to different simulation set-ups[12, 13], or proxies of realized volatility[14], As one would expect, the economic gain would be reduced if consideration is made of transaction costs. While the magnitude of this impact largely depends on the size of these costs, it imposes an impediment on real trade executions to realize profit from volatility forecasts.

2.5. CONCLUSION

The implication of this study is considered not only in terms of its contribution into the current body of literature in volatility-volume relation but also of future research into

[12] Volatility trading is also simulated in this study [using the VIX futures traded on the CBOE, similar to Konstantinidi et al (2008)] and tells the same tale. The integration of either implied volatility or volume or both leads to a better performance relative to the EGARCH (1,1) model, even though a comparison to other forecasting techniques shows no clear evidence of dominance.

[13] In addition, we re-performed straddle trading simulation to assess the robustness of our findings across three different sub-out-of-sample periods, following the recursive pseudo scheme suggested by Konstantinidi et al (2008). Main findings (statistical and economic significance) are not sensitive to the period under consideration.

[14] The same trading simulation set-up was re-applied where 22-day-average squared returns are used to proxy historical volatility. This is appropriate for the purpose of option trading since its construction has been designed to match closer with the volatility input required for option pricing. Results, not being reproduced here, yield a very similar observation to the above. We omitted the use of daily squared returns for being a bad proxy in our previous discussion.

volatility modeling and forecasting. While finding evidence in compliance with the sequential information hypothesis saying that trading volume contains useful information of future stock volatility, this study suggests its importance in volatility forecasting is shared between stock and option trading volume, with the latter possessing a better forecast quality. The information share would explain the inconsistency of results in previous studies, such as (Brooks 1998; Donaldson and Kamstra 2004) among other, since they fail to adequately account for all the inherent implications of options trading activities when investigating into the volume-volatility relation. Also in this paper we provide several simple model specifications where the information content of trading volume can be utilized to improve the predictive power of the ARCH approach, or a combination of ARCH and option implied volatility. Both in and out-of-sample tests reveal the value of adding volume. In particular, we find that the accuracy of volatility forecasts can be improved by combining information from option implied volatility and volume accordingly, most markedly by integrating both factors into the variance equation of the EGARCH (1,1) model.

Key findings in this study suggest further research into the information content of trading volume would be a worthwhile endeavor to improve volatility forecasts. In particular, future studies could embark on investigating the practicability of employing trading information to improve volatility forecasts for stocks which have less liquidity on their underlying options, as this paper has only focused on examining highly liquid assets.

CHAPTER 3

THE ROLE OF TRADING VOLUME IN FORECASTING THE SMILE DYNAMICS

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STATEMENT OF AUTHORSHIP

THE ROLE OF TRADING VOLUME IN FORECASTING THE SMILE DYNAMICS

Conference Paper

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For this paper (chapter), Van Le developed the theoretical framework and hypothesis, performed the data analysis, wrote the manuscript and acted as the corresponding author. Prof Ralf Zurbrugg assisted in guiding the theory development, supervised the development of work and provided evaluation and feedbacks.

The majority of the work and the primary authorship have been undertaken by Van Le.

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I hereby certify that the statement of contribution is accurate.

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Prof Ralf Zurbrugg (Principal Supervisor)

I hereby certify that the statement of contribution is accurate and I give permission for the inclusion of the paper in the thesis.

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THE RELATIONSHIP OF THIS CHAPTER TO THE THESIS

This chapter continues to place a strong emphasis on addressing the first research question in relation to the existence of informed trading activities in the option market. This study is conducted through an analysis of the predictive power of trading volume in forecasting the time-series dynamics of the implied volatility smile, which can be used to simultaneously derive forecasts of option implied volatility (prices). This research not only offers some indirect evidence showing that a proportion of informed trading has been initiated in the option market. It also further informs the first research question with reference to the information dissemination process into the market by suggesting that the predictive power of volume reflects the slow diffusion of information via option trades. In that sense, the principal research problem concerning whether informed traders participate in the option market has been explored.

Abstract

Practitioners have long tried to exploit the predictability of the option implied volatility smile. Motivated by the recent literature focusing on market-based option pricing arguments, this paper proposes the introduction of trading volume into the VAR structure to improve forecasts of the smile dynamics. We find that our augmented VAR-volume model produced high quality forecasts of the smile surface and explains relatively well its dynamic changes over time. In particular, ex-ante evidence suggests that the incorporation of trading volume leads to an outperformance over other alternative forecast approaches and yields statistically significant trading profit. This result is robust to a variety of perturbations of the sampling period and offers scope for investors to more accurately predict option implied volatility (price) in the future.

3.1. INTRODUCTION

In the empirical option pricing literature, option price departures from the Black and Scholes (1973) model are often characterised as the implied volatility smile (surface), whereby the implied volatility varies with the option strike price (and the date of expiration). Despite the extensive literature examining alternative explanations of the smile's existence at any given time, it is only recently that its time varying dynamics have captured the attention of researchers in financial modeling. In fact, only few investigations exist on the topic of forecasting the dynamics of the smile, despite its importance in derivative pricing[15] and portfolio and risk management[16]. In this article, we address this issue by proposing a simple approach, which is primarily based on the strong link existing between trading volume and the observed option prices, for forecasting the IVS dynamics.

Previous studies report that the smile dynamics is time-varying (Bates 1991; Gemmill 1996; Bollen and Whaley 2004; Gonçalves and Guidolin 2006). Essentially, Gemmill (1996) showed that the smile behaviour in time, being characterised by a single measure of skewness, was dependent on the price level of the underlying index. In particular, structural models, which have been developed to provide explanations for the existence of the smile, also offer justifications for its time-varying characteristic, implying that the smile is forecastable on the basis of information related to latent factors driving its changing shape. Most recent evidence in Bollen and Whaley (2004) and others suggest that option pricing has partly been driven by the market trading process to incorporate new information reflected in the net market order . The form of the relationship

[15] In derivative pricing, volatility reflects the consensus belief of the market participants and is intimately related to the fundamental pricing measure. Also, volatility is a required input for market makers to price and make markets in options all over the world.
[16] The option contract, with its distinct feature of high leverage, is an important investment instrument available for portfolio managers to manage asset allocation and risk. Accurate forecasts of implied volatility are needed to correctly price option to support portfolio decision. Besides, many trading strategies have been developed, purely based on implied volatility forecasts. Hedging activity on derivative trading is fundamentally based on the assessment of expected volatility.

between trading volume and the changing shape of the smile is, however, ambiguous. This gives rise to our line of inquiry which examines empirically the information content of trading volume in modelling the time series dynamics of the smile.

In this paper, we consider incorporating trading volume into the time series model of the IVS to examine if it contains information relevant to the latent factors driving the time variations of option prices. This is important for the validation of the economic explanations underlying the smile evolution, one of which is directly related to the arrival of new information to the market. In fact, economic theory has long established that a slow diffusion of news into the market may cause a lead-lag (causal) relation between volume and asset prices found empirically. While this proposition has well been ascertained in the equity market through the development of many influential theoretical models, such as the sequential information hypothesis (Copeland, 1976) and the noise trading hypothesis (Milton and Raviv, 1993; Brock and Lebaron, 1996; Iori, 2002), empirical work toward this line of query has received little attention in the field of option research. Our study therefore attempts to fill the gap in the literature by specificially seeking to examine whether past volume contains additional useful information about the future dyanamics of the smile. This is in constrast to the existing studies which have mainly focused on either a contemporaneous relationship between volume and option prices (Bollen and Whaley, 2004; Ni, Pan et al., 2008) or a lead-lag relationship between stock and option markets (Anthony, 1988; Chan, Chung et al., 2002).

Further, our special interest in the role of trading volume in forecasting the smile dynamics rests on the scarcity of studies which link the volume-implied volatility relation with forecasting applications. Previous studies which examine the effect of trading on option pricing do so primarily to investigate the efficiency of the option markets, not to improve the forecasts of the smile dynamics per se. In contrast, the primary and major focus of our paper is the determination of the importance of any lead-lag relationship between volume and option price which may exist, and aims at improving the option implied volatility (price) forecasts. Despite its importance in option pricing and trading, this line of query has not been pursued vigorously in the past, either because of the scarce evidence surrounding the nature of the volume-volatility relation discussed previously, or due to the complications related to explicitly modelling the dynamics of the smile[17].

We ask the following questions: (1) whether trading volume helps to explain the time-variations observed in the IVS; and particularly (2) whether it offers any improvement in modelling and forecasting the smile dynamics and hence the option prices. To answers these questions, we propose to incorporate trading volume into the vector-autoregressive (VAR) structure as part of the two-stage process to model the smile dynamics proposed in Gonçalves and Guidolin (2006), since this particular technique apprears to fare relatively well compared to other competitive forecasting models existing in the literature. This approach is intuitively appealing not only to determine the importance of the link that exists between volume and option pricing but also to highlight the potential information captured by trading activities. It delivers a simple yet effective mechanism which may prove to yield a beneficial improvement in forecasting the option implied volatility (price). To assess the performance of our proposed model, we use both statistical and economic criteria. Different simulated trading strategies have

[17] Previous studies, such as Dumas, Fleming et al. (1998) and Christoffersen and Jacobs (2004), report that the coefficients estimated on the cross sections of the S&P 500 index options are highly unstable, indicating that the time-variations of the smile dynamics is a critical issue and needs to be carefully addressed.

been performed with and without transaction costs to evaluate whether the inclusion of trading volume does lead to tangible benefits to option traders and practioners.

In particular, the role of trading volume in foreacasting the smile dynamics has been tested for options traded on the S&P 500 index for the period from 2nd January 1996 to 8th September 2009. Results produced by our investigation suggest that our augmented VAR-volume model produces high quality forecasts of the smile surface and explains relatively well its time series properties. Further, the ex-ante evidence indicates that the inclusion of trading volume leads to improved forecasts outperforming other alternate forecasting techniques. This would provide support to the extant research aiming to examine the information reflected by market trading activities. In particular, our findings offer an important insight into the empirical relation between volume and asset price in the context of option pricing, confirming that changes in the level of market trading activities are important for explaining the empirical time variations in the option implied volatility (price)[18]. Lastly, the augmented VAR-volume model developed in our paper presents a useful tool for forecasting that is applicable to practical option pricing and trading.

The remaining sections of the paper will be structured as follows. Section II describes the nature of the data set and the methodological design used to examine the information content of trading volume, outlining in detail the different assessment criteria employed to evaluate the forecast performance of our VAR-volume model in a direct comparison to other prominent forecasting techniques existing in the literature. Section III is devoted to the discussion of some key findings which emerged from our

[18] We view our approach as closely related to studies which either feature option pricing models based on a general equilibrium framework or employ market-based arguments to explain the time varying properties and other stylised facts of the IVS (see Garcia, Luger et al. 2003; Guidolin and Timmermann, 2003; Bollen and Whaley, 2004; Chan, Cheng et al., 2004; Kang and Park, 2008; Ni, Pan et al., 2008; Gârleanu, Pedersen et al., 2009). In this paper we extend the investigation to evaluate whether trading volume would capture the unobservable latent variables characterising the regime of the economy affecting option pricing and how this knowledge helps to improve forecasts of option implied volatility (price).

empirical results, while the final section (IV) presents conclusions and outlines some directions for future research.

3.2. DATA AND METHODOLOGY

3.2.1. Data

The primary data set employed in this study has been collected from SIRCA. The data consists of intra-day records of all trades of the S&P 500 index options transacted on the Chicago Board Options Exchange (CBOE) during the period from 2nd January 1996 to 8th September 2009. Of this sample, the first period from 2nd January 1996 to 26th January 2004 will be used for the in-the-sample hypothesis testing and model construction, while the remaining data is utilized for the out-of-sample evaluation. It is important to note that S&P 500 index options are of European style and expire on the third Friday of each calendar month. Each option is categorised as a put or a call and characterised by its strike price and time to expiration distinctively identified by its RIC. The data set is completed with minute-to-minute observations of the index level, which is also collected from SIRCA database. All the remaining data, including the dividend yield on the S&P 500 index and the 30-day T-bill yield, which we utilizeas the risk free rate, were collected from DataStream International.

In contrast to the OptionMetrics Ivy database, which only has records of the last trade of the day for each option series, employed in related studies, , our data report all transactions executed throughout the day with the exact time stamp of trading to the nearest millisecond. This allows us to apply a tight time sampling window on the daily observation of option trades available. In fact, we only use those options which are actively traded during the next-to-closing trading session from 3.00pm to 4.00pm every trading day[19]. This choice is optimal for the minimization of the effect of non-simultaneity of trades and other potential intra-day trading effects[20], while maintaining a sufficient number of traded options to construct the implied volatility surface each day. In addition, several other exclusionary filters analogous to those in Bakshi, Cao et al. (1997), Bollen and Whaley (2004) and Gonçalves and Guidolin (2006) have been applied to ensure the integrity of option data. Firstly, we only select options with less than 180 days to maturity to avoid problems associated with non-trading. Secondly, we exclude those with less than 5 days to maturity to eliminate any effect of option expiration[21]. Thirdly, options with absolute delta below 0.02 and above 0.98 are also excluded due to distortions caused by price discreteness, similarly to Bollen and Whaley (2004). Fourthly, trading dates which have less than 5 option series traded within the trading window previously specified are eliminated to avoid the adverse effect of trading illiquidity and price discreteness in fitting the daily smile surface. Lastly, we filter the data for any potential data errors, including any instances when (1) the trading price is zero and (2) there are violations of standard option bounds.

The option implied volatility has been computed by employing the Black-Scholes formula adjusted for dividends. We divide the data into thirty size sub-categories according to moneyness and time to maturity and specified as either puts or calls. With regards to moneyness, DITM denotes deep-in-the-money if $m>0.06$; ITM, in-the-money if $0.06 \geq m \geq 0.01$; ATM, at-the-money if $0.01 \geq m \geq -0.01$; OTM, out-of-the money if $-0.01 \geq m \geq -0.06$; and DOTM, deep-out-of-the-money if $-0.06 \geq m$ for *put* contracts. The

[19] Because the stock market is closed at 4.00 pm, closing option trades with time stamps later than 4.00 pm are eliminated to avoid the effect of non-synchronous trades when matching the index price level to each option trade. Battalio and Schultz (2006) pointed out that much of the apparent arbitrage opportunities identified using the Option Ivy database arises from the fact that closing option quotes have time stamps of 4:02pm while closing trades on the underlying stock are executed no later and possibly much earlier than 4:00pm.

[20] Please refer to Battalio and Schultz (2006) for a discussion of the problem of non-synchronous prices and microstructure issues responsible for most of the apparent arbitrage opportunities identified using the OptionMetrics IVY database. In particular, there may be a significant time lag between the closing trades of different option series transacted within the same trading day reported. Evidence of the intraday effect in option trading can be found in Chan, Chung et al. (1995)

[21] Gonçalves and Guidolin (2006) further argue that their prices contain liquidity-related biases and have little information on the time dimension of the IVS.

same classification applies to calls with *m* replaced by *–m* in the above inequalities. Contracts of either type will be categorised as short-term if days to expiration (henceforth DTE) is less than 60 days, medium-term if *180≥DTE≥60 days,* and long-term if *DTE≥180 days.*

3.2.2. Methodology

3.2.2.1. Modeling the dynamics of the implied volatility surface

In this paper, we adopt a two-step approach to model the IVS as proposed by Gonçalves and Guidolin (2006) (henceforth, G&G). In the first stage, a simple model, which is linear in the coefficients and nonlinear in moneyness and time to maturity, is fitted to a cross section of option contracts available each day. In particular, the model fitting the implied volatility surface each is structured as follows

$$\sigma_i = \beta_1 + \beta_2 M_i + \beta_3 M_i^{\ 2} + \beta_4 \tau_i + \beta_5 (M_i \times \tau_i) + \varepsilon_i \qquad (1)^{22}$$

where σ_i denotes the Black Scholes implied volatility for contract *i*-th with time to maturity τ_i, and moneyness M_i[23]. ε_i stands for the random error term, i =1, ... N with N to be the number of options traded each day, t=1,...M with M to be the number of days in our in-sample period. The time to maturity is measured as a fraction of the year. The model structure employed here is very similar to those adopted in previous studies such as those of Dumas, Fleming et al. (1998) and Diebold and Li (2006). It seems to provide the best fit to the observed implied volatilities[24] because it practically accounts

[22] Estimation of equation (1) will be based on ordinary least square regression (henceforth OLS)

[23] Similarly to G&G, we consider a time-adjusted measure of moneyness, ie $M_i \equiv \frac{\ln[K_i / \exp(r\tau_i)S]}{\sqrt{\tau_i}}$. G&G argue in their paper that this time adjustment is necessary to account for the stylized fact that the longer the time to maturity of an option, the larger the difference should be between the strike price and the forward stock price in order for it to achieve the same normalized moneyness as a short term option.

[24] Similarly to related work such as that of G&G and Dumas, Fleming et al (1998), we have estimated a number of other model specifications which singularly account for either the moneyness or the time to maturity factor both in singular and quadratic forms

for variations of the implied volatility across moneyness, ie "the smile effect", and the changing shape of the smile across time to maturity, ie "the maturity effect" of the smile.

In the second stage, the presence of time variation in the estimated coefficients estimated previously is captured by the vector autoregressive (VAR) model. In effect, the specification of the augmented-VAR model we employ to test the information content of the trading volume is as follows:

$$\widehat{\beta}_t = \mu + \sum_{j=1}^{p} \phi_j \hat{\beta}_{t-j} + \delta V_{t-1} + u_t \qquad (2)^{25,26}$$

with $u_t \; i.i.d.\; N(0,\Omega)$

$$\beta_t = (\beta_0, \beta_1, \beta_2, \beta_3, \beta_4)'_t$$

In this model's construction, $\beta_t = (\beta_0, \beta_1, \beta_2, \beta_3, \beta_4)'_t$ refer to the coefficient estimates derived in the first stage while u_t stands for the random error term. V_{t-1} is the lagged volume factor, which is defined as the natural logarithm of the daily number of option trades. It is designed to assess whether the option trading volume contains any useful information about the future dynamics of the IVS, beyond that which has been incorporated in its past movements.

as well as those without the interaction term, but they all show a worse fit as measured by their adjusted R^2 and the root mean squared error (RMSE) of implied volatilities. These are not reported here for brevity but are available upon request.

[25] The VAR model specified in equation 2 is optimal to pick up the autocorrelation and the cross-correlation between estimated coefficients if those series are stationary. Our preliminary analysis produced later shows that this condition is satisfied. Other alternatives available to model the IVS dynamics would include modeling the difference of the coefficient series as VAR model if they are non-stationary or using a multivariate-GARCH model if co-integration exists between coefficient series. These are not considered here given the characteristics exhibited in the data.

[26] The number of lags (p) will be selected using the Bayesian information criteria (BIC) to achieve the best fit.

3.2.2.2. Evaluating the forecast performance

In order to determine the role of trading volume in predicting the dynamics of the IVS, we assess the forecast performance of the augmented VAR-volume model against the original VAR structure, which is

$$\hat{\beta}_t = \mu + \sum_{j=1}^{p} \phi_j \hat{\beta}_{t-j} + u_t \tag{3}$$

Also for comparison purposes, we consider a number of other prominent forecasting techniques currently existing in the literature, including the ad-hoc straw man model posited by Dumas, Fleming et al. (1998), the autoregressive model (AR) model, the NGARCH option pricing model proposed by Heston and Nandi (2000), and the random walk model.

Dumas, Fleming et al. (1998) proposes the so-called ad-hoc straw man model, which specifies that today's set of coefficients provide the best forecast of tomorrow's IVS such that

$$\hat{\beta}_t = \hat{\beta}_{t-1} + u_t \tag{4}$$

As G&G pointed out, this model is a special case of the VAR structure where $\mu = 0,\ p = 1, \phi_1 = I_5$, a 5x5 identity matrix, $\phi_j = 0$ for j = 2,...,p and Ω a diagonal matrix. It has been shown in Christoffersen and Jacobs's (2004) empirical work to outperform many other prominent approaches, including the state-of-the-art structural models.

In addition, we consider that forecasts of each beta series can be generated independently by employing a standard AR model with the following specifications

$$\widehat{\beta}_{s,t} = \mu + \sum_{j=1}^{p} \phi_{s,j} \hat{\beta}_{s,t-j} + u_{s,t} \quad with\ s = 1\ to\ 5 \tag{5}$$

All of the above models produce forecasts of beta, which can then be used to generate forecasts of option implied volatility and price, given the moneyness level and time to maturity, by re-estimating equation (1). Taking a very different approach, Heston and Nandi (2000) propose an option pricing model which specifies that the stock price evolution follows a NGARCH process. It is reported in their paper that this model outperforms the Dumas, Fleming et al's (1998) ad-hoc straw man model when examining the weekly S&P 500 option data for the period from 1992 to 1994. In this paper, we will estimate option implied volatility (price) forecasts by employing their model in the form of an NGARCH (1,1) process, which is specified below.

$$\begin{aligned}
r_t &= r^f - \frac{1}{2}\sqrt{h_t} + \sqrt{h_t} z_t^* \\
h_t &= \omega + \beta h_{t-1} + \alpha (z_{t-1}^* - \gamma^* \sqrt{h_{t-1}})^2 \\
with \quad z_t^* &= z_t + (\lambda + \frac{1}{2}\sqrt{h_t}) \\
\gamma^* &= \gamma + \lambda + \frac{1}{2}
\end{aligned} \tag{6}$$

where r_t and r_f are the index return and the risk-free rate respectively. h_t is the conditional variance of the index return while z_t is a standard normal disturbance. In addition, it is required that $\beta + \alpha\gamma^2 < 1$ so that the first-order process remains stationary with finite mean and variance[27]. In contrast to the previous approaches which are based on an implicit assumption that the smile dynamics is time-varying, the NGARCH option pricing model does not allow for time-varying coefficients.

[27] Similarly to G&G, we estimate the NGARCH (1,1) model by minimizing the sum of the squared deviations of the Black-Scholes implied volatilities derived by inverting the NGARCH (1,1) option prices and the prevailing volatilities derived from the observed option prices.

Lastly, the random walk model assumes that for each option contract, today's implied volatility is the best forecasts of tomorrow's implied volatility, such that

$$\sigma_{i,t} = \sigma_{i,t-1} + \varepsilon_{i,t} \qquad (7)$$

where σ_i denotes the Black Scholes implied volatility for contract *i*-th. Harvey and Whaley (1992) emphasize that this model is widely used by practitioners in trading index options, despite its simplicity.

In order to evaluate the informational role of trading volume in forecasting the dynamics of the IVS, the performance of our model will be assessed on the in-sample fit as well as the out-of-sample forecasts in a horse-race with the other comparable models specified previously. In general, the assessment of the forecast performance will primarily be grounded on a number of criteria including: (1) the model's fitting into the observed IVS in the sample; (2) the forecast accuracy in predicting the dynamics of beta series, option implied volatilities and prices respectively for both in-the-sample and out-of-the sample periods; and finally (3) the economic significance of the forecast improvement, if any, via trading simulation which employs forecasts of future option implied volatilities (prices) to gain profit.

In generating out-of-sample forecasts, we perform both static and dynamic forecasting approaches over different forecast windows of 1, 5 and 22 days. As these are corresponding to daily, weekly and monthly forecasts, this resembles the forecasting exercises which are widely performed in practice for active trading and portfolio rebalancing purposes. With respect to the former approach, the coefficient estimates used to generate forecasts always remain constant because the in-sample period is kept unchanged. In contrast, the later involves repetitively rolling the in-sample period as time passes. In particular, for each day, we estimate the cross-sectional IVS parameters $\beta_t = (\beta_0, \beta_1, \beta_2, \beta_3, \beta_4)'_t$ by OLS to obtain the time series of β_t for the entire sample period. We then use the in-sample period from 2nd January 1996 to 26th January 2004 to obtain estimates of Π, the set of all parameters ϕ_j and δ of the multivariate VAR structure defined in equation (2). Hence, we will hold Π constant when generating forecasts of future β_t in the static approach and allow estimates of Π to be updated as time passes to generate dynamic forecasts. Because the set of β_t defines the shape of the IVS at time (t), forecasting β_t allows us to generate forecasts of the implied volatility and price for each option contract, given its time to maturity and moneyness level. The out-of-sample forecasts of the other three models, ie the original VAR structure, the Dumas, Fleming et al’s (1998) ad hoc straw man model, and the AR model specified in equations (3), (4) and (5) respectively, are generated in a similar fashion. In contrast, both the Heston and Nandi’s (2000) NGARCH model and the random walk model do not yield forecasts of beta series. Instead forecasts of the option implied volatility (price) can be derived directly from the historical value of implied volatility or by using the Heston and Nandi’s (2000) option pricing model[28] relevant to each contract. It is generally expected that the forecast improvement, if any, derived from the additional information captured by trading volume, will be better highlighted in the dynamically forecasting approach. In particular, continually updating the in-sample period guarantees that the dynamically changing market condition is best reflected by the smile structure and that past information on the dynamic properties of the IVS are used for prediction purpose.

[28]As discussed previously, the NGARCH (1,1) model does not allow for time-varying coefficients. Hence, out-of-sample forecasts have been generated by using the same set of coefficients estimated for the in-sample period from 2nd January 1996 to 26th January 2004.

The forecast accuracy can be assessed with reference to statistical loss functions, namely the mean absolute error (MAE), the mean absolute percent error (MAPE) and the mean squared error (MSE). In particular,

$$\begin{aligned}
MAE &= \frac{1}{N}\sum_{i=1}^{N}\left|S_i - \hat{S}_i\right| \\
MAPE &= \frac{1}{N}\sum_{i=1}^{N}\left|1 - \hat{S}_i \big/ S_i\right| \\
MSE &= \frac{1}{N}\sum_{i=1}^{N}\left(S_i - \hat{S}_i\right)^2
\end{aligned} \tag{8}$$

where $\hat{S}_i$ and S_i refer to the forecasted and observed quantities respectively. While these measurements of error entail different implications for the forecast accuracy, they have been used widely in the literature, due to their simplicity for calculation and interpretation purposes. In addition, we also employ the mean correct prediction (MCP) of the directional changes, which is defined as the percentage of observations for which the model predicts a change of the same sign as the expected movement of the quantity of interest. Its appraisal is often found in related work in volatility forecasting (Konstantinidi, Skiadopoulos et al., 2008; Le and Zurbruegg, 2010), due to the fact that correct direction forecasts of the stock volatility provide investors with profit opportunities through option trading. Given that the same argument applies to correct forecasts of the direction of changes in implied volatilities and option prices, it is strongly relevant to the employment of this measurement in our paper, and related work in predicting the dynamics of the IVS, such as that of G&G.

To evaluate the in-the-sample fitting and the out-of-sample forecast performance of the three models specified previously, we examine all four statistics of respective forecasts of betas, implied volatilities and option prices [29]. In effect, we compute the following twelve measures for each model.

- The MAE, MAPE, MSE and MCP of forecasts of β_t, which are estimated by following the procedure set out previously, given the model forecasts and the realized values of β_t series.
- The MAE, MAPE, MSE and MCP of forecasts of implied volatilities, computed in a similar fashion but with inference to deviations of the model's forecast implied volatilities from the observed Black-Scholes implied volatilities.
- The MAE, MAPE, MSE and MCP of forecasts of option prices which are based on the model's forecast option prices and the traded prices observed for the same set of option contracts.

In computing these measures, we have been using the Black-Scholes formula to convert between model forecasts of option prices and implied volatilities, as was employed in a similar fashion in G&G's work[30]. They have pointed out that the employment of this pricing scheme can fully be justified if the main purpose is to examine the accuracy of forecasting the dynamics of the IVS[31]. Further, we argue that its use in our paper sufficiently accommodates our priority goal of correctly evaluating the forecast improvement achieved from using trading volume[32].

[29] It is noticed that for evaluating the model forecasts of option prices, MAPE and MCP are the two statistical errors which are least subject to the inherent bias pertinent to the pricing variations across different option contract series.

[30]In particular, we use the Black-Scholes formula to compute the model's forecasts of option price for all traded contract series, using the corresponding volatility forecasts as inputs, conditional on other factors including the index level, the interest rate and the contract's features.

[31] They argue that the Black-Scholes formula, in spite of appearing inconsistent with the volatility being a function of moneyness and time to maturity, is often used by market makers and academics alike as a "black box" to transform between the price and the implied volatility quantities.

[32] G&G point out that the use of the Black-Scholes in forecasting evaluation in this same fashion is mainly subject to Christoffersen and Jacobs (2004)'s critique that the loss function used in model estimation is different from the out-of-sample loss function. Though we haven't been able to completely rule out this possibility, we have tested and found that our findings of the superior performance of our model in predicting future option prices would remain strong even if the option implied volatility used for in-sample estimation of the model was computed using the Black-Scholes formula. Further, we argue that any issue of model bias has a very minimal effect on a verdict on the relative performance of the three models considered in this paper, simply because we have applied this same pricing scheme across all model forecasts.

To formally assess the statistical significance of the difference in the out-of-sample performance of our model compared to that of each of the remaining models, we employ the equal predictive ability test proposed by Diebold and Mariano (1995) (henceforth, DM) for each of the ten performance indicators computed previously[33]. This statistic is extremely useful in our current exercise because it offers more compelling evidence for the forecast improvement if we can satisfactorily reject the null hypothesis of equal forecast accuracy of our model compared to that of the benchmark model using the one-tail test at 1% level of significance.

The accuracy of the generated out-of-sample forecasts are also evaluated in an economic setting, using trading simulation to determine if profit arises from correct forecasts of the dynamics of the IVS. This particular approach has been widely adopted in the volatility forecast literature (Day and Lewis 1992; Harvey and Whaley 1992), and in some more recent papers which have a particular focus on the dynamics of the IVS, such as those of G&G and Bollen and Whaley (2004). In effect, trading simulation provides an effective way to evaluate the out-of-sample forecasting performance of competing models, in terms of the economic consequences and significance of this predictability. Using the out-of-sample forecasts of implied volatilities produced from our models, we examine the trading profits that generated different trading rules to elucidate whether traders are able to benefit from the forecast improvementif any achieved from the use of trading volume in our model. In particular, we test whether the improved forecast accuracy allows traders to generate abnormal profits, which are

[33] Similarly to G&G and many others, we use the Newey-West (1987) heteroskedasticity and autocorrelation consistent variance estimator to compute the DM test

profits after adjusting for the risk exposure present in the trading strategies considered[34].

Specifically in our trading simulation design, we consider two types of risk management strategies commonly pursued by option traders: one assumes that option traders will only hedge his delta risk exposure while the other requires that both delta and vega risk are dealt with. For the delta-neutral trading strategy, we firstly construct a portfolio of S&P 500 index options based on the one-day-ahead forecasts of implied volatilities generated by our models. In particular, we will go long (short) on an option if our models forecast that its implied volatility will increase (decrease) the next day. In order to offset the price risk of this position, we simultaneously buy (sell) an amount of the underlying index equal to the Black-Scholes delta ratio for each unit of call (put) option bought. However, the issue of volatility has not been dealt with in this trading strategy. To this point, we consider the delta and vega hedge strategy which involves two separate steps, as outlined in Bollen and Whaley (2004). In this second strategy, we first determine which options to buy/sell based on our forecasts of implied volatilities and the number of ATM calls[35] needed to hedge this position before the delta hedge is put on at last. This trading exercise is repeated every day throughout the out-of-sample period. Other than employing dynamic option strategies, which basically require closing the position on the next trading dayin our trading simulation process, we also include in our analysis estimates of trading profit with and without the consideration of transaction costs[36] and various trading filters[37]. In calculating the rate of return, we also assume that

[34] Though we are not able to rule out entirely the possibility that the market is in its efficient form [hence we shouldn't expect to obtain abnormal trading profits, no matter what forecasting and trading strategies are employed], findings of any evidence to the contrary, and of abnormal trading profits in particular, simply highlight the role of trading volume in predicting the dynamics of the IVS.

[35] ATM calls are mainly used to construct the vega-hedge given that the least number of contracts are needed, as argued in Bollen and Whaley (2004).

[36] We consider the impact of fixed transaction cost per contract traded. This has been implemented at two different levels, \$0.05 per contract and \$0.1 per contract respectively in our return calculation.

[37] Given the CBOE's minimum tick requirement for most option contracts is \$0.10, we apply two price deviation filters in our trading exercise which take the value of \$0.10 and \$0.25 respectively. This implies that trading only occurs if the forecast price

funds may be freely invested at the risk free rate of interest[38]. In addition, we assess the significance of our trading profits by considering several trading rules similar to those examined in G&G's empirical work[39]. Finally, the economic significance of these trading strategies over the long run will be evaluated using traditional measurements of portfolio performance, namely the Sharpe ratio and the Leland's (1999) modified Alpha to account for non-normality[40]. These statistics will be reported along with their bootstrapped standard deviations.

3.3. EMPIRICAL RESULTS

3.3.1. Descriptive statistics

Following the two-step modeling procedure outlined previously, we first estimate the cross-sectional regression of daily implied volatility described in equation (1). In Figure 3.1, we plot the fitted IVS model corresponding to the cross section of option contracts available each day. The plot shows a close fitting of our estimated model to the daily IVS expressed as the cross section of the implied volatilities plotted against moneyness and time to maturity. Figure 3.2, which plots the time series of daily estimates of $\hat{\beta}$, clearly indicates the time-varying characteristics of daily IVS. This finding is similar to what found in G&G's paper, as they also document that the shape of the IVS appears to be highly unstable overtime, both in the moneyness and in the time to maturity

movement is greater than the price filter considered in each case. These filters have been applied across different trading settings considered to examine the profitability of trading generated from the model forecasts.

[38] This basically means that the return of a net-short position=trading profit + 2*risk free rate of return

[39] These include (1) only trading on the closest ATM, short-term contracts (henceforth trading rule A), (2) only trading on two contracts which each offers the best selling/buying profit (henceforth trading rule B), and (3) only trading on one contract which provides the highest expected trading profit, given the set of contracts available each day.

[40] Refer to Leland (1999) for the algorithm of the argument of why these metrics are more appropriate to measure the performance of portfolios containing options or assets with non-linear payoffs.

dimensions when examining the dynamics of the IVS for the period from 3rd January 1992 to 28th June 1996.

$$\sigma_i = \beta_1 + \beta_2 M_i + \beta_3 M_i^{\ 2} + \beta_4 \tau_i + \beta_5 (M_i \times \tau_i) + \varepsilon_i$$

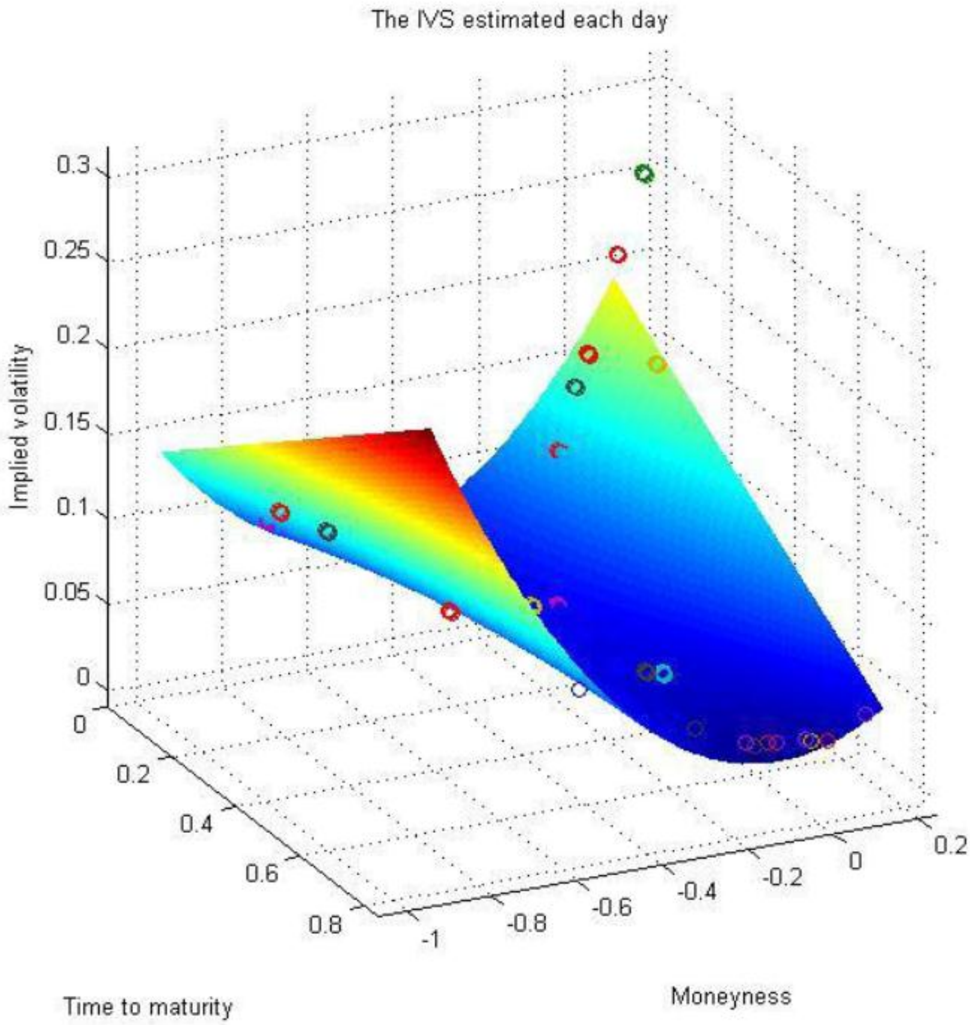

Figure 3.1

Fitting the daily IVS

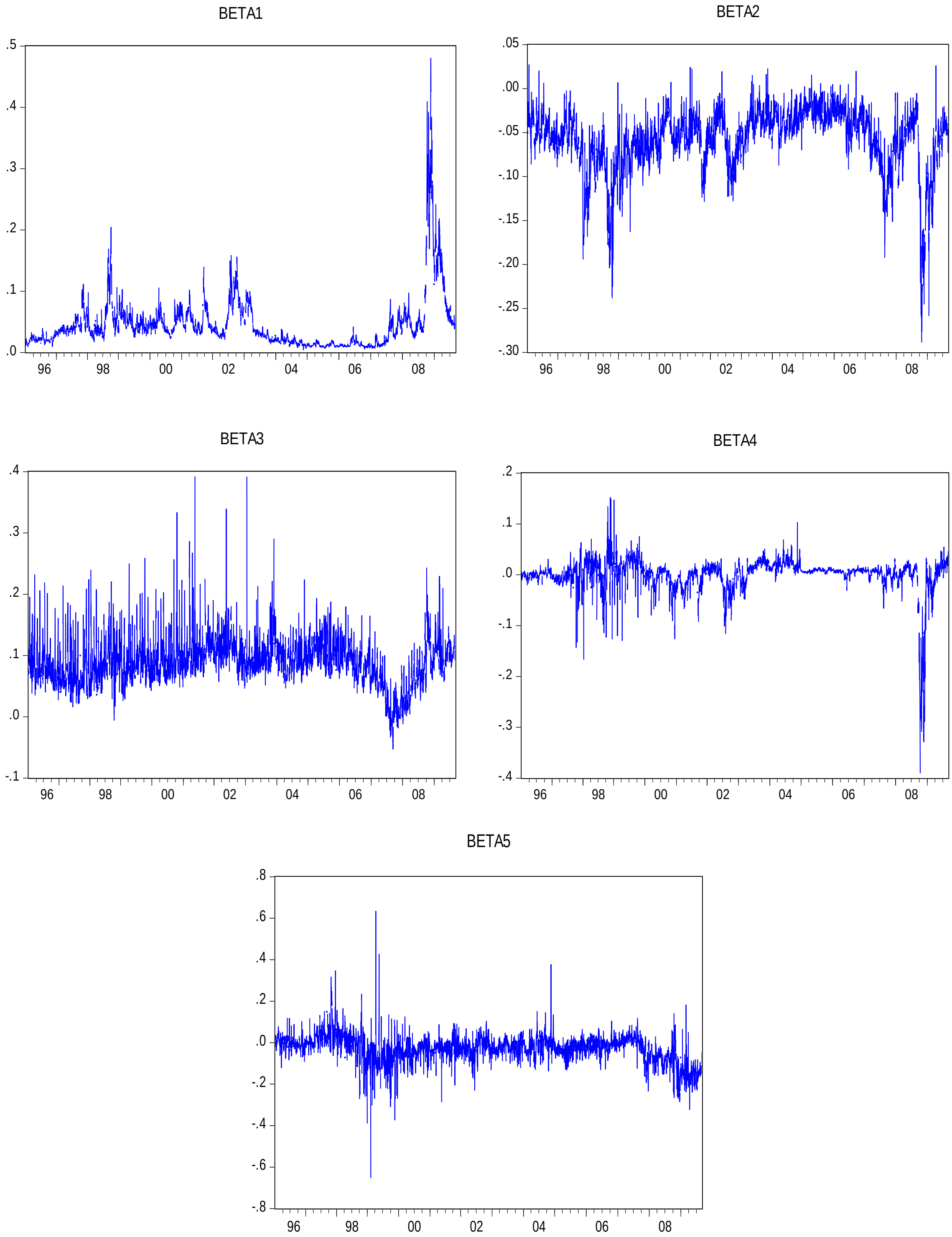

Figure 3.2

Time variations of the beta series

for the period 2nd January 1996 to 8th September 2009

Table 3.1

Preliminary statistics of beta series					
	BETA1	BETA2	BETA3	BETA4	BETA5
Mean	0.045	-0.058	0.090	0.000	-0.029
Std	0.045	0.037	0.039	0.036	0.069
Min	0.004	-0.289	-0.053	-0.391	-0.653
Max	0.480	0.174	0.392	0.153	0.634
Skewness	3.763	-1.508	0.701	-4.026	-0.306
Kurtosis	23.713	7.938	7.091	30.976	9.973
LB(1)	1262.866***	970.869***	323.238***	594.501***	355.376***
LB(10)	8886.419***	6451.960***	566.974***	2296.847***	1613.846***
LB(1) squares	1182.853***	1015.840***	191.929***	80.886***	15.404***
LB(10) squares	6987.513***	6353.094***	290.280***	382.726***	101.987***
ADF	-3.056***	-5.304***	-7.923***	-17.830***	-21.297***

The five beta series have been constructed by fitting the OLS regression on the cross-sectional estimates of option implied volatility available each day. These represent the parameter estimates of the IVS model specified in equation (1). The data sample covers the period from 2nd January 1996 to 8th September 2009 for a total number of 3430 daily observations.

Notes: LB (j) denotes the Ljung-Box statistics testing for the presence of autocorrelation . Under the null hypothesis of no serial correlation up to lag (j), the test statistic is asymtotically Chi-square distributed. The t-stat of the ADF test is also reported. Null hypothesis is the time series contains a unit root I(1) process.

*** indicates significance at the 1% level

** indicates significance at the 5% level

* indicates significance at the 10% level

Descriptive statistics reported in Table 3.1 further suggest the null hypothesis of normality is rejected for all five series of coefficient estimates, so called beta 1, beta 2, beta 3, beta 4 and beta 5. Further, the ADF test reflects that all beta series are stationary. The Ljung-Box statistic also reflects a high auto-correlation up to 10th lag in both levels and squares for all series[41]. This is consistent with the previous finding in G&G and

[41] In addition, the cross-correlograms between pairs of beta series, not reproduced here for clarity, show a strong cross-correlation between them.

indicates the appropriateness of multivariate models to model the structural dynamics of the set of parameter estimates from the cross-sectional regression of daily implied IVS described above.

3.3.2. In sample fit

In this paper, we use the VAR model which satisfactorily accounts for the auto-correlation and cross-correlation between series noted previously. To assess whether trading volume helps to improve forecasting the IVS, we examine the regression results of the augmented VAR-volume model specified in equation (2). Table 3.2 reports the regression results of the function form specified in equation (2), fitted to the set of cross-sectional coefficients estimated in the previous step. It is found that trading volume is significant at the conventional 5% level across all regression results. This suggests that trading volume has additional information content with regards to the future dynamics of the implied volatility smile. Theoretical argument on the relation between option trading volume and the IVS dynamics has been established in Bollen and Whaley (2004). The extant literature also suggests that trading volume and security price are often interrelated due to the trading mechanism with which new information is incorporated into the market. In particular, the sequential information arrival hypothesis (see Copelandand Friedman, 1987) and the noise-trading hypothesis (Milton and Raviv, 1993; Brock and Lebaron, 1996; Iori, 2002), which both suggest that a lead-lag relation between volume and price may also exist due to a slow diffusion of news into the market. In fact, our finding, that lagged trading volume stays significant in the VAR regressions for all series, suggests that it may capture the impact of trading activities attributable to the heterogeneity of traders at the arrival of new information.

Table 3.2

In-sample model estimation

Panel A reports regression results of the VAR-Volume model while Panel B provides comparable results of the same VAR structure without the volume factor. In specific, the specifications of these models are as follows

$$\hat{\beta}_t = \mu + \sum_{j=1}^{3} \phi_j \hat{\beta}_{t-j} + \delta V_{t-1} + u_t \qquad (1)$$

$$\hat{\beta}_t = \mu + \sum_{j=1}^{3} \phi_j \hat{\beta}_{t-j} + u_t \qquad (2)$$

with $\hat{\beta}_t = (\hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3, \hat{\beta}_4, \hat{\beta}_5)'_t$

$$\sigma_{i,t} = \beta_1 + \beta_2 M_{i,t} + \beta_3 M_{i,t}{}^2 + \beta_4 \tau_{i,t} + \beta_5 (M_{i,t} \times \tau_{i,t}) + \varepsilon_{i,t} \qquad (A)$$

u_t i.i.d. $N(0,\Omega_u)$; $\varepsilon_{i,t}$ i.i.d. $N(0,\Omega_\varepsilon)$

where σ(i,t), M(i,t) and τ(i,t) are the implied volatility, moneyness and time to expiry respectively of the option series (i) on day (t). βt is the set of estimated coefficients of the cross-sectional regression of option implied volatility across different contract series, as specified in equation (A). Vt-1 is the option trading volume on day t-1. These models have been estimated for the period from 2nd January 1996 to 26th January 2004.

Indepedent variables	Panel A: The augmented VAR-Volume model					Panel B: The VAR model				
	BETA1	BETA2	BETA3	BETA4	BETA5	BETA1	BETA2	BETA3	BETA4	BETA5
BETA1(-1)	0.973	-0.122	-0.153	-0.302	-0.829	1.007	-0.069	0.084	-0.330	-0.643
	(-0.014)***	(-0.031)***	(-0.060)**	(-0.035)***	(-0.105)***	(-0.013)***	(-0.028)**	(-0.056)	(-0.032)***	(-0.097)***
BETA2(-1)	-0.014	0.841	-0.058	-0.126	-0.376	0.003	0.867	0.061	-0.140	-0.282
	(-0.009)	(-0.020)***	(-0.039)	(-0.023)***	(-0.068)***	(-0.009)	(-0.019)***	(-0.038)	(-0.022)***	(-0.065)***
BETA3(-1)	-0.006	-0.097	0.414	0.013	-0.030	-0.005	-0.096	0.421	0.012	-0.025
	(-0.005)	(-0.011)***	(-0.022)***	(-0.013)	(-0.038)	(-0.005)	(-0.011)***	(-0.022)***	(-0.013)	(-0.039)
BETA4(-1)	0.071	-0.036	-0.140	0.525	-0.630	0.078	-0.025	-0.091	0.519	-0.591
	(-0.009)***	(-0.020)*	(-0.039)***	(-0.023)***	(-0.069)***	(-0.009)***	(-0.020)	(-0.040)**	(-0.023)***	(-0.068)***
BETA5(-1)	-0.002	0.029	-0.065	-0.049	0.386	0.002	0.034	-0.039	-0.052	0.407
	(-0.003)	(-0.007)***	(-0.013)***	(-0.008)***	(-0.023)***	(-0.003)	(-0.007)***	(-0.013)***	(-0.008)***	(-0.023)***
C	-0.019	-0.024	-0.077	0.020	-0.100	0.000	0.005	0.054	0.005	0.004
	(-0.003)***	(-0.007)***	(-0.014)***	(-0.008)**	(-0.024)***	(-0.001)	(-0.002)***	(-0.003)***	(-0.002)**	(-0.005)
Volume	0.003	0.004	0.018	-0.002	0.014					
	(0.000)***	(-0.001)***	(-0.002)***	(-0.001)**	(-0.003)***					
Adj R2	0.906	0.723	0.262	0.514	0.266	0.904	0.720	0.226	0.513	0.260
LLH	6883.225	5320.710	4002.156	5059.685	2870.707	6865.056	5311.741	3954.259	5057.710	2860.981
AIC	-6.880	-5.316	-3.997	-5.055	-2.865	-6.862	-5.308	-3.950	-5.054	-2.856
Schwarz	-6.860	-5.297	-3.978	-5.036	-2.846	-6.846	-5.292	-3.933	-5.037	-2.840
LLH	25742					25645				
AIC	-25.720					-25.628				
Schwarz	-25.622					-25.544				

Note: We report the t-stat in parentheses which are calculated based on White heteroskedasticity-corrected standard errors. LLH is the value of maximised Gaussian log likelihood. AIC (Akaike Information criteria) and Schwarz are two information criteria which indicate the model fit.

*** indicates significance at the 1% level

** indicates significance at the 5% level

* indicates significance at the 10% level

The forecasting quality of trading volume is further confirmed by the enhanced model fit, as illustrated by an improvement in the adjusted R-squared, the AIC, the Schwartz criteria and the log likelihood statistic of the augmented VAR-volume model relative to the original VAR model.

To provide further insight into the role of trading volume in forecasting the IVS dynamics, we assess the in-sample performance of the augmented VAR-volume model relative to a number of different benchmarks previously discussed, including the original VAR model, the ad-hoc straw man model, the AR model, the NGARCH option pricing model and the random walk model. The improved model fit derived from the incorporation of trading volume into the VAR structure has been highlighted in the results reported in Table 3.3, set out in terms of the MAE, MAPE, MSE and MCP for all five beta series. Further, the DM test of forecast accuracy shows that the new augmented VAR-volume model performs relatively better than all other forecast models, namely the original VAR model, the ad-hoc straw man model and the AR model. In particular, it outperforms the ad-hoc straw man model for all statistical loss functions considered at the 1% level of statistical significance.

Other than assessing the model fitting into the daily IVS dynamics described in terms of beta estimates, we also investigate the model's overall fit into the observed implied volatility and option prices[42]. The caveat of the above analysis is to examine whether the addition of trading can offer a statistically and economically significant improvement in modeling the IVS dynamics which fits better to the real option trading data. The MAPE emphasises the finding that the addition of volume leads to a significant improvement in VAR-based forecasts of option prices, even though other

[42] We follow G&G by converting the model's forecasts of implied volatility to the equivalent option prices using the Black-Scholes option pricing model. This simple and flexible technique being used commonly in the practice of option trading is sufficient, considering that our chief purpose is to evaluate the forecasting performance of our model relative to others.

Table 3.3

Statistics of in-sample performance

Panel A reports the in-sample model fit in terms of different statistical loss functions including the absolute error (AE), the absolute percentage error (APE), the squared error (SE) and the correct prediction percentage (CDP). All these metrics have been estimated for all five beta series of the IVS dynamics and for the implied volatility and price of individual option contracts, [please refer to the methodology section for details of the calculation]. Panel B reports results of the forecast accuracy test proposed Diebold and Mariano (1995) which assesses the performance of the VAR-Volume model (model 1) relative to other benchmarks, including the same VAR structure without the volume factor (model 2), the Dumas et al. (1998) ad hoc straw man model (model 3), the AR model (model 4), the NGARCH(1,1) model (model 5) and the random walk model (model 6), for those corresponding metrics. Except for model 5 which corresponds to the Heston-Nandi's (2000) NGARCH option pricing model explained in the methodology, the specifications of other models are simply represented as follows:

Models 1 – 4

$$\hat{\sigma}_{i,t} = \hat{\beta}_1 + \hat{\beta}_2 M_{i,t} + \hat{\beta}_3 M_{i,t}{}^2 + \hat{\beta}_4 \tau_{i,t} + \hat{\beta}_5 (M_{i,t} \times \tau_{i,t}) + \varepsilon_{i,t}$$

$$\text{where} \quad \beta_t = \mu + \sum_{j=1}^{3} \phi_j \beta_{t-j} + \delta V_{t-1} + u_t \qquad (1)$$

$$\beta_t = \mu + \sum_{j=1}^{3} \phi_j \beta_{t-j} + u_t \qquad (2)$$

$$\beta_t = \beta_{t-1} + u_t \qquad (3)$$

$$\beta_t = \mu + \sum_{j=1}^{3} \phi_j \beta_{t-j} + u_t \qquad (4)$$

$$u_t \ i.i.d.\ N(0,\Omega_u); \quad \varepsilon_{i,t} \ i.i.d.\ N(0,\Omega_\varepsilon);$$

Model 6

$$\hat{\sigma}_{i,t} = \hat{\sigma}_{i,t-1} + e_{i,t} \qquad (5)$$

$$\text{with} \quad \beta_t = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)'_t$$

$$e_{i,t} \ i.i.d.\ N(0,\Omega_e)$$

where σ(i,t), M(i,t) and τ(i,t) are the implied volatility, moneyness and time to expiry respectively of the option series (i) on day (t). βt is the set of estimated coefficients of the cross-sectional regression of option implied volatility across different contract series, as specified in equation (A). Vt-1 is the option trading volume on day t-1.These models have been estimated for the period from 2nd January 1996 to 26th January 2004.

Panel A: Prediction errors

		BETA1	BETA2	BETA3	BETA4	BETA5	IV	Price
Model 1: VAR-Volume model	AE	0.0051	0.0119	0.0224	0.0115	0.0363	0.0068	1.5601
	APE	0.1066	0.3136	0.2838	2.6966	3.7746	0.2276	0.3008
	SE	0.0001	0.0003	0.0011	0.0003	0.0031	0.0001	11.1264
	CDP	0.5618	0.6580	0.6530	0.5939	0.6845	0.5569	0.5568
Model 2: VAR model	AE	0.0051	0.0119	0.0225	0.0115	0.0364	0.0068	1.5530
	APE	0.1068	0.3141	0.2846	2.7342	3.9583	0.2277	0.3001
	SE	0.0001	0.0003	0.0011	0.0004	0.0031	0.0001	11.1180
	CDP	0.5633	0.6520	0.6475	0.5904	0.6890	0.5592	0.5591
Model 3: Ad-hoc straw man model	AE	0.0053	0.0133	0.0253	0.0123	0.0439	0.0070	1.6084
	APE	0.1089	0.3277	0.3026	3.5280	4.9383	0.1960	0.2380
	SE	0.0001	0.0004	0.0016	0.0005	0.0047	0.0001	10.9820
	CDP	NA	NA	NA	NA	NA	0.4760	0.4756
Benchmark 4: AR model	AE	0.0052	0.0121	0.0229	0.0114	0.0368	0.0070	1.6001
	APE	0.1097	0.3165	0.2961	2.4032	4.2691	0.2290	0.3059
	SE	0.0001	0.0003	0.0011	0.0004	0.0032	0.0001	11.1353
	CDP	0.5433	0.6465	0.6445	0.6059	0.6785	0.5255	0.5255
Benchmark 5: NGARCH model	AE						0.0592	13.3388
	APE						1.8217	4.0181
	SE						0.0060	286.1443
	CDP						0.4065	0.4065
Benchmark 6: Random-walk model	AE						0.0070	1.6084
	APE						0.1959	0.2374
	SE						0.0001	10.9877
	CDP						NA	NA

Panel B: Forecast accuracy tests (Model 1 against different benchmarks)								
		BETA1	BETA2	BETA3	BETA4	BETA5	IV	Price
Benchmark 1: VAR model	MAE	-1.633*	-1.024	-1.113	-0.926	-1.673**	18.597***	21.197***
	MAPE	-1.890**	-1.983**	-0.950	-0.450	-0.605	-0.121	2.947***
	MSE	-0.520	-0.961	-2.012**	-1.174	-1.342*	1.461*	1.123
	MCP	-0.318	2.452***	1.117	0.726	-1.116	-5.186***	-5.239***
Benchmark 2: Ad-hoc straw man model	MAE	-3.749***	-7.794***	-6.403***	-3.918***	-9.833***	-19.995***	-18.117***
	MAPE	-2.498***	-2.587***	-2.365***	-2.639***	-1.499*	2.005**	4.275***
	MSE	-3.728***	-6.804***	-6.191***	-4.806***	-5.405***	-9.962***	1.020
	MCP	NA	NA	NA	NA	NA	37.343***	37.341***
Benchmark 3: AR model	MAE	-3.477***	-2.642***	-3.409***	0.870	-2.543***	-36.873***	-24.656***
	MAPE	-4.141***	-1.114	-2.947***	1.076	-0.826	-0.381	-2.051**
	MSE	-3.330***	-3.302***	-3.824***	-2.749***	-2.768***	-12.155***	-0.207
	MCP	1.674**	1.245	1.187	-1.206	0.861	23.691***	23.667***
Benchmark 4: NGARCH model	MAE						-254.019***	-274.522***
	MAPE						-13.080***	-57.004***
	MSE						-135.532***	-137.415***
	MCP						60.846***	60.844***
Benchmark 5: Random walk model	MAE						-19.501***	-17.964***
	MAPE						2.003**	4.290***
	MSE						-10.582***	0.973
	MCP						NA	NA

Note: The ad-hoc straw man model (model 3) sets tomorrow's forecast of betas equal to today value. Hence, there is no expected change in beta values, ie MCP is not available (NA). Similarly, MCP of implied volatility forecasts is not calculated for the random walk model (model 6) because this model produces tomorrow's forecast equal to today's implied volatility for each option series. Both the NGARCH model (model 5) and the random-walk model (model 6) do not produce forecasts of betas.

*** indicates significance at the 1% level

** indicates significance at the 5% level

* indicates significance at the 10% level

statistics appear to suggest otherwise[43]. Further it is strongly confirmed that our model clearly outperforms all other forecast models, including the ad-hoc straw man model, the AR model, the NGARCH model and the random walk model, for generating better forecasts of option implied volatility when examining the results obtained from the DM test of forecast accuracy in Panel B. This is illustrated by the statistical significance of

[43] We argue that the result is still strongly in favor of our model performance, given that the MAPE is subject to less bias in evaluating forecasts of option prices because they take into account variations in the option pricing premium across different contracts.

the DM statistics consistently found across different measures of error. In fact, in all instances, we are able to effectively reject the null hypothesis of equal forecast accuracy of our model compared to each of those models at 1% level of significance. While forecasts of option prices yield less significant results, it is very clear that our model is statistically superior to the AR and the NGARCH model. Overall, the in-sample test clearly illustrates that the incorporation of trading volume leads to a significant improvement in forecasting the smile dynamics and option implied volatilities (prices).

3.3.3. Out of sample forecast performance

In this section, the out-of-sample forecast performance of our model is assessed based on the statistical measures and the economic significance of the forecast accuracy obtained through trading simulation, in direct comparison to two techniques previously considered. In addition, we also consider the random walk model which is popularly used in the practice of option trading and pricing. Dynamic forecasting has been performed for the period from 27th January 2004 to 8th September 2009 by repetitively rolling the whole set of data input following the in-sample period.

3.3.3.1. Statistical measures

Table 3.4 reports the out-of-sample forecast performance expressed in terms of different statistical loss functions analogous to those presented in the in-sample test in Table 3.3. Panel A presents the forecast errors of our augmented VAR-volume model and the five benchmarks models discussed previously. Panel B reports the results of the DM test of forecast accuracy of our model relative to each benchmark, following the same set of criteria. These panels address two major questions of interest: (1) whether trading volume helps to improve forecasts of the IVS dynamics in the VAR framework; and

(2) how our newly developed model performs relative to other forecasting techniques prominent in the literature.

To briefly summarize the results presented in Table 3.4, we find some evidence of the forecast improvement stemming from the use of trading volume in the VAR structure. This is reflected by the superior out-of-sample performance of our model's beta forecasts consistently found across different measures of errors when compared to those produced by the original VAR model. Except for the beta 4 series, our augmented VAR-volume model generates more accurate forecasts of the smile dynamics in all other dimensions. In particular, the role of trading volume can be highlighted by a consistent improvement in the direction of the forecast performance reflected by the MCP, and the statistical significance of the MAPE represented in Panel B. In addition, we found that in most instances, the model's forecasts of option implied volatility and prices dominate those generated by the VAR model at the 1% level of statistical significance. Further results also indicate that our model performs relatively better than all other benchmarks, including the ad-hoc straw man model, the AR model, the NGARCH model and the random walk model in forecasting betas and the option prices respectively. On the one hand, it is generally expected that our model should perform better than the ad-hoc straw man model, the AR model and the NGARCH model, since the VAR structure inherent in our model seems to fare better than those techniques, as shown by the forecasting performance of the original VAR model relative to those alternatives. On the other hand, it is particularly interesting to see that our model also outperforms the random walk model, which appears to yield a slightly better performance than the original VAR model. This finding clearly highlights the forecast improvement generated from the addition of trading volume into the VAR structure. In general, our results are similar to G&G's finding that the VAR structure is superior to

Table 3.4

Statistics of out-of-sample forecast performance

Panel A reports the out-of-sample forecast performance in terms of different statistical loss functions including the mean absolute error (MAE), the mean absolute percentage error (MAPE), the mean squared error (MSE) and the mean correct prediction of directional changes (MCP). All these metrics have been estimated for all five beta series of the IVS dynamics and for the implied volatility and price of individual option contracts, [please refer to the methodology section for details of the calculation]. Panel B reports results of the forecast accuracy test proposed Diebold and Mariano (1995) which assesses the performance of the VAR-Volume model (model 1) relative to other benchmarks, including the same VAR structure without the volume factor (model 2), the Dumas et al. (1998) ad hoc straw man model (model 3), the AR model (model 4), the NGARCH(1,1) model (model 5) and the random walk model (model 6), for those corresponding metrics. Except for model 5 which corresponds to the Heston-Nandi's (2000) NGARCH option pricing model explained in the methodology, the specifications of other models are simply represented as follows

$$\begin{aligned}
&\textit{Models } 1-4\\
&\hat{\sigma}_{i,t} = \hat{\beta}_1 + \hat{\beta}_2 M_{i,t} + \hat{\beta}_3 M_{i,t}{}^2 + \hat{\beta}_4 \tau_{i,t} + \hat{\beta}_5 (M_{i,t} \times \tau_{i,t}) + \varepsilon_{i,t}\\
&\textit{where} \quad \beta_t = \mu + \sum_{j=1}^{3} \phi_j \beta_{t-j} + \delta V_{t-1} + u_t && (1)\\
&\qquad \beta_t = \mu + \sum_{j=1}^{3} \phi_j \beta_{t-j} + u_t && (2)\\
&\qquad \beta_t = \beta_{t-1} + u_t && (3)\\
&\qquad \beta_t = \mu + \sum_{j=1}^{3} \phi_j \beta_{t-j} + u_t && (4)\\
&\qquad u_t \ \ i.i.d.\ N(0,\Omega_u); \ \ \varepsilon_{i,t} \ \ i.i.d.\ N(0,\Omega_\varepsilon);\\
&\textit{Model } 6\\
&\hat{\sigma}_{i,t} = \hat{\sigma}_{i,t-1} + e_{i,t} && (5)\\
&\textit{with} \quad \beta_t = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)'_t\\
&\qquad e_{i,t} \ \ i.i.d.\ N(0,\Omega_e)
\end{aligned}$$

where σ(i,t), M(i,t) and τ(i,t) are the implied volatility, moneyness and time to expiry respectively of the option series (i) on day (t). βt is the set of estimated coefficients of the cross-sectional regression of option implied volatility across different contract series, as specified in equation (A). Vt-1 is the option trading volume on day t-1.Daily forecasts are generated by rolling the sample forward and re-estimating the model parameters on a daily basis from 27th January 2004 to 8th September 2009.

Panel A: Prediction errors

		BETA1	BETA2	BETA3	BETA4	BETA5	IV	Price
Model 1: VAR-Volume model	MAE	0.0053	0.0103	0.0169	0.0080	0.0279	0.0087	2.1149
	MAPE	0.1228	0.8454	1.9596	3.2430	1.4075	0.1562	0.1988
	MSE	0.0002	0.0002	0.0005	0.0002	0.0016	0.0003	14.3768
	MCP	0.6480	0.7069	0.6551	0.6501	0.7033	0.5627	0.5627
Model 2: VAR model	MAE	0.0053	0.0103	0.0168	0.0078	0.0281	0.0088	2.0926
	MAPE	0.1234	0.8534	2.2954	3.2382	1.6352	0.1566	0.2058
	MSE	0.0002	0.0002	0.0005	0.0002	0.0016	0.0003	14.5921
	MCP	0.6622	0.7119	0.6622	0.6537	0.7005	0.4738	0.4733
Model 3: Ad-hoc straw man model	MAE	0.0054	0.0120	0.0173	0.0084	0.0348	0.0087	2.1215
	MAPE	0.1226	0.8046	1.1714	3.9543	2.4428	0.1590	0.2046
	MSE	0.0002	0.0003	0.0006	0.0003	0.0028	0.0003	14.3425
	MCP	NA	NA	NA	NA	NA	0.5479	0.5479
Model 4: AR model	MAE	0.0053	0.0094	0.0167	0.0068	0.0290	0.0090	2.1513
	MAPE	0.1366	0.8693	2.6816	3.4297	1.8277	0.1682	0.2256
	MSE	0.0002	0.0002	0.0005	0.0002	0.0017	0.0003	14.7226
	MCP	0.6238	0.7069	0.6650	0.6856	0.6962	0.4978	0.4977
Model 5: NGARCH model	MAE						0.0641	16.5518
	MAPE						2.8349	9.4033
	MSE						0.0076	436.7163
	MCP						0.3819	0.3819
Model 6: Random-walk model	MAE						0.0088	2.0899
	MAPE						0.1565	0.2055
	MSE						0.0003	14.5611
	MCP						NA	NA

Panel B: Forecast accuracy tests (Model 1 against different benchmarks)								
		BETA1	BETA2	BETA3	BETA4	BETA5	IV	Price
Benchmark 1: VAR model	MAE	-0.116	-0.031	1.232	8.972***	-1.391*	-16.084***	8.438***
	MAPE	-0.909	-1.107	-1.200	0.079	-4.064***	-1.917**	-11.929***
	MSE	-0.749	-0.120	0.424	2.070**	1.599*	-18.732***	-4.262***
	MCP	-1.633*	-0.896	-0.971	-0.662	0.431	40.919***	40.900***
Benchmark 2: Ad-hoc straw man model	MAE	-1.873**	-7.339***	-0.996	-1.930**	-9.117***	-22.214***	-10.566***
	MAPE	0.106	0.669	2.160**	-0.954	-6.537***	-53.280***	-40.473***
	MSE	-2.426***	-7.054***	-4.841***	-3.946***	-5.843***	-2.526***	4.542***
	MCP	NA	NA	NA	NA	NA	15.989***	15.980***
Benchmark 3: AR model	MAE	-2.068**	5.572***	1.034	10.873***	-3.620***	-39.446***	-15.352***
	MAPE	-6.483***	-0.938	-1.216	-0.324	-4.936***	-65.864***	-61.501***
	MSE	1.029	3.523***	0.410	3.290***	-1.367*	-15.624***	-8.287***
	MCP	1.648**	0.000	-1.080	-2.309**	0.762	39.856***	39.863***
Benchmark 4: NGARCH model	MAE						-209.555***	-241.569***
	MAPE						-170.101***	-62.596***
	MSE						-110.129***	-124.349***
	MCP						56.371***	56.359***
Benchmark 5: Random walk model	MAE						-14.583***	9.475***
	MAPE						-1.846**	-11.486***
	MSE						-17.657***	-3.573***
	MCP						NA	NA

Note: The ad-hoc straw man model (model 3) sets tomorrow's forecast of betas equal to today value. Hence, there is no expected change in beta values, ie MCP is not available (NA). Similarly, MCP of implied volatility forecasts is not calculated for the random walk model (model 6) because this model produces tomorrow's forecast equal to today's implied volatility for each option series. Both the NGARCH model (model 5) and the random-walk model (model 6) do not produce forecasts of betas.

*** indicates significance at the 1% level

** indicates significance at the 5% level

* indicates significance at the 10% level

the ad-hoc statics modeling techniques and confirm that the incorporation of time variations is statistically important in modeling and forecasting the dynamics of the IVS. An improvement in our model is provided by the addition of a trading volume factor which allows investors' learning and trading on new information to affect the equilibrium option prices, as suggested by economic theory. In sum, our results thus far illustrate that such an intuitively simple approach is sufficient to capture the dynamic property and hence significantly improve the predictability of the IVS.

Table 3.5

Out-of-sample Mean Statistical Errors by Moneyness and Maturity

Part A: Out-of-sample Mean Statistical Errors of Implied Volatility Forecasts by Moneyness and Maturity

This table illustrates how the average statistical error varies across different subcategories of option contracts classified by moneyness and maturity. In specific, the mean absolute error (MAE) has been estimated for forecasts of the implied volatility generated by six different models previously examined, including the VAR-Volume model (model 1), the same VAR structure without the volume factor (model 2), the Dumas et al. (1998) ad hoc straw man model (model 3), the AR model (model 4), the Heston and Nandi's (2000) NGARCH option pricing model (model 5) and the random walk model (model 6) [please refer to the methodology section for details of the calculation of the AE and model specifications]. Panel A and B report the average statistical errors estimated for calls and puts respectively while the corresponding figures reported in Panel C have been calculated for all option contracts. Daily forecasts are generated by rolling the sample forward and re-estimating the model parameters on a daily basis from 27th January 2004 to 8th September 2009.

		Panel A: Calls			Panel B: Puts			Panel C: All contracts		
		Short-Term	Medium-Term	Long-Term	Short-Term	Medium-Term	Long-Term	Short-Term	Medium-Term	Long-Term
DITM	Model 1	0.0088^	0.0084^	0.0060	0.0148	0.0273	0.0272	0.0103^	0.0107^	0.0076
	Model 2	0.0092	0.0090	0.0056	0.0144	0.0267	0.0264	0.0104	0.0111	0.0072
	Model 3	0.0096	0.0088	0.0050	0.0143	0.0275	0.0263	0.0108	0.0110	0.0066
	Model 4	0.0099	0.0097	0.0046	0.0141	0.0265	0.0246	0.0109	0.0117	0.0061
	Model 5	0.1039	0.0878	0.0648	0.0946	0.0614	0.0413	0.1016	0.0847	0.0630
	Model 6	0.0095	0.0088	0.0050	0.0144	0.0276	0.0263	0.0107	0.0110	0.0066
ITM	Model 1	0.0107^	0.0117^	0.0080	0.0109^	0.0156	0.0175	0.0108^	0.0127^	0.0095
	Model 2	0.0109	0.0120	0.0080	0.0110	0.0155	0.0171	0.0109	0.0129	0.0094
	Model 3	0.0112	0.0121	0.0075	0.0113	0.0157	0.0166	0.0112	0.0130	0.0090
	Model 4	0.0116	0.0132	0.0081	0.0114	0.0160	0.0157	0.0115	0.0139	0.0093
	Model 5	0.0551	0.0449	0.0330	0.0490	0.0373	0.0243	0.0527	0.0429	0.0316
	Model 6	0.0112	0.0120	0.0075	0.0113	0.0157	0.0166	0.0112	0.0129	0.0090
ATM	Model 1	0.0086^	0.0114^	0.0116	0.0084^	0.0118^	0.0113	0.0085^	0.0116^	0.0115
	Model 2	0.0087	0.0115	0.0115	0.0085	0.0118	0.0113	0.0086	0.0116	0.0114
	Model 3	0.0088	0.0117	0.0121	0.0088	0.0121	0.0106	0.0088	0.0119	0.0114
	Model 4	0.0088	0.0118	0.0118	0.0089	0.0124	0.0108	0.0088	0.0121	0.0113
	Model 5	0.0319	0.0365	0.0317	0.0354	0.0474	0.0450	0.0336	0.0416	0.0373
	Model 6	0.0088	0.0116	0.0121	0.0088	0.0120	0.0106	0.0088	0.0118	0.0114
OTM	Model 1	0.0083	0.0085	0.0090	0.0079^	0.0106^	0.0078	0.0081^	0.0101	0.0080
	Model 2	0.0084	0.0084	0.0089	0.0080	0.0106	0.0078	0.0081	0.0101	0.0080
	Model 3	0.0082	0.0086	0.0098	0.0082	0.0109	0.0073	0.0082	0.0104	0.0077
	Model 4	0.0082	0.0079	0.0089	0.0082	0.0111	0.0080	0.0082	0.0103	0.0082
	Model 5	NA	0.2009	0.0400	NA	0.1569	0.1228	NA	0.1642	0.1062
	Model 6	0.0082	0.0086	0.0098	0.0082	0.0109	0.0073	0.0082	0.0103	0.0077
DOTM	Model 1	0.0094	0.0098	0.0115	0.0071^	0.0086	0.0045^	0.0077^	0.0087	0.0049^
	Model 2	0.0094	0.0095	0.0114	0.0071	0.0086	0.0045	0.0077	0.0087	0.0049
	Model 3	0.0091	0.0098	0.0124	0.0074	0.0090	0.0047	0.0078	0.0091	0.0052
	Model 4	0.0091	0.0086	0.0111	0.0072	0.0091	0.0047	0.0077	0.0090	0.0051
	Model 5	NA	NA	NA	NA	NA	NA	NA	NA	NA
	Model 6	0.0091	0.0098	0.0124	0.0074	0.0089	0.0047	0.0078	0.0090	0.0052

Note: ^ indicates that model 1 generates the lowest forecast error when compared all other models considered.

Part B: Out-of-sample Mean Statistical Errors of Option Price Forecasts by Moneyness and Maturity

This table illustrates how the average statistical error varies across different subcategories of option contracts classified by moneyness and maturity. In specific, the mean absolute error (MAE) has been estimated for forecasts of option price generated by six different models previously examined, including the VAR-Volume model (model 1), the same VAR structure without the volume factor (model 2), the Dumas et al. (1998) ad hoc straw man model (model 3), the AR model (model 4), the Heston and Nandi's (2000) NGARCH option pricing model (model 5) and the random walk model (model 6) [please refer to the methodology section for details of the calculation of the AE and model specifications]. Panel A and B report the average statistical errors estimated for calls and puts respectively while the corresponding figures reported in Panel C have been calculated for all option contracts. Daily forecasts are generated by rolling the sample forward and re-estimating the model parameters on a daily basis from 27th January 2004 to 8th September 2009.

		Panel A: Calls			Panel B: Puts			Panel C: All contracts		
		Short-Term	Medium-Term	Long-Term	Short-Term	Medium-Term	Long-Term	Short-Term	Medium-Term	Long-Term
DITM										
	Model 1	0.9276^	1.9676	4.4526	1.4300	6.3831	14.0177	1.0514^	2.4949	5.1803
	Model 2	0.9822	2.0511	4.0191	1.4217	6.2993	13.4378	1.0905	2.5584	4.7356
	Model 3	0.9641	1.8486	3.0898	1.4376	6.3826	11.7649	1.0809	2.3900	3.7497
	Model 4	1.0469	2.0235	2.7456	1.4568	6.2246	11.3959	1.1480	2.5252	3.4037
	Model 5	17.1815	27.7030	42.6265	15.0741	22.2730	39.3855	16.6619	27.0545	42.3800
	Model 6	0.9628	1.8442	3.0976	1.4411	6.3943	11.7837	1.0807	2.3876	3.7584
ITM	Model 1	1.7898^	3.5126	5.8038	1.8533^	4.5848	11.3202	1.8145^	3.7867	6.6879
	Model 2	1.8705	3.6266	5.6132	1.8882	4.5729	11.0200	1.8774	3.8686	6.4797
	Model 3	1.8222	3.4862	4.9033	1.8927	4.5474	9.9520	1.8496	3.7575	5.7131
	Model 4	1.9896	3.7451	5.0063	2.0144	4.6259	9.5419	1.9992	3.9703	5.7332
	Model 5	12.1934	17.1933	24.0298	11.0697	15.2081	21.7064	11.7567	16.6857	23.6574
	Model 6	1.8201	3.4705	4.9027	1.8946	4.5490	9.9783	1.8491	3.7463	5.7169
ATM	Model 1	2.0706^	4.1875^	7.6256	1.9828^	4.0963^	7.6110	2.0269^	4.1418^	7.6188
	Model 2	2.1215	4.2142	7.5716	2.0169	4.1189	7.5505	2.0694	4.1664	7.5617
	Model 3	2.0804	4.2874	8.0118	2.0379	4.1276	6.5684	2.0592	4.2073	7.3368
	Model 4	2.1717	4.2743	7.6464	2.1689	4.3381	6.8299	2.1703	4.3063	7.2646
	Model 5	8.3531	16.2718	25.0841	9.4392	20.6997	33.6523	8.8762	18.3317	28.6484
	Model 6	2.0809	4.2695	8.0109	2.0378	4.1183	6.5908	2.0594	4.1937	7.3469
OTM	Model 1	1.7185	3.1569	5.7773	1.5659^	3.2362	4.6523	1.6243^	3.2178	4.8483
	Model 2	1.7441	3.0596	5.7244	1.5835	3.2238	4.6688	1.6450	3.1858	4.8527
	Model 3	1.6945	3.2225	6.5095	1.6237	3.3178	4.0379	1.6508	3.2957	4.4684
	Model 4	1.7751	2.8863	5.7700	1.7194	3.4278	4.5347	1.7407	3.3024	4.7499
	Model 5	NA	89.5907	16.1797	NA	52.1365	59.9418	NA	58.3789	51.1893
	Model 6	1.6978	3.2153	6.5061	1.6219	3.3032	4.0409	1.6510	3.2829	4.4703
DOTM	Model 1	1.3643	3.1184	5.4098	0.9787^	2.1302	2.3745	1.0749^	2.2441	2.5562
	Model 2	1.3703	2.9708	5.2432	0.9818	2.0819	2.4006	1.0787	2.1843	2.5708
	Model 3	1.3250	3.1166	6.2282	1.0268	2.2188	2.2756	1.1012	2.3223	2.5122
	Model 4	1.3814	2.6125	5.1718	1.0671	2.2130	2.3832	1.1456	2.2591	2.5501
	Model 5	NA	NA	NA	NA	NA	NA	NA	NA	NA
	Model 6	1.3288	3.1119	6.2185	1.0241	2.2026	2.2724	1.1001	2.3074	2.5087

Note: ^ indicates that model 1 generates the lowest forecast error when compared all other models considered.

In order to further analyze the nature of the forecasting improvement generated from the addition of trading volume in the VAR structure, we estimate the out-of-sample mean statistical errors of the model forecasts of implied volatilities and prices categorized by option moneyness and maturity. The out-of-sample MAE for forecasts of implied volatilities and prices, generated from our VAR-volume model and five other benchmark models previously examined, are reported in Part A and Part B of Table 3.5 respectively. These statistics have been estimated for each subsample of call contracts (in Panel A) or put contracts (in Panel B) and for the whole sample (puts and call together) in Panel C.

It is important to note that results of the evaluation of forecasts of option prices presented in Part A show that the forecast improvement has mainly been generated for short-term and medium-term contracts. In particular, it is found in Panel C that our VAR-volume model outperforms all other models in all moneyness categories for short-term and medium-term contracts. Further analysis into subcategories of calls and puts in panels A and B respectively indicates that the superior forecasting performance is generally realized for the first three moneyness categories (DITM, ITM and ATM) of call contracts and the last three moneyness categories (ATM, OTM and DOTM) of put contracts. Most interestingly, very similar results have been found in Part B when we examine the MAE of forecast of option prices, confirming the significance of our finding[44]. We conduct several tests to check the robustness of these results. Firstly, we employ different measures of volume and/or different VAR structures in our model construction. The resulting regression coefficient estimates and the statistical loss results change somewhat from specification to specification but the basic findings remain. Secondly, we assess whether our results are subject to the sampling bias by (1)

[44] It is also noticed that the results, not being reproduced here, yield a very similar observation when we examine other statistical measures of the model forecast performance, including the MAPE, the MSE and the MCP, across moneyness and maturity.

re-performing all the analysis again after re-assigning the in-sample period, (2) re-evaluating the out-of-sample performance over different sub periods, following the recursive pseudo scheme suggested by Konstantinidi, Skiadopoulos et al. (2008), and (3) considering different filters on option contracts to those previously applied in the main analysis. The results of these tests, not being reproduced here, yield a very similar observation to the previous findings.

3.3.3.2. Trading simulation

In spite of our surmise that trading volume helps to improve forecasts of the IVS dynamics having been supported by the statistical results presented thus far, we cannot rule out entirely the possibility that our results are subject to biases inherent in the statistical measurements employed in our analysis. As an additional test, we now examine the economic consequences and significance of this forecast exercise. Also this analytical appraisal offers an additional perspective on the forecast performance of our augmented VAR-volume model. This analysis aims to assess whether real option traders would be able to devise any trading profit from a forecasting exercise which employs trading volume in modeling the IVS dynamics. Similarly to Day and Lewis (1992) and Harvey and Whaley (1992), we compare the trading profit of our model forecasts with those generated by other competing models under a number of different trading simulation settings, i.e., following different trading rules with/without the consideration of transaction costs and trading filters as outlined in the methodology section. This will help to address some major questions of interest, including: (1) whether higher trading profit can be realized from more accurate forecasts derived from the incorporation of trading volume in modeling the IVS dynamics; (2) whether abnormal profits can be generated from our model forecasts using different trading strategies; and (3) whether this profitability is sensitive to trading costs. The last research question is particularly useful to assess the practical implications of our findings as the analytical setting most closely resembles real-world option trading.

Table 3.6 presents the simulated results generated from competing models' forecasts without transaction costs being considered. The profitability of model forecasts is generally expressed in terms of the Sharpe ratio and the Leland's Alpha presented in Panel A and Panel B respectively. Both are reported with their bootstrapped standard errors. As discussed in Le and Zurbruegg (2010), the Leland's Alpha seems to provide a better reference of the profitability of non-linear payoffs by taking into account the non-normality of the return distribution, which is likely to occur in the context of option trading as is being investigated in this paper. For each model, we report the trading profit under separate trading rules when either a delta-neutral or a delta-vega-neutral is employed. Moving across the whole table, it is clearly demonstrated that the magnitude and the statistical significance of the model trading profit increases as a more selective trading rule is adopted when moving from trading rule 1 to trading rule 3. This is found for both delta neutral and delta-vega neutral trading strategies and applies consistently across panels A and B, where the Sharpe ratio and Leland's alpha have been estimated respectively. For instance, when the delta-vega neutral option trading is employed, for our model forecast, trading rule 1 which allows trading taken on all contracts available implies a daily loss of 6.3% with a standard deviation of 2.2%, followed by trading rule 2 (a daily loss of 0.6% with a standard deviation of 3.1%) and trading rule 3 (a daily profit of 12.9% with a standard deviation of 1.7%). While it is generally expected that trading rule 3 should represent the best possible outcome, the higher profitability obtained from trading rule 2 relative to trading rule 1 to some extent highlights the finding that the forecast improvement most often realizes for short-term ATM contracts – those which stay closer to the centre of the smile. This confirms our finding of the

Table 3.6

Simulated trading profits before transaction costs

This table reports the profitability of option trading which is based on implied volatility forecasts generated from alternative forecast models, without considering transaction costs. It has been measured in terms of the Sharpe ratio (Panel A) and the Leland's Alpha (Panel B). Two option trading strategies have been employed to trade on implied volatility forecasts, including the Delta neutral trading and Delta-Vega neutral trading. In addition, we examine how profitability of each strategy varies when different trading rules are employed. For trading rule 1, transactions are executed for all option contracts whenever there are expected changes in the option implied volatility generated from the model forecasts. Trading rule 2 only employs trades on ATM, short-term contracts, whereas trading rule 3 only concerns trading on one contract which provides the highest expected trading profit, given the set of contracts available each day.

These trading strategies have been executed based on daily option implied volatitlily forecasts obtained from the VAR-Volume model (Model 1), the same VAR structure without the volume factor (model 2), the Dumas et al.'s (1998) ad hoc straw man model (model 3), the AR model (model 4), the Heston and Nandi's (2000) NGARCH option pricing model (model 5) and the random walk model (model 6). Implied volatility forecasts are generated by rolling the sample forward and re-estimating the model's parameters on a daily basis over the period from 27th January 2004 to 8th September 2009.

Panel A : Sharpe Ratio

	Delta neutral			Delta-Vega neutral		
	Trading rule 1	Trading rule 2	Trading rule 3	Trading rule 1	Trading rule 2	Trading rule 3
Model 1: VAR-Volume model	-0.022	-0.020	0.119***	-0.063***	-0.006	0.129***
	(0.027)	(0.028)	(0.016)	(0.022)	(0.031)	(0.017)
Model 2: VAR model	-0.002	0.024	0.106***	-0.046**	-0.020	0.122***
	(0.034)	(0.027)	(0.018)	(0.022)	(0.028)	(0.017)
Model 3: Ad-hoc straw man model	-0.012	0.004	0.105***	-0.039*	-0.016	0.122***
	(0.030)	(0.035)	(0.021)	(0.024)	(0.028)	(0.020)
Model 4: Random walk model	0.027	-0.030	0.062***	0.005	-0.041**	0.109***
	(0.027)	(0.024)	(0.024)	(0.037)	(0.022)	(0.018)
Model 5: AR model	0.004	0.005	0.105***	-0.003	0.001	0.058**
	(0.033)	(0.038)	(0.024)	(0.030)	(0.031)	(0.026)
Model 6: NGARCH model	-0.009	0.003	0.103***	-0.036	-0.026	0.121***
	(0.031)	(0.035)	(0.021)	(0.031)	(0.026)	(0.020)

Panel B : Leland's Alpha

	Delta neutral			Delta-Vega neutral		
	Trading rule 1	Trading rule 2	Trading rule 3	Trading rule 1	Trading rule 2	Trading rule 3
Model 1: VAR-Volume model	-0.006	-0.006	0.009***	-0.004**	-0.001	0.009***
	(0.006)	(0.007)	(0.002)	(0.002)	(0.004)	(0.002)
Model 2: VAR model	-0.002	0.004	0.008***	-0.004*	-0.006	0.008***
	(0.006)	(0.004)	(0.002)	(0.002)	(0.007)	(0.002)
Model 3: Ad-hoc straw man model	-0.004	-0.001	0.008***	-0.003*	-0.006	0.008***
	(0.006)	(0.003)	(0.002)	(0.002)	(0.008)	(0.002)
Model 4: Random walk model	0.003	-0.009	0.004**	0.008	-0.010*	0.007***
	(0.003)	(0.007)	(0.002)	(0.011)	(0.007)	(0.002)
Model 5: AR model	-0.001	-0.001	0.001***	-0.001	0.000	0.001**
	(0.007)	(0.002)	(0.000)	(0.009)	(0.001)	(0.001)
Model 6: Random walk model	-0.003	-0.001	0.008***	-0.001	-0.007	0.008***
	(0.006)	(0.003)	(0.002)	(0.001)	(0.007)	(0.002)

Note: We report in parentheses the bootstrapped standard error of the Sharpe ratio (Leland's Alpha) estimated.

*** indicates significance at the 1% level

** indicates significance at the 5% level

* indicates significance at the 10% level

forecast quality variations across moneyness and maturity documented previously. It is somewhat to be expected, given that option contracts of shorter-term and nearer to the money are often most liquidly traded, and hence trading volume should convey more information on the future dynamics of the smile. It is important to note also that when trading rule 3 is employed, all models significantly yield statistically significant returns, being expressed either in term of the Sharpe's Ratio or the Leland's Alpha. Positive values of the Leland's Alpha suggest that the trading profits are sufficient to compensate for the risk exposure under trading rule 3. Further, it is noticeable that the magnitude of the Sharpe Ratio measure of profit is truly abnormal in those cases. This effect is found consistently for both delta neutral and delta-vega neutral trading strategies. In particular, what is of more interest is that our model achieves the best return among all models considered in those cases. In particular, it yields a statistically significant return of 0.9% when either a delta neutral or a delta-vega neutral trading is undertaken, even after taking into account the features of higher-order moments of the empirical distribution of trading profit. In overall, the forecasting improvement seems to be maximised when a delta-vega neutral trading strategy is employed, and particularly when a more selective trading rule is employed (as in the case of trading rules 2 and 3 in our current settings).

Given the above finding, we further analyse how the profitability of delta-vega neutral option trading varies when different trading filters apply. Table 3.7 reports the trading profits generated from all model forecasts, considering two distinct trading filters of \$0.10 and \$0.25 respectively. This basically means that trading is only executed for contracts whose price deviations exceed the specific filter imposed. Given the current exchange rule imposing a minimum tick requirement of \$0.10 for most option trades, this not only offers a more realistic assessment of the profitability of option trading

Table 3.7

Delta-Vega Neutral Trading Profits with different filters before transaction costs

This table examines how the profitability of delta-vega neutral option trading, which employs the model forecasts of implied volatility, varies when different trading filters apply in the manner described in the methodology section. Transaction costs have been excluded in this trading simulation exercise. In addition, we examine how profitability of each strategy varies when different trading rules are employed. For trading rule 1, transactions are executed for all option contracts whenever there are expected changes in the option implied volatility generated from the model forecasts. Trading rule 2 only employs trades on ATM, short-term contracts, whereas trading rule 3 only concerns trading on one contract which provides the highest expected trading profit, given the set of contracts available each day. Similar to previous tables, trading profit is measured in terms of the Sharpe ratio (Panel A) and the Leland's Alpha (Panel B).

These trading strategies have been executed based on daily option implied volatitlily forecasts obtained from the VAR-Volume model (Model 1), the same VAR structure without the volume factor (model 2), the Dumas et al.'s (1998) ad hoc straw man model (model 3), the AR model (model 4), the Heston and Nandi's (2000) NGARCH option pricing model (model 5) and the random walk model (model 6). Implied volatility forecasts are generated by rolling the sample forward and re-estimating the model's parameters on a daily basis over the period from 27th January 2004 to 8th September 2009.

Panel A : Sharpe Ratio

	Filter = $0.10			Filter = $0.25		
	Trading rule 1	Trading rule 2	Trading rule 3	Trading rule 1	Trading rule 2	Trading rule 3
Model 1: VAR-Volume model	-0.009	-0.010	0.130***	-0.050***	-0.007	0.127***
	(0.032)	(0.030)	(0.017)	(0.019)	(0.030)	(0.017)
Model 2: VAR model	-0.035*	-0.021	0.121***	-0.005	-0.021	0.119***
	(0.026)	(0.027)	(0.016)	(0.033)	(0.028)	(0.016)
Model 3: Ad-hoc straw man model	-0.033*	-0.017	0.121***	-0.072***	-0.018	0.119***
	(0.020)	(0.028)	(0.019)	(0.019)	(0.029)	(0.019)
Model 4: Random walk model	-0.041*	-0.041**	0.108***	-0.035*	-0.040**	0.105***
	(0.030)	(0.022)	(0.017)	(0.024)	(0.022)	(0.018)
Model 5: AR model	0.000	-0.051**	0.053**	-0.007	-0.037*	0.042*
	(0.031)	(0.023)	(0.026)	(0.030)	(0.025)	(0.027)
Model 6: NGARCH model	-0.033*	-0.030	0.121***	-0.072***	-0.031	0.118***
	(0.021)	(0.024)	(0.019)	(0.018)	(0.025)	(0.019)

Panel B : Leland's Alpha

	Filter = $0.10			Filter = $0.25		
	Trading rule 1	Trading rule 2	Trading rule 3	Trading rule 1	Trading rule 2	Trading rule 3
Model 1: VAR-Volume model	-0.0004	-0.001	0.009***	-0.011*	-0.001	0.009***
	(0.004)	(0.004)	(0.002)	(0.007)	(0.004)	(0.002)
Model 2: VAR model	-0.004	-0.006	0.008***	0.002	-0.007	0.008***
	(0.003)	(0.007)	(0.002)	(0.013)	(0.007)	(0.002)
Model 3: Ad-hoc straw man model	-0.014	-0.006	0.008***	-0.015**	-0.006	0.008***
	(0.012)	(0.008)	(0.002)	(0.008)	(0.008)	(0.002)
Model 4: Random walk model	-0.002*	-0.010*	0.007***	-0.009	-0.009*	0.007***
	(0.001)	(0.007)	(0.002)	(0.008)	(0.007)	(0.002)
Model 5: AR model	0.000	-0.002**	0.001**	-0.002	-0.002*	0.001*
	(0.009)	(0.001)	(0.001)	(0.010)	(0.002)	(0.001)
Model 6: NGARCH model	-0.014	-0.008	0.008***	-0.015**	-0.008	0.008***
	(0.013)	(0.007)	(0.002)	(0.008)	(0.007)	(0.002)

Note: We report in parentheses the bootstrapped standard error of the Sharpe ratio (Leland's Alpha) estimated.

*** indicates significance at the 1% level

** indicates significance at the 5% level

* indicates significance at the 10% level

based on the smile forecasts, but also offers more insight on how our forecasting model performs relative to other alternatives. It is clearly illustrated that trading profit slightly worsens for most model forecasts as the size of the filter increases. This effect seems to be more pronounced for less selective trading rules when moving across the table from trading rule 1 to trading rule 3. In particular, the statistical significance of profit found for trading rule 3 remains unchanged, indicating a strong evidence of the abnormal profit can be generated from accurate forecasts of the smile dynamics. It is found that our VAR-volume model continues to dominate other models in achieving the highest (lowest) trading profit (loss), expressed both in terms of the Sharpe ratio and the Leland's Alpha in most instances. The only exception is when a filter of $0.25 is applied to trading rule 1, in which case our model's forecasts appear to generate statistically a greater loss, compared to the original VAR model. On the whole, the finding that our VAR-volume model consistently outperforms other models for trading rules 2 and 3, once again, confirms that the forecast improvement has been concentrated on short-term and near-the-money contracts.

The effect of transaction costs is taken into account in the results reported in Table 3.8, for which we recomputed the rate of returns for trading rules 1 to 3 when a fixed transaction cost per contract traded is imposed. We apply two different levels of unit cost, i.e. $0.05 (Part A) and $0.1 (Part B), to test the robustness of our results and also to examine whether our model profitability is sensitive to trading frictions. Moving across these tables, it is noticed that the magnitude of profits becomes lower, as transaction costs increase. In most cases, the statistical significance lessens (strengthens) for positive (negative) returns for higher trading costs. For instance, when transaction cost is as low as $0.05 per round-trip trade execution, the sign of trading profit generated from delta-vega neutral trading under trading rule 3 remains positive in most cases. In contrast, when transaction costs increase to \$0.10, this same specific trading rule tends to produce a loss for all models' forecasts. Despite these variations, it is very clear that the inclusion of trading costs barely affects the conclusion reached previously, as we find that the model ranking remains unchanged and clearly indicates our model's superior performance in most cases.

Overall, our results indicate the dominance of our model relative to others from an economic perspective. The magnitude and significance of the profitability of our model compared to others depends however on the fine details of the trading rules and on assumptions on the strength of market frictions; thus our findings of abnormal profitability in many cases are not necessarily in contradiction with the notion of market efficiency. The superior performance of our model relative to many benchmarks considered in this trading exercise once again confirms our previous finding, namely that the addition of trading volume into the VAR structure improves forecasts of the option smile.

Table 3.8

Simulated trading profits with transaction costs

Part A: Simulated trading profits with transactions of $0.05

This table reports the profitability of option trading which is based on implied volatility forecasts generated from alternative forecast models, when transaction costs of 5 cents per contract traded, on a round trip basis, are imposed. Two option trading strategies have been employed to trade on implied volatility forecasts, including the Delta neutral trading and Delta-Vega neutral trading. In addition, we examine how profitability of each strategy varies when different trading rules are employed. For trading rule 1, transactions are executed for all option contracts whenever there are expected changes in the option implied volatility generated from the model forecasts. Trading rule 2 only employs trades on ATM, short-term contracts, whereas trading rule 3 only concerns trading on one contract which provides the highest expected trading profit, given the set of contracts available each day. It is noted that a trading filter of $0.1 has been applied in this trading simulation exercise. Similar to previous tables, trading profit has been measured in terms of the Sharpe ratio (Panel A) and the Leland's Alpha (Panel B).

These trading strategies have been executed based on daily option implied volatitlily forecasts obtained from the VAR-Volume model (Model 1), the same VAR structure without the volume factor (model 2), the Dumas et al.'s (1998) ad hoc straw man model (model 3), the AR model (model 4), the Heston and Nandi's (2000) NGARCH option pricing model (model 5) and the random walk model (model 6). Implied volatility forecasts are generated by rolling the sample forward and re-estimating the model's parameters on a daily basis over the period from 27th January 2004 to 8th September 2009.

Panel A : Sharpe Ratio

	Delta neutral			Delta-Vega neutral		
	Trading rule 1	Trading rule 2	Trading rule 3	Trading rule 1	Trading rule 2	Trading rule 3
Model 1: VAR-Volume model	-0.031*	-0.019	-0.135***	-0.084*	-0.065**	0.041*
	(0.021)	(0.030)	(0.026)	(0.062)	(0.036)	(0.026)
Model 2: VAR model	-0.032*	0.005	-0.162***	-0.098*	-0.057**	0.038*
	(0.020)	(0.039)	(0.021)	(0.061)	(0.025)	(0.025)
Model 3: Ad-hoc straw man model	-0.033**	-0.042*	-0.154***	-0.074**	-0.050**	0.013
	(0.019)	(0.032)	(0.024)	(0.039)	(0.024)	(0.029)
Model 4: Random walk model	-0.033*	-0.055***	-0.156***	-0.308***	-0.078***	0.023
	(0.020)	(0.023)	(0.020)	(0.059)	(0.031)	(0.028)
Model 5: AR model	-0.015	-0.115***	-0.042**	-0.088*	-0.266***	-0.024
	(0.029)	(0.040)	(0.023)	(0.054)	(0.025)	(0.028)
Model 6: NGARCH model	-0.036**	-0.051**	-0.155***	-0.075**	-0.064***	0.013
	(0.017)	(0.022)	(0.024)	(0.040)	(0.025)	(0.029)

Panel B : Leland's Alpha

	Delta neutral			Delta-Vega neutral		
	Trading rule 1	Trading rule 2	Trading rule 3	Trading rule 1	Trading rule 2	Trading rule 3
Model 1: VAR-Volume model	-0.095	-0.006	-0.005***	-0.023**	-0.007**	0.003*
	(0.091)	(0.008)	(0.001)	(0.011)	(0.004)	(0.002)
Model 2: VAR model	-0.096	0.002	-0.005***	-0.030***	-0.013**	0.003*
	(0.090)	(0.005)	(0.001)	(0.011)	(0.007)	(0.002)
Model 3: Ad-hoc straw man model	-0.100	-0.004	-0.006***	-0.055**	-0.012**	0.001
	(0.094)	(0.003)	(0.001)	(0.030)	(0.007)	(0.002)
Model 4: Random walk model	-0.097	-0.012*	-0.006***	-0.036***	-0.016**	0.002
	(0.090)	(0.007)	(0.001)	(0.004)	(0.007)	(0.002)
Model 5: AR model	-0.005	-0.003***	-0.001*	-0.022***	-0.018***	-0.001
	(0.008)	(0.001)	(0.001)	(0.010)	(0.002)	(0.001)
Model 6: NGARCH model	-0.100	-0.007**	-0.006***	-0.058**	-0.014**	0.001
	(0.091)	(0.004)	(0.001)	(0.030)	(0.007)	(0.002)

Note: We report in parentheses the bootstrapped standard error of the Sharpe ratio (Leland's Alpha) estimated.

*** indicates significance at the 1% level

** indicates significance at the 5% level

* indicates significance at the 10% level

Part B: Simulated trading profits with transactions of $0.1

This table reports the profitability of option trading which is based on implied volatility forecasts generated from alternative forecast models, when transaction costs of 10 cents per contract traded, on a round trip basis, are imposed. Two option trading strategies have been employed to trade on implied volatility forecasts, including the Delta neutral trading and Delta-Vega neutral trading. In addition, we examine how profitability of each strategy varies when different trading rules are employed. For trading rule 1, transactions are executed for all option contracts whenever there are expected changes in the option implied volatility generated from the model forecasts. Trading rule 2 only employs trades on ATM, short-term contracts, whereas trading rule 3 only concerns trading on one contract which provides the highest expected trading profit, given the set of contracts available each day. It is noted that a trading filter of $0.1 has been applied in this trading simulation exercise. Similar to previous tables, trading profit has been measured in terms of the Sharpe ratio (Panel A) and the Leland's Alpha (Panel B).

These trading strategies have been executed based on daily option implied volatitlily forecasts obtained from the VAR-Volume model (Model 1), the same VAR structure without the volume factor (model 2), the Dumas et al.'s (1998) ad hoc straw man model (model 3), the AR model (model 4), the Heston and Nandi's (2000) NGARCH option pricing model (model 5) and the random walk model (model 6). Implied volatility forecasts are generated by rolling the sample forward and re-estimating the model's parameters on a daily basis over the period from 27th January 2004 to 8th September 2009.

Panel A : Sharpe Ratio

	Delta neutral			Delta-Vega neutral		
	Trading rule 1	Trading rule 2	Trading rule 3	Trading rule 1	Trading rule 2	Trading rule 3
Model 1: VAR-Volume model	-0.034**	-0.026	-0.177***	-0.088	-0.114***	-0.026
	(0.019)	(0.031)	(0.016)	(0.069)	(0.044)	(0.032)
Model 2: VAR model	-0.037**	-0.012	-0.200***	-0.099*	-0.089***	-0.030
	(0.020)	(0.048)	(0.016)	(0.063)	(0.032)	(0.034)
Model 3: Ad-hoc straw man model	-0.035**	-0.084**	-0.200***	-0.074**	-0.077***	-0.062**
	(0.020)	(0.049)	(0.017)	(0.037)	(0.027)	(0.037)
Model 4: Random walk model	-0.036**	-0.077**	-0.185***	-0.317***	-0.111***	-0.039
	(0.020)	(0.043)	(0.015)	(0.060)	(0.046)	(0.034)
Model 5: AR model	-0.031	-0.157***	-0.077***	-0.153**	-0.297***	-0.056***
	(0.028)	(0.052)	(0.027)	(0.067)	(0.032)	(0.022)
Model 6: NGARCH model	-0.037**	-0.078***	-0.201***	-0.078**	-0.092***	-0.061**
	(0.018)	(0.030)	(0.016)	(0.039)	(0.029)	(0.035)

Panel B : Leland's Alpha

	Delta neutral			Delta-Vega neutral		
	Trading rule 1	Trading rule 2	Trading rule 3	Trading rule 1	Trading rule 2	Trading rule 3
Model 1: VAR-Volume model	-0.112	-0.007	-0.010***	-0.045**	-0.013***	-0.002
	(0.102)	(0.008)	(0.002)	(0.021)	(0.004)	(0.003)
Model 2: VAR model	-0.108	0.000	-0.011***	-0.056***	-0.019***	-0.002
	(0.102)	(0.005)	(0.002)	(0.022)	(0.007)	(0.003)
Model 3: Ad-hoc straw man model	-0.108	-0.006**	-0.012***	-0.098**	-0.018***	-0.005**
	(0.104)	(0.003)	(0.002)	(0.049)	(0.008)	(0.003)
Model 4: Random walk model	-0.121	-0.015**	-0.011***	-0.071***	-0.022***	-0.003
	(0.107)	(0.008)	(0.002)	(0.007)	(0.007)	(0.003)
Model 5: AR model	-0.009	-0.007***	-0.004**	-0.044***	-0.034***	-0.003**
	(0.008)	(0.001)	(0.002)	(0.010)	(0.003)	(0.002)
Model 6: NGARCH model	-0.116	-0.010***	-0.012***	-0.101**	-0.020***	-0.005**
	(0.108)	(0.004)	(0.002)	(0.048)	(0.007)	(0.003)

Note: We report in parentheses the bootstrapped standard error of the Sharpe ratio (Leland's Alpha) estimated.

*** indicates significance at the 1% level

** indicates significance at the 5% level

* indicates significance at the 10% level

3.4. CONCLUSION

Economic models, such as those that allow for investors' learning to affect equilibrium option prices, have long suggested a dynamic relationship existing between asset prices and trading volume. In fact, such a topic has been studied heavily in the equity market, leading to many important forecasting applications being documented recently (Donaldson and Kamstra 2005; Le and Zurbruegg 2010). There is, however, comparatively less investigation undertaken in the option market toward this end. In this paper, we examine role of trading volume in modelling the dynamics of the IVS on the basis that it may capture the information related to the latent factors driving the time variations of the smile. In particular, we exploit the strong link existing between volume and the observed option prices by proposing a simple approach for forecasting the IVS dynamics.

The results of our investigation reveal that our augmented VAR-volume model produces high quality forecasts of the smile surface and explains relatively well its dynamic changes over time. Using both standard statistical measures and profitability-based criteria to evaluate the model performance, we find that the accuracy of the model forecasts can be significantly improved via a simple inclusion of volume into the VAR structure. In particular, ex-ante evidence indicates that the incorporation of volume leads to an outperformance over other alternate forecast approaches. This result is robust for a variety of perturbations of the sampling period and different measures of volume and model specifications.

Key findings in our paper offer many contributions to the existing literature in option price modeling and forecasting. In fact, they indicate that trading volume contains useful information about the time variations of option prices. In addition, they suggest that modeling the IVS dynamics may benefit from expanding the traditional VAR information set by including other factors such as trading volume. It is important to note however that our results have solely been based on index options for which the Black-Scholes model pricing errors are minimal. Empirical evidence also documents that the smile of index options has a distinctive shape different to that of stock options. Hence, it would be interesting to examine whether such a strong link between volume and the smile dynamics found in this paper will continue to hold for individual stocks. Considering that the efficiency of the option market which determines how quickly new information is incorporated into the trading prices has a great influence on the information content of volume, it may be worthwhile as a future research endeavor to investigate whether trading volume still plays an important role in modeling and forecasting the smile dynamics for stock options, especially those which are far less liquid.

CHAPTER 4

THE ALLOCATION OF INFORMED TRADING ACROSS RELATED MARKETS: AN ANALYSIS OF THE IMPACT OF THE 2008 SHORT-SALE BAN

Paper will be presented at the *2012 FMA Annual Meeting*, October 2012, Atlanta, US

STATEMENT OF AUTHORSHIP

THE ALLOCATION OF INFORMED TRADING ACROSS RELATED MARKETS: AN ANALYSIS OF THE IMPACT OF THE 2008 SHORT-SALE BAN

Conference Paper

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For this paper (chapter), Van Le developed the theoretical framework and hypothesis, performed the data analysis, wrote the manuscript and acted as the corresponding author. Prof Ralf Zurbrugg assisted in guiding the theory development, supervised the development of work and provided evaluation and feedbacks.

The majority of the work and the primary authorship have been undertaken by Van Le.

Van Le (Candidate)

I hereby certify that the statement of contribution is accurate.

Signed____________________________________ Date: 17/05/2012

Prof Ralf Zurbrugg (Principal Supervisor)

I hereby certify that the statement of contribution is accurate and I give permission for the inclusion of the paper in the thesis.

Signed____________________________________ Date: 17/05/2012

THE RELATIONSHIP OF THIS CHAPTER TO THE THESIS

In this chapter, the research attention has been placed on the short-sale restrictions implemented by SEC in 2008 in the midst of the global financial crisis. This study seeks to significantly contribute to the second research question by examining the way in which traders respond to the increasing transaction costs and trading restrictions induced by the implementation of the short-sale ban. Indeed, by analysing how informed traders react differently to uninformed traders during and after the ban and how this consequently affects the trader composition in two related markets, this study provides an informative answer to the issue of the factors that drive traders' decisions to trade in the option market. In addition, it offers many important insights into how the market microstructure and the informational linkage between the option and stock markets have been affected by this regulatory change. The second issue concerning the implication of informed traders' activities for the informational linkage between two related markets, therefore, has also been partially addressed in this sense.

Abstract

This paper examines the impact of the 2008 short-sale ban on the liquidity and trade informativeness of the options and underlying stock markets. Based on one year of intraday data, we find that a trader-switching effect from banned to unbanned stocks occurs in both related markets during the Emergency Order period. We also find that traders respond differently to two distinct short sales regulations that were implemented, providing support for Diamond and Verracchia's (1987) prediction which distinguishes between the short-prohibition effect and the short-restriction effect of short-selling constraints.

4.1. INTRODUCTION

The effect that short sales restrictions have on market efficiency has been studied extensively in the literature. In general, the results of these studies indicate that short-sale constraints have an adverse effect on market liquidity and the speed of price adjustments to negative news (see, e.g., Miller, 1977; Figlewski, 1981; Danielsen and Sorescu, 2001; Jones and Lamont, 2002; Ofek and Richardson, 2003; Bris et al., 2007; Chang et al., 2007; Boehmer et al., 2008; Chen and Rhee, 2010). Within this line of query, several studies have focused on examining whether option trading can lessen the impact of short sales restrictions (SSR hereafter) on the price efficiency of underlying stock, as it is often argued that the option market offers an alternative trading venue for investors with unfavourable information to sell short indirectly. While this argument has been supported by the empirical evidence found in Figlewski and Webb (1993), Sorescu (2000), Danielsen and Sorescu (2001), Nilsson (2008) and Blake (2011), the literature is far from conclusive about the role of option trading in mitigating short-sale constraints.

This paper undertakes a new investigation of the connection between short selling and option trading empirically by examining the effect of the 2008 short-sale ban (SSB hereafter) on the market microstructure of both the option and underlying stock markets. It provides three major contributions to the existing finance literature. Firstly, it examines how the SSB on the equity market would affect the option trading activities given the arbitrage link between two markets[47]. Despite its importance in policy

[47] In fact, the relative composition of different investor groups in the option market may be altered because speculators and informed traders, in comparison to liquidity traders, are more likely to circumvent the ban by taking a synthetic short position in the option market. Further, it is argued that SSR may lead to changes in the market microstructure if a certain class of investors is more sensitive to changes in transaction costs in making a trading venue decision (Mayhew et al., 1995).

making, the question about regulations for a specific market affecting related markets has not yet been addressed satisfactorily in the literature. Secondly, this paper aims to provide additional insights into the impact of the ban on certain aspects which have not been fully considered in previous studies centering on the 2008 SSB. In particular, it will examine how the implementation of SSR affects the informational efficiency of the option market, measured by the degree of contribution of option trades towards the price discovery of the underlying stock and the changing dynamics of the lead-lag relation between stock and option trades. Thirdly, by analyzing the impact of SSR on the market microstructure of both the option and stock markets, this paper offers additional insights on the relative allocation of informed trading in related markets and how it has been affected by the SSB.

We argue that the SSR implemented during the global financial crisis (GFC hereafter) provides unique institutional settings to further investigate traders' short-selling activities and the way in which the SSB affects their trading behavior. More specifically, if traders' sensitivity to SSR is different between informed and uninformed traders given different trade motives, we would expect to observe its effect manifested through changes in the trader composition. This line of argument is similar to DV's prediction which states that "imposing a cost on short selling both reduces the number of short-sales and influences the mix of relatively informed and relatively uninformed traders". Most importantly, the distinct features of the two different short-sale regulations implemented during the course of the GFC, ie the Emergency Order that effectively restricted naked short selling for nineteen stocks (ban 1 hereafter) and the outright ban on 797 financial stocks which followed (ban 2 hereafter), provide a unique opportunity to validate the effectiveness of different regulatory settings and to test the empirical implications of Diamond and Verrecchia's ((1987), hereafter DV) theoretical model, which exclusively distinguishes between "the short-restriction effect" (SRE hereafter) and "the short-prohibition effect" (SPE hereafter) of SSR[48,49].

Our results indicate that a significant proportion of traders switch their trades from stocks for which short-sales were banned (banned stocks) to others which are not subject to SSR (unbanned stocks) during the first ban period to mitigate the effect of SSR. While this is somewhat analogous to Boulton and Braga-Alves's (2010) finding[50], we also find a similar switching effect prevailing in the option market, evidenced by decreases in the option volume and its "information share"[51] while the opposite holds for unbanned stocks. Further diagnostics indicate that this flow of traders appears to be dominated by relatively uninformed traders. We interpret this finding as supporting the hypothesis that uninformed traders are more sensitive to increasing costs of short-sales, as predicted by DV's SRE. As for the second ban, we find no accompanying change in the relative composition of traders either in the stock market or in the option market during the ban period. This is consistent with DV's SPE which predicts that the prohibition of short-sales does not provoke any changes in the trader composition, merely because informed and uninformed traders should have been affected in the same

[48] DV's SRE predicts that increasing costs of short sales tends to affect the mix of informed and uninformed traders whereas prohibitions on short-selling impose no impact on the trader composition. Kolasinski et al.'s (2010) empirical work also pursues this same line of argument, though the scope of their analysis has been limited to examine the stock trading activities only.

[49] While the main features of the two bans examined in our paper fit into the separate categories of SSR identified in DV's paper, it is important to note that the key theoretical predictions drawn in their paper have solely focused on the implications of SSR on stock trading activities. When combined with the notion that option trading can reduce the effect of SSR by establishing what-is-effectively a short position, these implications have empirical contents which require further examination. We thank an anonymous referee for pointing this out.

[50] They found that short sellers switched from banned stocks to unbanned stocks during the restricted period when examining the trading activities on those relevant stocks.

[51] It is estimated using a modification of Hasbrouck's (1995) approach, as similar to Chakravarty et al.'s (2004) and Anand and Chakravarty's (2007) empirical work.

way. Finally, we provide some additional evidence on the lead-lag relationship between option and stock markets and on the price impact in the option market which conform with our previous conjecture about how the trader composition in each market changes in response to SSR.

It is possible that these results may be driven by other economy wide factors that influence the market conditions during the period under investigation. Although it is difficult to rule out this possibility[52], it is noted that our findings for banned stocks do not hold for the matched sample of unbanned stocks.

The remainder of this paper is organized as follows. In section II, we develop the empirical predictions based on various models and theories suggested by the current literature. Section III describes the characteristics of the data set and key variables employed to address the main research questions presented earlier. The main empirical results are reported in section IV with some discussion following in section V. Section VI concludes our paper and provides suggestions for future research.

4.2. THE PREDICTIONS

Our analysis generally concerns the effect of the 2008 SSB on the market microstructure of both the option and underlying stock markets. In this section, we briefly discuss the empirical predictions suggested by the theory for each market in turn, with inference to some existing evidence in the literature.

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[52] We have tried to control for this and other relevant effects by (1) including variables controlling for the general market condition and other inherent factors, including the market volatility level captured by the CBOE implied volatility index VIX, the stock return, volume and volatility; and (2) employing a control sample of unbanned stocks in our examination.

4.2.1. The impact of SSR on option trading

Our first focus is to examine the impact of the SSB on the option market. If option trading is used to circumvent the SSB[53], we expect to see it manifested in various ways.

Firstly, we should see changes in the liquidity of the option market in terms of changes in its trading volume and bid-ask spread. The adverse selection component of the bid-ask spread generally depends on the degree of information asymmetry between the quoted prices and informed traders (see, Copeland and Galai, 1983; Glosten and Milgrom, 1985). If the imposition of the SSB leads to a higher proportion of informed, as compared to uninformed, traders migrating to the option market, this will increase the relative concentration of informed traders there and result in a wider bid-ask spread. In addition, the influx of traders who wish to create a synthetic-shorting-stock position would impose an upwards net buying (selling) pressure on puts (calls) which in turn would lead to increased ask (decreased bid) prices for puts (calls) demanded by market makers (Bollen and Whaley, 2004). The option spread may also increase because market makers, who take the net supply side of the synthetic short position, may be facing higher hedging costs attributable to overpricing of the underlying stock and/or a higher stock spread during the ban period (Boehmer et al., 2009)[54]. Considering these arguments collectively, we expect to observe a wider option bid-ask spread as a result

[53] It can be argued that during the ban, institutional and individual investors who are subject to SSR on stock trading can create a synthetic short position using options. Some supporting evidence has been found in Figlewski and Webb (1993), Sorescu (2000), Danielsen and Sorescu (2001), Nilsson (2008) and Blake (2011). The extant literature also suggests that options play an important role in the pricing discovery of the underlying assets (e.g., Anthony, 1988; Ni et al., 2008); and that informed traders may prefer to trade in the option market due to the high financial leverage and reduced transactions costs (Black, 1975).

[54] A more subtle reason for the increase in the option bid-ask spread is due to increasing uncertainty stemming from the market conditions amidst the GFC. Not only does the market marker's inventory cost increase with the escalation of uncertainty, the solvency concern may also lead to higher cost of borrowing if the market maker wishes to hedge by shorting the underlying stock. While we cannot rule out this possibility, we try to control for it by comparing it with a control group of unbanned stocks

of the ban. The literature is however less clear and divided on the net impact of the SSB on the option trading volume. On the one hand, the increase in option bid-ask spreads may cause some existing traders to exit the market when facing higher trading costs. On the other hand, option-trading volume may increase due to the surge of heterogeneity of traders' beliefs (as predicted by DV[55]) and to the substitution effect of option trades suggested in the extant literature (e.g., Figlewski and Webb, 1993; Sorescu, 2000; Danielsen and Sorescu, 2001; Nilsson, 2008; Blake, 2011)[56]. Recent studies, such as Battalio and Schultz (2010) and Grundy et al. (2010), indicate that SSR cause deteriorating liquidity of the option market in terms of lower trading volume and higher spread during the ban period, but the focus of their studies has been restricted to the second ban. Due to the distinctive regulatory implications of the two bans considered, we argue it is necessary to distinguish between them so as to allow a more in-depth examination of the role of options in mitigating SSR.

Secondly, we may expect to observe some changes in the informational efficiency of the option market. In fact, the relative composition of informed and uninformed traders in the option market might have been altered as a result of traders switching from the stock to the option market in response to SSR and higher trading costs. While the existing literature (Mayhew et al., 1995) suggests that uninformed traders tend to be more sensitive to changes in transaction costs, the question of whether SSR would result in an influx of relatively more uninformed traders into the option market is far from conclusive. On the one hand, it can be argued that SSR implemented during the ban would cause relatively more uninformed traders exiting the stock market due to

[55] See also Hong and Stein (2003), Grundy and McNichols (1989), Harris and Raviv (1993) and Cao and Ou-Yang (2009).

[56] This conjecture doesn't receive much support from more recent research, however, given that either no relationship or a significant negative relationship between short sale constraint proxies and option trading volume was found in Mayhew and Mihov 's (2005) investigation into option trading volume following the option introduction

higher costs of short sales. This will lead to a relatively higher proportion of uninformed traders entering the option market if this same mix of investors switches from stock to option trades. On the other hand, it is often contended that the option substitution effect is only applicable to sophisticated traders who are relatively more informed[57]. Hence, it is more likely that the trader flow from the stock market to the option market is dominated by informed traders. Apart from these contradictory predictions currently existing in the literature, it is unclear to what extent the option substitution effect can be directly attributable to increasing costs of short sales in the underlying stock market. In fact, the higher cost of short sales may not necessarily lead to any effect of trader immigration if there is no real cost savings achieved. This is because those who switch to the option market might end up facing the higher option premium demanded by market makers as a recompense for higher costs of hedging incurred in the underlying market. Further, it is suggested that the higher cost of short sales may actually entail an adverse effect on option trading, as certain synthetic trading strategies using both option and stock will incur higher costs. This discussion suggests that the impact of SSR on the informational efficiency of the option market is an empirical question.

4.2.2. The impact of short sale restrictions on stock trading

Our second objective is to examine the impact of the 2008 SSB on the stock market quality. While the issue of how SSR affect the market quality is not new[58], our study is different to earlier studies in many aspects. Firstly, we consider how the effect of SSR on the market quality is linked to the relative responses of informed versus uninformed

[57] Please refer to Black (1975) and Easley et al. (1998) for the argument that option trades are primarily information-based.

[58] In particular, recent studies, including Boehmer et al. (2009), Harris et al. (2009), Boulton and Braga-Alves (2010), Kolasinski et al. (2010) and Beber and Pagano (2011) document several ways that the 2008 SSB affects the stock market.

traders and the effect of trader migration between the stock and option markets. Secondly, we aim to distinguish the separate effects of the two distinct short-sale regulations implemented during the course of the GFC by employing the theoretical framework established in the DV paper[59]. Similarly to Kolasinski et al. (2010), we argue that the first ban provokes higher costs of short-sales and fits closely to the SRE while the second ban ties to the SPE[60]. Given DV's model predictions, we expect to observe a greater concentration of informed traders in the stock market during the first ban and no significant change of trader composition in the second ban. Further, we argue that, since the first ban only targets a small set of stocks, traders may have incentives to substitute trades of banned stocks for those of closely matched unbanned stocks to avoid the SSR. This does not happen in the second ban because traders are unlikely to find a close substitute to those included in the long list of banned stocks. Lastly, this paper examines the effect of SSR on the speed of stock price adjustments, an aspect which has not yet been examined in the context of the 2008 SSB[61]. Despite the theoretical prediction that SSR are detrimental to stock price adjustments to news, especially negative news (Miller, 1977; Diamond and Verrecchia, 1981), the empirical

[59] They argue that uninformed traders are more sensitive to changing costs of short-sales than informed traders. Hence, SSR which effectively increase the costs of short-sales would simply induce changes in the trader composition, as relatively more uninformed traders exit the market in response. In contrast, a ban which prohibits short-sales activities would affect uninformed and informed traders equally. These distinctive predictions are referred to in their paper as the SRE and the SPE respectively.

[60] The first ban forces short sellers to borrow or arrange to borrow shares before trading, rather than merely locating a potential lender, as was previously required. As discussed in Kolasinski et al. (2010), this increases the costs of short-sales because borrowing becomes mandatory and incurs at a higher fee charged by lenders. These features of the first ban closely fit the short-restriction effect in DV's argument. In contrast, the second ban prohibits all short-selling activities, with the only exemption given to market makers undertaking short sales for hedging purposes.

[61] Though Beber and Pagano (2011) document that the SSB slows down the price discovery of banned stocks, they did not directly measure the speed of price adjustments. We adopt Hasbrouck's (1991) dynamic vector autoregressive model to test the speed of price adjustment to the information contained in each trade and how it was affected during the 2008 SSB, as similar to Chen and Rhee (2010).

evidence on the impact of the ban on the speed of stock price adjustments still poses an appealing research question, owing to the dynamic link between option and stock trading. In fact, SSR may effectively induce more informed short-selling activities if more informed traders switch to option trades to mitigate the ban. This possibility arises because the option market marker, who is not subject to SSR, would presumably need to hedge his exposure via short-selling whenever individual traders wished to take a synthetic short position using options.

To sum up the above discussion suggests that the impact of the SSB on the trading activities in both the option and stock markets is an empirical question, which has not yet been addressed satisfactorily in the literature.

4.3. SAMPLE AND EMPIRICAL SPECIFICATION

In this section we will briefly describe the SSR implemented during the course of the GFC in 2008. This is then followed by a short account of the data base used, the nature of the data and sample construction and finally the process of preparing the data for analysis. In addition to using some usual transaction measures such as volume and spread, we have constructed various variables of interest to address the main research questions presented earlier.

4.3.1. The 2008 short-sale ban

SSR were implemented twice within a five month period after the summer of 2008. The first ban was implemented on 21st July after the US Securities and Exchange Commission (SEC) issued an Emergency Order (34-58166) temporarily halting naked short selling in 19 financial stocks on 15th July. Before the ban, investors were not required to actually borrow the shares before executing short-sales. This practice, known as naked short selling which sometimes causes failure to deliver shares on the settlement day, was the intended target of the Emergency Order. While the order was initially scheduled to lapse on 30th July, it was later extended by SEC and continued through to 12th August.

In response to the fear that the market would collapse as prices of financial stocks continued to plummet, a permanent ban on naked short-selling was then issued for all US firms (Emergency Order 34-58572) after the market close on 17th September, effective at midnight that evening. Also on the next day, the SEC issued another Emergency Order (34-58592) halting all short-selling on 797 financial stocks, effective immediately, with limited exception for "certain bona fide market makers" unless they *knew* that their customers' or counterparties' transactions would result in an increase in their economic net short position[62]. This list of banned stocks was further extended in the following trading days after the SEC granted each exchange the authority to add more firms to the list. Though the ban was initially set to expire in 10 days, it was extended on 2nd October and lapsed at midnight on 8th October, which was three days after the President's signing of the Emergency Economic Stabilization Act 2008. Short selling activities resumed in the market, though the naked SSB has continuously remained in place since then.

4.3.2. Sample construction and matching procedure

Given the timeline and unique features of the series of short-sale bans outlined above, the data set and the sampling period in this paper has been selected so as to ensure that

[62] Boehmer et al (2009) argue that this provision seems to give market makers an incentive to avoid knowing their customers' trading intention.

our analysis would be based on (1) comparable data sets between the first and the second bans; (2) similar option characteristics in the pre and post ban periods; and (3) controlling for the impact of economy-wide factors. Firstly, we identify the set of 19 financial stocks included in the first ban (Emergency order 34-58166), including 17 Wall Street firms and 2 mortgages lending giants (Fannie Mae and Freddie Mac). With the exceptions of BNP Paribas Securities Corp. and Daiwa Securities Group Inc which trade over the counter, all other firms are traded on the NYSE and have options listed on the CBOE. This situation results in the exclusion of those two securities in our first sample set of financial stocks targeted in the first ban, as the SIRCA database does not keep records of firms traded on the pink sheet. Given that the 17 NYSE-listed stocks remained were also included in the long list of banned stocks in the second ban which followed in September, we construct 2 matched samples of this list using other stocks which must also have listed options over the ban period. The first match sample contains 17 financial stocks which are included in the ban list of the second ban but not of the first ban, while the other comprises of 17 non-banned stocks. The behaviors of these two matched samples are examined in a direct comparison with the original ban list during and after the ban period in order to (1) highlight the differential impact of SSR on stocks included in the ban list; and (2) to ensure that our results are not driven by economy-wide factors.

The matching procedure has been performed so as to find stocks which are comparable to stocks subject to SSR in the first Emergency Order[63]. Similar to Boulton and Braga-

[63] The nature of the events under investigation makes choosing the matched sample a challenging task. In particular, the second ban covers the majority of financial stocks. This makes it impossible to find comparable non-banned stocks within the same industry to those included in the ban list. The matching procedure, therefore, have been performed across industries while we acknowledge this issue would potentially hinder the robustness of our results.

Alves's (2010) approach, the match for each stock in the original ban list is determined by finding the stock that minimizes the following expression

$$Distance = \sum_i \left| (factor_i^{restricted} - factor_i^{matched}) / [(factor_i^{restricted} + factor_i^{matched}) / 2] \right| \qquad (A.1)$$

Factors considered in the above specification include the market value of shares outstanding, closing stock price, daily turnover, return volatility and option trading volume for the pre-sample period from 1st January 2007 to 31st December 2007. Matches are performed without replacement, resulting in a unique match for each restricted firm. A detailed list of all selected stocks is included in Appendix 4.A. We have provided here in Table 4.A the summary statistics of the stock and option trading activities of the three sub-samples considered, namely the ban list (group 1 hereafter), the matched ban list (group 2 hereafter)and the matched non-ban list (group 3 hereafter). The t-test of the difference of means[64] indicate that no significant difference exists between the first two groups of stocks for any of the five matching criteria. The last group, however, seems to consist of common stocks which are significantly smaller and have less-volatile stock returns than those included in the first and the second groups.

Both the option and stock transaction data are obtained from SIRCA and contain details of the date, the time stamp, the exchange for every single trade (quote) record, the bid (ask) price and the size for quotes and the settlement price and volume for trades. All records are time-stamped to the nearest millisecond, allowing us to merge the two data sets. The option market trading data are collected under the Options Price Reporting Authority (OPRA) plan for Reporting of Consolidated Last Sale Reports and Quotation

[64]The same conclusion is reached when we apply the Wilcoxon's test of the difference of medians on the same set of statistics. The results are not included here for clarity but they are available upon request.

Information. The nature of our data gives us some advantages over related studies into the option market which are based on either the OptionMetric IVY database or the Berkeley Option database. In fact, our data set allows us to analyze the informed trading

Table 4.A

Summary statistics of stock and option trading activities categorised by groups

This table provides summary statistics of 51 optionable stocks examined. Our stock sample can be categorised into three groups. Group 1 (G1) comprises of 17 stocks which are subject to the first Emergency Order implemented on 21st July 2008 (ban 1). Group 2 (G2) is the matched sample of 17 stocks which are subject to the subsequent outright ban implemented on 19th September 2008 (ban 2) while Group 3 is the second matched sample of 17 stocks which are not subject to the 2008 short sale regulations. Panel A reports the key stock charateristics including the market value of shares outstanding (MV), the daily closing stock price, the daily turnover and the daily return volatility. Turnover measures the number of shares traded as a percentage of the total number of shares outstanding. These stock characteristics and the liquidity of the option market (ie measured by the daily option trading volume) have been the key statistics considered in the process of constructing the matching samples. Panel B and C reports other descriptive statistics of stock and option trading activities respectively. These include the daily stock return and volume, the number of stock trades per day, the average size and the average spread of stock trades, the daily option volume, the number of option trades per day, the average size of option trades, the option spread, the average level and slope of the implied volatility smile. The relative bid-ask spread measure has been used for both option and stock whereby spread is measured as a percentage of the quote midpoint. The daily average of stock spread is then calculated by simply taking the average of spreads of all stock trades, whereas the daily option spread is the weighted average of spreads of all option trades [with the option moneyness being used as the weight as descried in the variable construction section] . All variables have been calculated by taking the mean value for the entire sample period from 2nd January 2008 to 26th December 2008 though the values reported for each group have been the medians. The P-values are for Wilcoxon rank sums tests for the difference of medians between groups1 and 2 (Prob(G1 vs G2)), groups 2 and 3 (Prob(G1 vs G2)) and groups 1 and 2 (Prob(G1 vs G2)) respectively.

Panel A : Stock characteristics

	All	G1	G2	G3	P-value (G1 vs G2)	P-value (G2 vs G3)	P-value (G1 vs G3)
Number of firms	51	17	17	17			
MV ($)	9,197,501	19,678,889	16,441,981	5,160,593	33.48%	0.65%	1.45%
Stock Price	36.53	30.71	42.82	38.54	17.92%	60.54%	60.54%
Daily Turnover	16.64	26.95	13.80	16.02	25.57%	44.86%	31.79%
Volatility	0.27%	0.38%	0.29%	0.23%	30.15%	1.08%	0.24%

Panel B : Daily stock trading activities

	All	G1	G2	G3	P-value (G1 vs G2)	P-value (G2 vs G3)	P-value (G1 vs G3)
Stock Return	-0.27%	-0.46%	-0.29%	-0.17%	12.96%	0.06%	0.00%
Number of stock trades	21,963	86,780	24,888	11,043	50.95%	1.51%	4.00%
Average stock trade size	188	218	167	173	0.21%	80.65%	1.67%
Average stock spread	0.001	0.001	0.001	0.001	41.78%	98.50%	86.53%

Panel C : Daily option trading activities

	All	G1	G2	G3	P-value (G1 vs G2)	P-value (G2 vs G3)	P-value (G1 vs G3)
Option Volume	378	3,808	778	227	16.29%	9.33%	3.02%
Number of option trades	23	136	49	20	19.98%	12.67%	4.37%
Average option trade size	11	17	11	9	4.56%	74.86%	1.09%
Average option spread	0.404	0.364	0.317	0.585	24.24%	3.31%	28.26%
Average implied volatility	34%	37%	35%	29%	90.99%	2.49%	7.33%
Average implied volatility ATM	30%	34%	33%	27%	99.00%	3.01%	3.99%
Average slope of the IVS	0.07	0.07	0.08	0.07	10.49%	6.74%	95.49%

activity using data from all option markets (if a stock has multiple option contracts traded on different option exchanges) while avoiding the problems of nonsynchronous trading records pertinent in the OptionMetrics IVY database. Reference can be made to Battalio and Schultz (2006) for a discussion of the problem of nonsynchronous prices and microstructure issues responsible for most of the apparent arbitrage opportunities identified using the OptionMetrics IVY database[65]. Also Anand and Chakravarty (2007) provide some argument as to why it is appropriate to combine trades from all exchanges in examining the price discovery in the option market. Apart from transaction data, we also source from SIRCA data of discrete cash dividends paid on the equities. All the remaining data, including the 30-day T-bill yield which we utilize as the risk free rate, the daily S&P 500 index level and the daily CBOE's VIX index level, are collected from DataStream International.

We apply some standard filters analogous to those in Bollen and Whaley (2004) and Battalio and Schultz (2006) to ensure the integrity of option trading data. Firstly, we only select options with less than 180 days to maturity to avoid problems associated with non-trading. Secondly, we exclude those with less than 5 days to maturity to eliminate any effect of option expiration. Thirdly, options with absolute delta below 0.02 and above 0.98 are also excluded due to distortions caused by price discreteness. Fourthly, we restrict our data set to trades and quotes recorded earlier than 4pm Central Standard Time for both stocks and options to ensure better matching of option trades with contemporaneous price of the underlying stock. Also for an option series to be included, we require that at least two trades are included on a trading date. This is

[65] Battalio and Schultz (2006) argue that much of the apparent arbitrage opportunities identified using the Option Ivy database arises from the fact that closing option quotes have time stamps of 4:02pm while closing trades on the underlying stock that are executed no later and possibly much earlier than 4:00pm.

analogous to Anand and Chakravarty (2007) to ensure the liquidity of the option contracts employed in our analysis of the information share of options towards the price discovery of the underlying stock. Lastly, we filter the data for any potential data errors, including any instances when (1) the trading price is zero; (2) the settlement price stays outside the closing bid-ask range; (3) the closing ask price is less than the closing bid price; or (4) when there are violations of standard American option bounds in the option transaction data. This standard procedure is similar to work done by Ofek, Richardson et al. (2004) and Grundy, Lim et al (2010). Table 4.B reports summary statistics for put and call options of the firms included in our sample over the complete sample period.

Table 4.B

Descriptive statistics of option trading activities categorised into puts and calls

This table provides summary statistics of option trading activites of 51 optionable stocks examined in terms of puts and calls trading. These include the daily option volume, the number of option trades per day, the average size of option trades, the option spread, the average level and slope of the implied volatility smile. The relative bid-ask spread measure has been used for both option and stock whereby spread is measured as a percentage of the quote midpoint. The daily option spread is simply the weighted average of spreads of all option trades [with the option moneyness being used as the weight as described in the variable construction section] . All variables have been calculated by taking the mean value for the entire sample period from 2nd January 2008 to 26th December 2008. Our stock sample can be categorised into three groups. Group 1 (G1) comprises of 17 stocks which are subject to the first Emergency Order implemented on 21st July 2008 (ban 1). Group 2 (G2) is the matched sample of 17 stocks which are subject to the subsequent outright ban implemented on 19th September 2008 (ban 2) while Group 3 is the second matched sample of 17 stocks which are not subject to the 2008 short sale regulations.

	All		G1		G2		G3	
	Put	Call	Put	Call	Put	Call	Put	Call
Option Volume	4,355	4,085	11,237	10,335	854	872	1,804	1,819
Number of option trades	199	220	473	541	45	54	111	106
Average option trade size	15	13	22	16	12	13	12	12
Average option spread	0.79	0.29	0.70	0.26	0.55	0.25	1.09	0.35
Average implied volatility	35%	31%	39%	37%	38%	34%	28%	24%
Average implied volatility ATM	32%	30%	36%	35%	35%	32%	25%	22%
Average slope of the IVS	0.06	0.07	0.05	0.08	0.08	0.08	0.06	0.08
Daily number of observations	199	220	473	541	45	54	111	106
Daily Volume per traded option	230	220	583	524	78	96	72	79
Average ln(S/K)	0.045	-0.084	0.064	-0.101	0.042	-0.088	0.031	-0.064
Average number of days to expiration	68	70	69	72	64	66	70	72

Table 4.C

Summary statistics of stock and option trading activities for the two ban periods

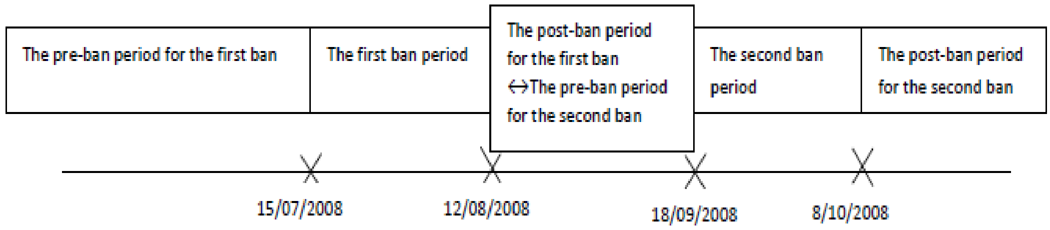
Panels A and B report the descriptive statistics of stock and option trading activities for 51 optionable stocks examined for the two bans periods, ie the first Emergency Order implemented on 15th July 2008 (ban 1) and the subsequent outright ban implemented on 19th September 2008 (ban 2) respectively. In our analysis, the ban period considered in our sample are between 15th July 2008 and 12th August 2008 for the first ban and between 19th September 2008 and 8th October 2008 for the second ban. The pre-ban period of the first ban is from 2nd January 2008 until 14th July 2008 . The period between the two bans, from 12th August to 18th September, is deemed to be the post-ban period of the first ban and the pre-ban period of the second ban. The period from 19th October 2008 until 26th December 2008 is defined as the post-ban period of the second ban. Our stock sample consists of 17 stocks which are subject to short-sale regulations in both ban periods (Group 1), 17 stocks subject to short-sale restrictions in the second ban (Group 2) and 17 stocks which are not subject to any short sale regulations (Group 3). Hence, the sample of banned stocks considered for the first ban only comprises of 17 stocks in Group 1, whereas all 34 stocks in Group 1 and 2 are classified as banned stocks in the second ban. Key statistics of option and stock trading activities considered are the daily stock return and volume, the number of stock trades per day, the average size and the average spread of stock trades, the daily option volume, the number of option trades per day, the average size and the average spread of option trades, the average level and slope of the implied volatility smile. The relative bid-ask spread measure has been used for both options and stocks whereby the spread is measured as a percentage of the quote midpoint. The daily average of stock spread is then calculated by simply taking the average of spreads of all stock trades, whereas the daily option spread is the weighted average of spreads of all option trades [with the option moneyness being used as the weight as described in the variable construction section] . All variables reported have been calculated by taking the mean value in each period.

	Panel A : First ban						Panel B : Second ban					
	Pre-ban period		Ban period		Post-ban period		Pre-ban period		Ban period		Post-ban period	
	Banned stocks	Unbanned stocks	Banned stocks	Unbanned stocks	Banned stocks	Unbanned stocks	Banned stocks	Unbanned stocks	Banned stocks	Unbanned stocks	Banned stocks	Unbanned stocks
Stock Return	-0.16%	-0.27%	0.31%	0.57%	-0.74%	-0.45%	-0.46%	-0.72%	-1.60%	-1.71%	-0.49%	-0.42%
Stock Volume	4,953,474	20,095,916	6,770,867	27,479,471	5,852,185	25,711,297	17,765,633	21,743,513	21,659,840	37,511,620	23,542,796	45,649,026
Number of stock trades	65,141	20,595	123,122	34,183	119,203	31,270	79,243	22,723	83,519	33,455	73,865	40,551
Average stock trade size	256	193	261	189	265	179	214	197	238	203	208	205
Average stock spread	0.001	0.028	0.001	0.001	0.001	0.015	0.014	0.001	0.073	0.001	0.045	0.002
Option Volume	19,815	2,444	21,795	2,201	15,653	3,272	9,061	4,076	10,055	3,063	6,032	3,028
Number of option trades	851	129	962	151	765	170	441	221	643	229	372	266
Average option trade size	19	11	20	11	16	14	15	13	11	10	13	11
Average option spread	0.599	0.528	0.671	0.471	0.386	0.505	0.368	0.660	0.535	0.934	0.409	0.585
Average implied volatility	30%	22%	37%	31%	40%	28%	37%	21%	60%	37%	78%	60%
Average implied volatility ATM	26%	19%	34%	27%	35%	24%	33%	17%	56%	31%	77%	56%
Average slope of the IVS	0.06	0.07	0.04	0.06	0.04	0.08	0.07	0.06	0.10	0.08	0.07	0.10

Given the timing of the two bans, the full sample period spanning from 2nd January 2008 to 30th June 2009 has been partitioned into five episodes classified into the pre-ban, ban and post-ban periods for each ban, as outlined in Figure 4.1.

Figure 4.1

Timeline of the two bans



The summary statistics reported in Table 4.C illustrate significant changes in the level of the stock and option trading activities during and/or after the implementation of each ban, which call for further investigation.

4.3.3. Definitions of variables used in the analysis

In order to test the propositions discussed previously, we use various measures of market quality such as the trading volume and the spread of both option and stock. Other variables of interest include the option implied volatility, a measure of the information share of option trades towards the price discovery of the underlying stock, the speed of stock price adjustments and the PIN proposed in Easley, Kiefer et al. (1996). In this section, the construction and treatment of each variable will be discussed together with how it will be used to address the previous research questions.

In order to examine the effect of the ban on the market liquidity, we estimate the daily volume and spread for both option and stock. In this paper, a number of alternative measures of trading volume have been used to signify any changes in the stock/option trading activities that occurred during the ban period. Those include the total trading volume, the total number of trades, the option to stock trading volume ratio and the net trading volume after classifying trades into seller or buyer-initiated for each option moneyness categories for either calls or puts. However, only the results which are based on the total trading volume are reported throughout this paper for clarity. As for the spread measure, we employ a separate weighting scheme which effectively accounts for the trading cost and how it varies across different option moneyness. Specifically, the procedure to calculate the daily spread measures of stock and option can be briefly outlined as follows. For every trade we calculate the relative spread which is defined as the ratio of the quote bid-ask spread to the quote midpoint at the time of trade. The daily stock spread is simply the weighted average of all relative spreads quoted in a day. The option spread has also been adjusted by the option delta in order to effectively account for the cost of trade relative to the option's value for each trade, following the standard scheme employed by Lee and Yi (2001).This adjustment itself represents an effective weighting scheme which allows us to combine all trades of different option series traded on the same underlying asset in order to derive one composite value of the daily spread of option.

Further, to analyze the effect of SSR on the trader composition and the informational efficiency of the option market, we first examine the significance of the price impact of the option trades during and after the ban period. Despite the extensive number of option contracts traded on one single underlying asset, the price impact is estimated as the change in the average level of implied volatility of at-the-money (ATM hereafter) put and call contracts[66]. In addition, we employ the information share approach developed by Hasbrouck (1995) to further examine whether the ban affects how option trading activities contribute to the price innovations in the underlying asset. Hasbrouck (1995) proposes a robust VAR-based technique for estimating the exchange's contribution to price discovery for stocks traded simultaneously in multiple exchanges. We employ the same methodology to examine the information content about future stock price movements inherent in option trades. The key assumption underpinning our approach is that prices of stocks and options, due to the arbitrage link, depend on the same underlying state variables, commonly referred to as the efficient price. The information share of a market is measured as that market's contribution to the total variance of the common random-walk component. In the case of option and stock whose prices are linked by arbitrage, we can simply use the binomial tree option pricing model, which accounts for the early exercise feature and multiple discrete dividends of American stock options, to convert option prices into so-called implied stock prices, in the spirit of Chakravarty, Gulen et al.'s (2004) and Anand and Chakravarty's (2007) work. Hence, we have two cointegrated price series, including the observed stock price and the implied stock price, whose innovations can be expressed as a vector error correction model (VECM) of order N as follows

$$p_t = \begin{bmatrix} S_t \\ I_t \end{bmatrix} = \begin{bmatrix} V_t + e_{S,t} \\ V_t + e_{I,t} \end{bmatrix}$$
$$\Delta p_t = A_1 \Delta p_{t-1} + A_2 \Delta p_{t-1} + ... + A_N \Delta p_{t-1} + \gamma(z_{t-1} - \mu) + \varepsilon_t \qquad (A.2)$$

where p_t is a 2 x 1 vector of two prices, V_t denotes the common efficient price which is assumed to follow a random walk $V_t = V_{t-1} + u_t$ with $E(u_t) = 0, E(u_t^2) = \sigma_2^2$ and

[66] The option implied volatility is calculated from the observed trading prices using the binomial tree that explicitly account for early exercise and discrete dividends. We follow the procedure outlined in Harvery and Whaley (1992), conducted in Matlab.

$E(u_t u_s) = 0 \ for \ t \neq s$, A_i is a 2 x 2 matrix of autoregressive coefficients corresponding to lag (i) and $\gamma(z_{t-1} - \mu)$ is the error correction term with $z_{t-1} = p_{1t-1} - p_{2t-1}$ and $\mu = E(z_t)$. Alternatively, the price vector p_t can be represented as a vector moving average (VMA) model as follows: $\Delta p_t = \varepsilon_t + \psi_1 \varepsilon_{t-1} + \psi_{21} \varepsilon_{t-2} + \ldots$, where ε_t is a 2 x 1 vector of zero mean innovations with variance matrix Ω. In this particular specification, the sum of all moving average coefficient matrices $\psi(1) = I + \psi_1 + \psi_2 + \cdots$ has the identical rows ψ. If Ω is diagonal then the information share of market (j) is $S_j = \frac{\psi_j^2 \Omega_{jj}}{\psi \Omega \psi'}$ where ψ_j indicates the j element of ψ and Ω_{jj} represents the *jth* diagonal element of Ω.The information share is not uniquely defined however, if price innovations across both markets are correlated. This is usually the case, whereby a range of values, instead of a point estimate, will be available. Hence our measure of information share will be the average of the upper and lower bounds of this range. Given the transaction data obtained in both the option and stock markets, we have been able to calculate the daily lower and upper bounds of the information share of the option market for each stock. In particular, we segregate the information share across option moneyness to inspect whether SSR are directly accountable for changes in the dynamics of information share.

Lastly, to measure the changes in the degree of asymmetric information in the stock market driven by the trader flows in response to the effect of SSR during and after the ban, we employ explicit measures of the speed of price adjustments and PIN developed in the literature. Firstly, the speed of the stock price adjustments to new information is calculated straightforwardly by employing Hasbrouck's (1991) dynamic vector autoregression (VAR) model. This particular approach captures the interactions of security trades and quote revisions to analyze the information effect of trades. Similar to

Mayhew, Sarin et al. (1995) and Chen and Rhee (2010), we estimate the following VAR model

$$
\begin{aligned}
r_t &= \sum_{i=1}^{5} a_i r_{t-1} + \sum_{i=0}^{5} b_i Q_{t-1} + v_{1,t} \\
Q_t &= \sum_{i=1}^{5} c_i r_{t-1} + \sum_{i=1}^{5} d_i Q_{t-1} + v_{2,t}
\end{aligned}
\qquad (A.3)
$$

where r_t is the log quote-midpoint change due to the transaction which occurs at time *(t)*, while Q_t is the buy-sell indicator having a value of [-1, 0, 1] if the trade occurs [above, at, below] the quote-midpoint, following a similar algorithm to Lee and Ready's (1991). The error terms have zero means and are serially uncorrelated, with $Var(v_{1,t}) = \sigma_1^2, Var(v_{2,t}) = \sigma_2^2$. As before, we estimate the VMA representation corresponding to the VAR model, with the model specifications described below

$$
\begin{aligned}
r_t &= v_{1,t} + \sum_{i=1}^{5} a_i^* v_{1,t-i} + \sum_{i=0}^{5} b_i^* v_{2,t-i} \\
Q_t &= \sum_{i=0}^{5} c_i^* v_{1,t-i} + v_{2,t} + \sum_{i=1}^{5} d_i^* v_{2,t-i}
\end{aligned}
\qquad (A.4)
$$

In this framework, the measure of information asymmetry (R_w^2) is estimated daily for each firm as follows

$$
R_w^2 = \sigma_{w,x}^2 \big/ \sigma_w^2 \quad where \;\; \sigma_{w,x}^2 = \sum_j^{\infty} b_j^* \Omega b_j'^* \;\; and \;\; \sigma_w^2 = \sigma_{w,x}^2 + \left(1 + \sum_j^{\infty} a_j^*\right)^2 \sigma_1^2 \qquad (A.5)
$$

Secondly, we employ Easley, Kiefer et al.'s (1996) model to directly measure the PIN of the stock market. This technique is based on the assumption that the market maker is a Bayesian who uses the arrival of trades, and the rate of trading to update his beliefs about the occurrence of information events. In their model, the PIN is defined as follows

$$PIN(t) = \frac{\mu(1-P_n(t))}{\mu(1-P_n(t))+2\varepsilon} \qquad (A.6)$$

where $P(t) = (P_n(t), P_b(t), P_g(t))$ is the market maker's prior belief about the events of "no news", "bad news" and "good news" respectively, and $P_n(0) = (1-\alpha, \alpha\delta, \alpha(1-\delta))$ at time (0); μ is the rate of informed trade arrival while ε is the rate of uninformed buy and sell trade arrival; and α and δ are the probability of an information event and the probability of a low signal respectively. Using transaction data, we first classify trades as buyer-initiated or seller-initiated according to Lee and Ready's (1991) algorithm. Then we estimate the set of parameters $\theta = (\alpha, \delta, \varepsilon, \mu)$ simultaneously by maximizing the log likelihood function $L(M/\theta) = \prod_{i=1}^{I} L(\theta / B_i, S_i)$ with $M = (B_i, S_i)_{i=1}^{I}$, the set of buys and sells data observed over *(I)* days, and the daily likelihood of

$$L(\theta / B_i, S_i) = (1-\alpha) * e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} + \alpha\delta * e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-(\mu+\varepsilon)T}\frac{[(\mu+\varepsilon)T]^S}{S!} + \alpha(1-\delta) * e^{-(\mu+\varepsilon)T}\frac{[(\mu+\varepsilon)T]^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} \qquad (A.7)$$

This provides a direct estimate of the information event structure surrounding a particular stock, and most importantly the rate of informed and uninformed trading used to calculate the daily PIN defined previously.

The other variables we control for in our analysis are the general level of the market volatility proxied by the CBOE's VIX index and the individual stock daily return and volatility. Daily stock returns are computed from closing prices, i.e. $r_t = \ln(P_t) - \ln(P_{t-1})$ while daily volatility is calculated based on the integrated volatility process using five minute intraday prices. Specifically, the daily volatility is defined as $RV_t = (1/\tau)\sum_{i=t+1}^{T} r_i^2$ with τ being the frequency of observations.

4.4. EMPIRICAL RESULTS

In this section, we document how the 2008 SSB affects the market quality of both the option and stock markets. We start in subsections (1) and (2) by documenting the effects of the two bans on basic statistics of the market liquidity, including trading volume and spread. It is established that SSR lead to trader flows between markets, as reflected by significant changes in the volume and spread for both option and stock during and/or after the bans. Next, the remainder of our analysis is devoted to a further examination of the nature of traders' asymmetric responses to a different set of short-sale regulations and to an explication of how this affects the degree of information asymmetry and the pricing efficiency of both markets as reflected in changes in the information share and the price impact of option trades, the speed of stock price adjustments and the PIN in stock trading. Further, we test whether this would also be reflected by any changes in the lead-lag relation between option and stock. Specifically, we expect to observe that (1) option trading volume should be more informative of expected changes in future stock volume and/or volatility; and (2) option implied volatility should be more informative of expected changes in future stock volatility, if there are a greater proportion of informed traders entering the option market. In particular, we are able to distinguish the separate effects of the two bans by employing the theoretical framework established in DV's renowned work in this paper.

4.4.1. The impact of the bans on the option and stock trading volume

In this paper, we analyze the impact of the bans on the option and stock trading volume by estimating the cross-sectional regressions using the natural logarithms of the daily trading volume of option/stock as the dependent variables and factors known to affect the option and stock trading volumes as independent variables. Specifically, the estimated models are specified as follows

$$\begin{aligned} Stock\ volume = {} & \alpha_0 + \alpha_2\ Stock\ return + \alpha_3\ Stock\ volatility + \alpha_4\ VIX \\ & + \beta_1 Banned + \beta_2\ ban + \beta_3\ (Banned \times Ban) + \beta_4 PostBan + \beta_5\ (Banned \times PostBan\ ) + \varepsilon \qquad (1) \\ Option\ volume = {} & \alpha_0 + \alpha_1\ Stock\ volume + \alpha_2\ Stock\ return + \alpha_3\ Stock\ volatility + \alpha_4\ VIX \\ & + \beta_1\ Banned + \beta_2\ Ban + \beta_3\ (Banned \times Ban) + \beta_4 PostBan + \beta_5\ (Banned \times PostBan\ ) + \varepsilon \qquad (2) \end{aligned}$$

In the above specifications, *Stock return* and S*tock volatility* refer to the daily return and volatility of the underlying stock respectively. *VIX* is the daily closing value of the CBOE Volatility index. Our regressions allow for the link between the stock return (volatility) and trading volume previously documented in the literature[67]. In addition, the inclusion of the *VIX* term in the given specifications accommodates the fact that option trades may increase as a result of increasing demand stemming from a rising market-wide uncertainty captured by a higher level of the VIX. In all regressions used throughout our analysis, we employ three dummy variables to account for the effect of the SSB. The first is *banned* which is equal to one if the underlying stock is on the SEC list of banned stocks and zero otherwise. The second dummy variable is *ban* that is assigned a value of one if the observation date is within the ban period and zero otherwise. Similarly, the dummy *postban* is equal to one if the observation date is after the ban period and zero otherwise. We also include different interaction terms between *banned*, *ban* and *postban* in the regression since we expect the impact of the SSB on banned stocks would be distinctively different to those excluded from the ban list. In particular, we run regression (2) on sub-samples of puts and calls to achieve a more in-depth analysis of variants in option trading activities as we expect traders' decisions to trade a particular option and the way in which they might be affected by the ban would

[67] It is noticed here that such a relation should hold for both stock or option trading volumes because they are arguably alternate trading venues which accommodate the incorporation of news.

vary across option moneyness. This might occur because we know different option contract types (put vs. call) with different moneyness provide traders with different exposures to the underlying price movements.

In addition, we estimate the regression of the natural logarithm of the ratio of the volume of trades in options to the volume of trades in the underlying stock, *OptStkVol*, against the explanatory variables identified previously. This is done in order to examine any potential effect of traders' migration between stock and option markets induced by SSR implemented during the ban.

$$\begin{aligned} OptStkVol = {} & \alpha_0 + \alpha_2\, Stock\ return + \alpha_3\, Stock\ volatility + \alpha_4\, VIX \\ & + \beta_1\, Banned + \beta_2\, Ban + \beta_3\, (Banned \times Ban) + \beta_4 PostBan + \beta_5\, (Banned \times PostBan) + \varepsilon \end{aligned} \tag{3}$$

Table 4.1 presents the estimate of the parameters along with the t-statistics calculated using White's (1980) heteroskedasticity-consistent standard errors for both bans.

The first focus of our analysis is on the stock trading volume. While changes in the stock return have no effect on the stock trading volume, there seems to be a contemporaneous and negative relationship between volume and volatility given a significantly negative coefficient for *Stock volatility* in the results reported. In addition, while it is shown that the stock trading volume significantly increases for both groups during the first ban period, the increase is significantly higher for banned stocks than for unbanned stocks. After the first ban, the trading volume of banned stocks significantly reduces whereas the trading volume of unbanned stocks stays slightly higher than the pre-ban trading level. The key finding here is that both during and after the ban, the trading volume for unbanned stocks has always increased while the opposite applies for banned stocks. The distinction between both groups has always been significant, underscoring the effect of traders switching from banned to unbanned stocks in response to regulatory changes. In line with our current findings, Boulton and

Table 4.1

Impact of the ban on stock and option trading volume

This table reports the results of the following cross-sectional regressions

$$Stock\ volume = \alpha_0 + \alpha_2\ Stock\ return + \alpha_3\ Stock\ volatility + \alpha_4\ VIX$$
$$+ \beta_1 Banned + \beta_2\ ban + \beta_3\ (Banned \times Ban) + \beta_4 PostBan + \beta_5\ (Banned \times PostBan) + \varepsilon$$
$$Option\ volume = \alpha_0 + \alpha_1\ Stock\ volume + \alpha_2\ Stock\ return + \alpha_3\ Stock\ volatility + \alpha_4\ VIX$$
$$+ \beta_1\ Banned + \beta_2\ Ban + \beta_3\ (Banned \times Ban) + \beta_4 PostBan + \beta_5\ (Banned \times PostBan) + \varepsilon$$
$$OptStkVol = \alpha_0 + \alpha_2\ Stock\ return + \alpha_3\ Stock\ volatility + \alpha_4\ VIX$$
$$+ \beta_1\ Banned + \beta_2\ Ban + \beta_3\ (Banned \times Ban) + \beta_4 PostBan + \beta_5\ (Banned \times PostBan) + \varepsilon$$

where Stock volume and Option volume measure the natural logarithms of the daily total volume of stock and option respectively, while OptStkVol refers to the natural logarithms of option to stock volume ratio. Stock return and Stock volatility are the daily return and volatility of the underlying stock respectively; VIX is the daily closing value of the CBOE Volatility index; banned is the dummy variable which takes the value of one if the underlying stock is on the SEC list of banned stocks and zero otherwise; ban is the dummy variable which is assigned the value of one if the observation date is within the ban period and zero otherwise; postban is a dummy variable which is equal to one if the observation date is after the ban period and zero otherwise. These regressions examine the impact of SSR on the option and stock trading volume of 51 optionable stocks. This sample set comprises of 17 stocks which are subject to the first Emergency Order implemented on 21st July 2008 (ban 1), a matched sample of 17 stocks subject to the subsequent outright ban implemented on 19th September 2008 (ban 2) and another matched sample of 17 stocks not subject to short sale regulations. It is noticed that seperate regressions have been run for each ban period. The sample period for the first ban is between 2nd January 2008 and 18th September 2008 while it covers from 12th August 2008 to 26th December 2008 for the second ban.

Indepedent variables	Dependent variables							
	Ban 1				Ban 2			
	Stock Volume	Put Volume	Call Volume	OptStkVol	Stock Volume	Put Volume	Call Volume	OptStkVol
Intercept	13.855	-3.383	-2.880	-10.113	13.842	-1.823	-1.413	-10.102
	(231.660)**	(-13.835)**	(-11.792)**	(-105.161)**	(225.133)**	(-6.415)**	(-5.456)**	(-116.770)**
Stock Volume		0.497	0.496			0.397	0.376	
		(31.672)**	(31.885)**			(20.552)**	(21.400)**	
StockSR	-0.178	0.086	0.122	0.194	0.085	0.139	0.292	0.161
	(-1.025)	(0.583)	(0.705)	(1.023)	(0.238)	(0.541)	(1.217)	(0.428)
StockSV	-2.828	-1.078	-0.775	0.488	-4.893	-2.620	-1.781	0.808
	(-15.482)**	(-5.201)**	(-3.560)**	(2.335)*	(-10.804)**	(-7.608)**	(-4.936)**	(1.820)
VIX	0.035	-0.016	-0.027	-0.039	0.020	-0.004	-0.004	-0.017
	(14.259)**	(-3.008)**	(-4.972)**	(-9.854)**	(10.948)**	(-1.114)	(-1.396)	(-6.549)**
banned	1.316	1.628	1.269	0.788	1.170	0.451	0.432	-0.279
	(69.904)**	(33.611)**	(25.841)**	(25.274)**	(21.351)**	(4.095)**	(4.167)**	(-3.457)**
ban	0.487	0.100	0.151	-0.120	0.071	-0.118	0.005	-0.103
	(18.210)**	(1.605)	(2.367)*	(-2.494)*	(0.936)	(-0.833)	(0.034)	(-0.953)
postban	0.087	0.503	0.374	0.396	-0.337	-0.561	-0.465	-0.296
	(2.417)*	(7.816)**	(5.950)**	(7.522)**	(-3.869)**	(-3.477)**	(-3.184)**	(-2.427)*
banned x ban	-0.272	-0.749	-0.816	-0.644	-0.556	0.248	0.139	0.539
	(-4.677)**	(-5.851)**	(-6.389)**	(-6.967)**	(-6.144)**	(1.536)	(0.876)	(4.271)**
bannedx postban	-0.165	-1.173	-0.939	-0.974	-0.238	0.650	0.472	0.700
	(-2.702)**	(-9.516)**	(-7.635)**	(-10.411)**	(-3.669)**	(5.066)**	(3.956)**	(7.254)**
R-squared	0.180	0.231	0.198	0.026	0.097	0.145	0.131	0.016
AIC	21074	24853	24059	51940	17686	12844	13506	29599
Schwarz	21149	24930	24135	52015	17755	12913	13576	29668

Note: We report the t-stat in parentheses which are calculated based on White heteroskedasticity-corrected standard errors.

** indicates significance at the 1% level

* indicates significance at the 5% level

Braga-Alves (2010) document that SSR implemented during the first ban lead to a dramatic increase in naked short selling activities during the ban period of closely substituted stocks, as compared to those included in the ban list. In contrast, the second ban leads to a significant reduction in the trading volume of banned stocks whereas unbanned stocks still experience a slight increase in trading volume during the ban period. While trading volume further reduces for both after the second ban, the negative coefficient of the interaction between dummy variables *banned* and *ban* in the regression once again indicates that banned stocks experience a significantly larger reduction in trading volume. Overall, the results thus far consistently show that SSR negatively affect the market liquidity of affected stocks because a proportion of short-sellers are forced to exit the market, as is suggested by the theory.

In the option trading volume regression, we observe similar variants in the option trading activity across put and call contracts, though the two bans appear to impose different impacts on the total option trading volume for each group. It is evident that option trading volume increases for unbanned stocks during the first ban while the net effect on banned stocks is a reduction in both put and call volumes, as shown by negative coefficients of -0.649 (=-0.749+0.100) and -0.665 (=-0.816+0.151) for put and call respectively. This evidence seems to suggest also that certain traders switch their option trading from banned to unbanned stocks in response to SSR implemented in the underlying market. This is a very interesting finding, as it indicates that SSR applied to the underlying stock may impose a negative effect on option trading volume. This contradicts the argument of the short-selling mitigation role of options commonly discussed in the literature (e.g., Figlewski and Webb, 1993; Sorescu, 2000; Blake, 2011), which predicts that SSR should lead to increasing option trading volume instead. We argue that a finding of the net decrease in the option trading volume for affected stocks during the first ban may arise simply because a proportion of short-selling activities have been undertaken as part of synthetic trading strategies. Hence, option trading volume would reduce simply because these trading strategies are no longer pursued by traders because they are facing higher costs. It is further argued that traders would have a strong incentive to simply replace their option trades on unbanned stocks to those on banned stocks if transaction costs incurred for one increases relative to another. This is very likely to be the case, as we find out later the option spread for banned stocks in fact increases significantly relative to unbanned stocks during the ban. After the first ban, the effect of traders' migration seems to persist or even intensify, given that we find unbanned stocks experience a greater increase in option trading volume. Also our results indicate that the difference between banned and unbanned stocks seems to increase, as shown by a more negative coefficient of the interaction term between the *banned* and *postban* dummy variables found in both put and call volume regressions. Surprisingly, the second ban imposes no significant effect on option trading volume observed during the ban. The coefficient estimates suggest that banned stocks may experience a slightly greater increase in option trading volume compared to unbanned stocks but the difference between them appears to be insignificant. Nevertheless, we find a significantly positive coefficient on the interaction term between the *banned* and *postban* dummy variables, highlighting the finding that the disparity between two groups becomes significant after the ban. Specifically, option trading activities marginally improve for banned stocks after the removal of SSR whereas unbanned stocks experience a significant reduction in option volume. One possible explanation for this is that naked SSR became mandatory for all stocks, even after the second ban was lifted[68].

[68]In fact, we will demonstrate later that banned stocks seem to experience a trader influx from the stock to the option market to

The regression of the option stock volume ratio on the same set of explanatory variables produces very similar signs and significance on all coefficient estimates to those obtained in the option trading volume regression. In particular, the increases in the option stock volume ratio observed during and after the first ban appear consistent with and reinforce our previous finding of the option traders' migration effect from banned to unbanned stock, in response to regulatory changes. Of particular interest in this regression is the finding of a significantly positive coefficient for the interaction term between *banned* and *ban* for the second ban. This, standing in contrast to a negative coefficient found for unbanned stocks, indicates that the option to stock trading volume ratio of banned stocks significantly increases due to the implementation of SSR, and that this increase is unlikely to be driven by other economy-wide factors. This evidence seems to suggest that a portion of option traders did migrate from the stock to the option market in order to mitigate SSR, as suggested by the theory. Further, the significant coefficient estimates in opposite signs found for the term *postban* and the interaction term of *banned* and *postban* confirm that the difference between banned stocks and unbanned stocks is evidently amplified after the second ban. This is similar to the regression results reported previously [69].

mitigate naked SSR implemented permanently after the second ban period. In contrast, the illiquidity of the option market for the group of unbanned stocks appears to be a sensible reason which makes it unappealing for traders to use synthetic option trades to mitigate naked SSR after they become mandatory. As a consequence, both option and stock trading volume significantly drop for unbanned stocks, as illustrated in our reported results.

[69] It is noted that the main findings reported in this paper are not results of spurious regression problems potentially caused by high auto-correlations in the stock (option) trading volume documented previously in the literature. We run the augmented Dickey-Fuller tests and find that we can reject at the 95% confidence level a null hypothesis of autocorrelation for at least 80% of all stocks examined. The results, not being reproduced here, are available from the author upon requests.

Subsample analysis

We next examine whether the effect of the ban on option trading activities varies across different option moneyness[70], given the fact that these different option categories provide traders with different exposures to changes in the underlying prices. One possible reason for our previous finding of no significant evidence of increasing option trading volume is arguably because the SSB might have led to increasing trading on some particular options while reducing demand for others. As a result, there is no significant trading improvement overall. More specifically, we may expect, on the one hand, that synthetic option-stock trading strategies applicable to a short-selling position on stocks [for instance, short-selling a stock coupled with going long on a call] may no longer be pursued after the implementation of SSR. This consequently may lead to reduced trading activities in some particular options. On the other hand, traders who wish to mitigate SSR may find option trading an attractive venue to substitute restricted stock trades through arbitrage. For instance, to-be short-sellers may establish a synthetic position in puts and calls to replace a no-longer-applicable short-selling position in the underlying stock. Alternatively, trading with a bearish view of future stock price movements can simply be achieved by going long in puts or short in calls. Further to this line of argument, it is often contended that a finding of different price sensitivities of option price changes to stock price changes at different moneyness levels means that to-be-short sellers may prefer one particular option over another. For instance, if aiming

[70] Similar to Grundy et al.'s (2010) paper, we measure the option moneyness by taking the natural logarithm of the stock price divided by the option strike price, ie $m= \ln(S/K)$. We partition our sample of daily observations (aggregated from trade-by-trade data) across three ranges of moneyness. For call contracts, ITM denotes in the money options if $0.3>m>0.1$, ATM denotes at the money if $0.1\geq m\geq -0.1$ and OUT denotes out of the money if $-0.1>m>-0.3$. The same classification applies to puts with m replaced by $-m$ in the above inequalities.

Table 4.2

Impact of the ban on option volume across moneyness

This table reports the results of the following cross-sectional regression

$$Option\ volume = \alpha_0 + \alpha_1 Stock volume + \alpha_2 Stock return + \alpha_3 Stock volatility + \alpha_4 VIX$$
$$+ \beta_1 Banned + \beta_2 Ban + \beta_3 (Banned \times Ban) + \beta_4 PostBan + \beta_5 (Banned \times PostBan) + \varepsilon$$

where Stock return and Stock volatility are the daily return and volatility of the underlying stock respectively; VIX is the daily closing value of the CBOE Volatility index; banned is the dummy variable which takes the value of one if the underlying stock is on the SEC list of banned stocks and zero otherwise; ban is the dummy variable which is assigned the value of one if the observation date is within the ban period and zero otherwise; postban is a dummy variable which is equal to one if the observation date is after the ban period and zero otherwise. This regression examines the impact of SSR on the option trading volume of 51 optionable stocks across different moneyness categories and contract types. This sample set comprises of 17 stocks which are subject to the first Emergency Order implemented on 21st July 2008 (ban 1), a matched sample of 17 stocks subject to the subsequent outright ban implemented on 19th September 2008 (ban 2) and another matched sample of 17 stocks not subject to short sale regulations. It is noticed that seperate regressions have been run for each ban period, using the natural logarithms of daily option trading volume of three contract categories, including in the money (ITM), out of the money (OTM) and at the money (ATM), of put and call respectively. The sample period for the first ban is between 2nd January 2008 and 18th September 2008 while it covers from 12th August 2008 to 26th December 2008 for the second ban.

Indepedent variables	Dependent variables											
	Ban 1						Ban 2					
	ITM Put	OTM Put	ATM Put	OTM Call	ITM Call	ATM Call	ITM Put	OTM Put	ATM Put	OTM Call	ITM Call	ATM Call
Intercept	-6.384	-4.797	-3.259	-5.438	-4.603	-1.796	-4.502	-1.085	-0.738	-1.507	-3.208	0.223
	(-11.534)**	(-10.485)**	(-8.288)**	(-12.126)**	(-8.715)**	(-4.721)**	(-6.913)**	(-2.083)*	(-1.605)	(-3.407)**	(-5.048)**	(0.509)
logStockTvol	0.554	0.576	0.527	0.608	0.480	0.508	0.495	0.352	0.336	0.355	0.433	0.318
	(15.559)**	(19.491)**	(20.775)**	(21.139)**	(14.146)**	(20.653)**	(11.438)**	(10.115)**	(10.532)**	(11.956)**	(9.595)**	(10.625)**
StockSR	-0.302	0.387	0.111	-0.054	0.281	0.242	-0.372	0.450	0.077	0.076	0.083	0.411
	(-0.691)	(1.342)	(0.487)	(-0.149)	(0.635)	(0.980)	(-0.528)	(0.978)	(0.222)	(0.179)	(0.103)	(1.136)
StockSV	-0.378	-1.113	-1.313	-0.542	-0.309	-1.419	-2.671	-3.106	-3.248	-2.791	-1.160	-2.837
	(-0.820)	(-2.674)**	(-3.993)**	(-1.115)	(-0.607)	(-4.258)**	(-5.134)**	(-4.345)**	(-5.637)**	(-4.662)**	(-0.840)	(-4.964)**
VIX	0.021	-0.005	-0.016	0.004	0.003	-0.056	0.011	-0.010	0.004	-0.003	-0.015	-0.014
	(2.004)*	(-0.527)	(-1.839)	(0.427)	(0.238)	(-6.636)**	(1.735)	(-1.425)	(0.646)	(-0.509)	(-1.964)*	(-2.319)*
banned	1.854	1.757	1.743	1.862	1.267	1.328	0.111	0.768	0.936	1.062	-0.021	0.702
	(19.775)**	(20.408)**	(21.454)**	(22.085)**	(13.283)**	(16.708)**	(0.445)	(4.095)**	(5.088)**	(6.737)**	(-0.090)	(4.336)**
ban	-0.020	0.284	0.215	0.365	-0.214	0.356	0.070	-0.015	-0.207	0.446	0.129	0.182
	(-0.171)	(2.568)*	(2.038)*	(3.708)**	(-1.702)	(3.632)**	(0.235)	(-0.058)	(-0.852)	(2.126)*	(0.459)	(0.811)
postban	0.539	0.689	0.529	0.530	0.109	0.504	-0.614	-0.376	-0.803	0.169	0.296	-0.505
	(4.012)**	(6.034)**	(4.837)**	(5.286)**	(0.855)	(5.089)**	(-1.863)	(-1.227)	(-2.727)**	(0.704)	(0.827)	(-1.915)
banned x ban	-0.769	-0.871	-0.897	-1.385	-0.229	-1.072	0.250	0.317	-0.259	-0.260	0.853	-0.068
	(-3.077)**	(-3.788)**	(-3.842)**	(-6.194)**	(-0.942)	(-4.787)**	(0.761)	(1.079)	(-0.914)	(-1.028)	(2.605)**	(-0.258)
bannedx postban	-1.220	-1.537	-1.130	-1.420	-0.769	-1.034	0.468	0.919	0.314	-0.019	0.841	0.356
	(-5.158)**	(-6.714)**	(-5.183)**	(-6.458)**	(-3.198)**	(-5.185)**	(1.722)	(3.960)**	(1.403)	(-0.102)	(3.128)**	(1.763)
R-squared	0.369	0.281	0.219	0.315	0.295	0.191	0.188	0.178	0.129	0.149	0.200	0.129
AIC	3285	6665	10454	6791	2828	10534	2251	3135	4708	4272	1497	4810
Schwarz	3344	6729	10521	6856	2887	10602	2305	3190	4766	4331	1548	4870

Note: We report the t-stat in parentheses which are calculated based on White heteroskedasticity-corrected standard errors.

** indicates significance at the 1% level

* indicates significance at the 5% level

to achieve a greater leverage of their investment, some may favor going long in out-of-the-money puts instead of in-the money puts.

The regression results provided in Table 4.2 clearly highlight the switching effect, previously discussed, which took place during and after the first ban. In fact, we find a significant decrease in the option volume of banned stocks accompanied by a significant increase in the option volume of unbanned stocks across all three levels of moneyness for both puts and calls. Interestingly, the scale of this switching effect appears to increase after the ban across all moneyness. This is shown by our findings that all estimated coefficients are of greater magnitude. As for the second ban, we found evidence that option trading which aims to substitute short-sales of banned stocks appears to take place in three specific option sub-categories of ITM puts, OTM puts and ITM calls. In particular, banned stocks experience a significantly greater increase in option volume of ITM calls when compared to unbanned stocks. This suggests that to-be short sellers might favor shorting ITM call options to replace their short positions of banned stocks during the ban period. After the ban, the difference between banned and unbanned stocks increases across all moneyness categories, except for OTM calls. These results, once again, reinforce our previous findings on the aggregate volume information.

4.4.2. The impact of the bans on the option and stock quoted spreads

The previous section provides some evidence that option traders' migration from banned to unbanned stocks occurs during and after the first ban as reflected by changes in the trading volume of both stock and options. We also found some evidence of traders migrating from the stock market to the option market to mitigate SSR implemented during the second ban. Further, our regression results suggest that a portion of traders might have exited the option market of unbanned stocks whereas banned stocks might have experienced an influx of option traders after the second ban. To examine these issues further, we will examine the impact of the SSB on the quoted spreads for both stocks and options. While it has been well established in previous literature (Copeland and Galai, 1983; Chiang and Venkatesh, 1988) that variations in the quoted spread reflect changes in the trader composition of the market, we expect to uncover how the degree of information asymmetry in each market has been affected by regulatory changes.

It is noticed that the previous literature (Lee, Mucklow et al., 1993; Kim and Verrecchia, 1994; Chordia, Roll et al., 2001) indicates that spread and trading volume might have been determined jointly, with decrease in spread, ceteris paribus, indicating an improvement in liquidity. This suggests that an analysis of the SSB on the quoted spread would also have to control for variables known to affect trading volume. Therefore, we examine the impact of the SSB on the quoted spread of stock and options by estimating the following regression equations

$$\begin{aligned} Stock\ spread = {} & \alpha_0 + \alpha_2\, Stock\ return + \alpha_3\, Stock\ volatility + \alpha_4\, VIX \\ & + \beta_1\, Banned + \beta_2\, Ban + \beta_3\,(Banned \times Ban) + \beta_4 PostBan + \beta_5\,(Banned \times PostBan) + \varepsilon \end{aligned} \tag{4}$$

$$\begin{aligned} Option\ spread = {} & \alpha_0 + \alpha_2\, Stock\ return + \alpha_3\, Stock\ volatility + \alpha_4\, VIX \\ & + \beta_1\, Banned + \beta_2\, Ban + \beta_3\,(Banned \times Ban) + \beta_4 PostBan + \beta_5\,(Banned \times PostBan) + \varepsilon \end{aligned} \tag{5}$$

In the above equations, *Option spread* and *Stock spread* are measured by taking the daily weighted relative bid-ask spreads [with the option moneyness being used as the weight to calculate the daily option spread and equal weights used for the daily stock spread- refer to the previous section of variable construction for details]. All other variables are the same as equation (1) and (2). Again, our emphasis will be placed on the sign and the significance of β_2 to β_5.

Table 4.3

Impact of the ban on stock and option spread

This table reports the results of the following cross-sectional regressions

$$Stock\,spread = \alpha_0 + \alpha_2\,Stock\,return + \alpha_3\,Stock\,volatility + \alpha_4\,VIX$$
$$+ \beta_1\,Banned + \beta_2\,Ban + \beta_3\,(Banned \times Ban) + \beta_4 PostBan + \beta_5\,(Banned \times PostBan) + \varepsilon$$
$$Option\,spread = \alpha_0 + \alpha_2\,Stock\,return + \alpha_3\,Stock\,volatility + \alpha_4\,VIX$$
$$+ \beta_1\,Banned + \beta_2\,Ban + \beta_3\,(Banned \times Ban) + \beta_4 PostBan + \beta_5\,(Banned \times PostBan) + \varepsilon$$

where Stock return and Stock volatility are the daily return and volatility of the underlying stock respectively; VIX is the daily closing value of the CBOE Volatility index; banned is the dummy variable which takes the value of one if the underlying stock is on the SEC list of banned stocks and zero otherwise; ban is the dummy variable which is assigned the value of one if the observation date is within the ban period and zero otherwise; postban is a dummy variable which is equal to one if the observation date is after the ban period and zero otherwise. These regressions examine the impact of SSR on the liquidity of option and stock trading on 51 optionable stocks. This sample set comprises of 17 stocks which are subject to the first Emergency Order implemented on 21st July 2008 (ban 1), a matched sample of 17 stocks subject to the subsequent outright ban implemented on 19th September 2008 (ban 2) and another matched sample of 17 stocks not subject to short sale regulations. It is noticed that seperate regressions have been run for each ban period, using the daily weighted relative bid-ask spreads of option and stock [with the option moneyness being used as the weight to calculate the daily option spread and equal weights used for the daily stock spread- please refer to the section of variable construction for details]. The sample period for the first ban is between 2nd January 2008 and 18th September 2008 while it covers from 12th August 2008 to 26th December 2008 for the second ban.

Indepedent variables	Dependent variables							
	Ban 1				Ban 2			
	Stock Spread	Option Spread	Put spread	Call spread	Stock Spread	Option Spread	Put spread	Call spread
Intercept	-0.008	0.763	1.327	0.200	0.001	0.735	1.284	0.236
	(-4.001)**	(14.667)**	(13.495)**	(12.087)**	(0.511)	(14.581)**	(12.787)**	(13.972)**
StockSR	0.001	-0.003	0.033	-0.040	-0.006	-0.037	-0.114	0.037
	(0.102)	(-0.090)	(0.702)	(-1.119)	(-0.252)	(-0.846)	(-1.364)	(1.357)
StockSV	0.200	0.121	0.099	0.122	0.268	0.341	0.554	0.124
	(10.849)**	(2.286)*	(1.114)	(3.272)**	(7.828)**	(3.870)**	(3.284)**	(2.426)*
VIX	0.000	-0.009	-0.021	0.002	0.000	-0.002	-0.008	0.003
	(4.564)**	(-4.177)**	(-5.077)**	(3.416)**	(-0.442)	(-1.954)	(-4.100)**	(6.241)**
banned	-0.005	-0.137	-0.242	-0.031	0.007	-0.322	-0.565	-0.110
	(-10.454)**	(-8.672)**	(-8.070)**	(-5.310)**	(4.686)**	(-6.813)**	(-6.113)**	(-7.989)**
ban	-0.003	-0.123	-0.220	-0.024	0.000	0.142	0.163	0.108
	(-6.734)**	(-5.863)**	(-5.554)**	(-3.140)**	(0.244)	(1.329)	(0.783)	(4.227)**
postban	0.010	-0.065	-0.117	-0.011	0.001	-0.107	-0.182	0.011
	(5.495)**	(-2.811)**	(-2.673)**	(-1.408)	(0.306)	(-1.788)	(-1.521)	(0.465)
banned x ban	0.003	0.196	0.375	0.011	0.004	0.007	0.047	0.009
	(4.305)**	(5.243)**	(5.375)**	(0.797)	(1.384)	(0.071)	(0.248)	(0.309)
bannedx postban	-0.010	0.066	0.128	0.003	-0.008	0.140	0.365	-0.054
	(-5.141)**	(1.837)	(1.902)	(0.211)	(-4.660)**	(2.817)**	(3.731)**	(-2.982)**
R-squared	0.168	0.003	0.006	0.004	0.093	0.019	0.027	0.064
AIC	-196445	8682	13690	-37679	-90050	-550	4692	-17701
Schwarz	-196370	8766	13767	-37603	-89981	-473	4761	-17630

Note: We report the t-stat in parentheses which are calculated based on White heteroskedasticity-corrected standard errors.

** indicates significance at the 1% level

* indicates significance at the 5% level

The results of the parameter estimates presented in Table 4.3 are of expected signs for all control variables in both stock and option spread regressions. In fact, it is shown that a significantly positive relationship between spread and stock volatility/market volatility holds for both option and stock across the table, except for the case of put whose spread is negatively correlated to the market level of uncertainty reflected by the VIX level. The coefficient estimate (t-statistic) of the *banned* dummy variable in the stock spread regression is -0.003 (6.734) in the first ban and 0.000 (0.244) in the second ban. This suggests that the banned stock sample appears to be more liquid than the unbanned sample before the first ban while there is no statistically significant difference between the two samples in the second ban. It is clear, however, that options traded on banned stocks are more liquid than those of the unbanned sample, given that a significant negative coefficient estimated for the *banned* dummy variable is found across the whole table.

For the stock spread equation, we find that the spread for banned stocks significantly increases during the first ban whereas the spread for unbanned stocks significantly decreases over the same period. As for the second ban, the results indicate no significant change in the spread for both groups during the ban period. We argue that both of these findings are consistent with DV's theoretical model which distinguishes the SRE against the SPE discussed previously. The former finding closely fits DV's argument on the SRE which predicts that higher costs of short-sales arising from SSR implemented in the first ban cause relatively more uninformed traders to exit the market. Furthermore, if this same trader mix subsequently finds that it is more cost effective to switch to substitute trades on unbanned stocks, this will lead to a higher proportion of uninformed traders in the market of unbanned stocks. In contrast, DV's argument about the SPE implies that we should not expect to observe any significant changes in the trader composition during the second ban, because the ban would have affected informed and uninformed traders similarly. In both cases, the results indicate that banned stock experiences a slight improvement in liquidity relative to unbanned stocks after the ban, as illustrated by a statistically negative coefficient on the interaction term between *banned* and *postban* dummy variables. This simply highlights the reverse effect once SSR are lifted[71].

Further, there are some other interesting findings in the results of the three option spread regressions presented in Table 4.3. As for the first ban, the coefficient estimates indicate that the liquidity of the option market traded on unbanned stocks tends to improve significantly during and even after the ban period whereas the opposite holds for banned stocks. In particular, these results stay consistently across put and call regressions and reinforce our finding of the traders' switching effect discussed previously. Also, a significantly negative coefficient on the dummy variable *ban* and a significantly positive coefficient on the interaction term between dummy variables *banned* and *ban* found in the regression of option weighted spread; as a result one may further argue that the observed results can be attributed to a migration of relatively more uninformed option traders from banned stocks to unbanned stocks during the ban. This follows from the fact that the option volume increase (decrease) for unbanned (banned) stocks has been accompanied by a substantial reduction (increase) in the equilibrium level of the option bid-ask spread. Given that variations in the spread often reflect

[71]In fact, after the first ban is lifted, it seems that a portion of traders resume their trading on banned stocks and switch back from unbanned to banned stocks. Also, it seems that this flow of traders is more likely to be dominated by uninformed traders, as it has the net effect of increasing (decreasing) the spread of unbanned (banned) stocks. As for the second ban, however, we will argue later that (1) the reduction in the spread for banned stock is more likely to be driven by the flow of traders switching from the stock to option market since mandatory naked SSB becomes permanent after the second ban period; and (2) that this flow of traders is more likely to be dominated by sophisticated and relatively more informed traders, as expected.

changes in the trader composition, these results indicate that: first, as more uninformed traders migrate to (from) the option market of unbanned (banned) stocks relative to informed traders during the ban, option market makers will be faced with a smaller (greater) fraction of information-motivated trades; and second, they will subsequently revise their quoted spreads downwards (upwards). Further, it is noticeable that the effect of option traders switching their trades from banned to unbanned stocks has been alleviated after the ban is lifted, as we find changes in option spread and volume are lessened and become less significant for both groups. This is to some extent expected, given that some short-sellers would return to trade in the option market once SSR are lifted for banned stocks. It is shown, however, that part of the switching effect may still linger after the ban, probably because of increasing market expectation that SSR will soon resume due to deteriorating market conditions. As for the second ban, we find no evidence to support the notation that the implementation of the second ban would lead to traders' migration from the stock market to the option market. In fact, the regression results show no significant change in the trader composition for either group of stocks, as variations in the spread measurement appear to be statistically insignificant[72]. Neither was there any substantial change in option trading activities reflected by the total trading volume level discussed previously[73]. In sum, it appears that this systematic behavior reflects increasing costs borne by market makers, possibly due to higher costs of borrowing stocks driven by a greater uncertainty about solvency during the global

[72] It is important to emphasize that the results presented in this paper are by no mean contradictory to previous studies such as Boehmer, Jones and Zhang (2009) and Battalio and Schultz (2010). In spite of being statistically insignificant, the key variables of interest still present the expected sign, consistent to those studies. In addition, the authors wish to acknowledge that some dissimilarity may also arise due to the different sample set and control variables used in this study when compared to others.

[73]Strictly speaking, one can speculate that traders' migration may occur specifically in a segment of the market for in-the-money calls, as indicated by a significant increase in trading volume. However, the negligible impact on the option spread indicates that the trader composition has not been affected by this traders' influx.

financial crisis. This seems to be a sensible reason which helps to explain why to-be-short sellers, after exiting the stock market, were not tempted to enter the option market during the time the second ban was in place, as found previously. After the second ban is lifted, we find that the banned group is subject to a significant increase (decrease) in option (stock) spread. Also it was documented previously that stock (option) trading volume for the banned group decreases (increases) significantly after the ban. Hence, we interpret this evidence as indicative of traders switching from the stock market to the option market after the naked SSB becomes permanent. Further, it is clear that this flow of traders is more likely to be dominated by sophisticated and relatively more informed traders, consistent with what is predicted in the theory. In contrast, we find that options traded on unbanned stocks experience no significant change in the spread measure. This evidence, combined with our previous finding of lower option and stock volume, seems to suggest that the naked SSB, once becoming permanent, has effectively diminished the short interest for unbanned stocks, i.e. traders fall out of the stock and option markets simultaneously in response to the ban. We further argue that the reason for this happening is possibly due to the illiquidity of the option market found in those stocks[74], which makes it unappealing for traders to use synthetic option trades to mitigate naked SSR after it becomes mandatory.

4.4.3. The impact of the bans on the information share between option and stock

Given our previous finding of traders migrating from one market to another, it is useful for us to further examine whether this has any effect on the informational efficiency of

[74] In fact, we found that unbanned stocks considered in the second ban are subject to significantly higher spread than banned stocks. Our regression results clearly show that the average difference in option spreads between banned and unbanned stocks, i.e. reflected by the coefficient term on the dummy variable *banned* in our regression, in the second ban is approximately three times bigger than what it is in the first ban. This highlight a clear difference in the degree of market liquidity between options traded on those stocks.

both option and stock markets, and in particular the role of option trades in the process of stock price discovery. It is important to note that several approaches have been developed in the literature to estimate the degree of price discovery which takes place in the option market (Easley, O'Hara et al., 1998; Chakravarty, Gulen et al., 2004; Pan and Poteshman, 2006; Anand and Chakravarty, 2007; Kang and Park, 2008). In this paper, we employ a modification of Hasbrouck‘s (1995) approach to estimate the fraction of price discovery attributable to option trades. This has been calculated on a daily basis following the procedure previously discussed, using intraday data of both securities. To understand whether the ban would have led to changes in the information share of option trades for each group, we regress the option information share against the same set of explanatory variables used in previous equations, as follows

$$\begin{aligned} Option\ \ Information\ \ Share &= \alpha_0 + \alpha_2\, Stock\ return + \alpha_3\, Stock\ volatility + \alpha_4\, VIX \\ &+ \beta_1\, Banned + \beta_2\, Ban + \beta_3\,(Banned \times Ban) + \beta_4 PostBan + \beta_5\,(Banned \times PostBan) + \varepsilon \qquad (6) \end{aligned}$$

It is worth pointing out that the results presented in the previous sections consistently show the flow of option traders who switch their trades from banned stocks to unbanned stocks during and after the first ban. Given the net trader flow out of the option market for banned stocks during (after) the first ban, it is reasonable to expect that the option trades should contribute less to the price discovery of those stocks, as there are fewer traders remained in the market. On the contrary, we anticipate that the influx of traders entering the option market for unbanned stocks during (after) the first ban would have led to a greater contribution of option trades towards the price discovery of those stocks. Within this line of argument, we also expect that the flow of traders in (out) of the option market for banned (unbanned) stocks after the second ban is lifted will directly translate into a significant increase (decrease) in the information share of options trades for those stocks. Our argument has strongly been supported by the empirical results presented in Table 4.4.

Table 4.4

Impact of the ban on the information share of option trades

This table reports the results of the following cross-sectional regression

$$Option\ \ Information\ \ Share = \alpha_0 + \alpha_2\, Stock\ return + \alpha_3\, Stock\ volatility + \alpha_4\, VIX$$
$$+ \beta_1\, Banned + \beta_2\, Ban + \beta_3 (Banned \times Ban) + \beta_4 PostBan + \beta_5 (Banned \times PostBan) + \varepsilon$$

where Stock return and Stock volatility are the daily return and volatility of the underlying stock respectively; VIX is the daily closing value of the CBOE Volatility index; banned is the dummy variable which takes the value of one if the underlying stock is on the SEC list of banned stocks and zero otherwise; ban is the dummy variable which is assigned the value of one if the observation date is within the ban period and zero otherwise; postban is a dummy variable which is equal to one if the observation date is after the ban period and zero otherwise. Similar to (Chakravarty, Gulen et al. 2004; Anand and Chakravarty 2007), we employ a modification of the (Hasbrouck 1995) ‘s approach to estimate the Option Information Share variable, which is defined as the fraction of stock price discovery attributable to option trades. This regression examines the impact of SSR on the informational efficiency of the option market of 51 optionable stocks. This sample set comprises of 17 stocks which are subject to the first Emergency Order implemented on 21st July 2008 (ban 1), a matched sample of 17 stocks subject to the subsequent outright ban implemented on 19th September 2008 (ban 2) and another matched sample of 17 stocks not subject to short sale regulations. It is noticed that seperate regressions have been run for each ban period. The sample period for the first ban is between 2nd January 2008 and 18th September 2008 while it covers from 12th August 2008 to 26th December 2008 for the second ban.

Indepedent variables	Dependent variables	
	Ban 1	Ban 2
	Option information share	Option information share
Intercept	0.485	0.513
	(29.810)**	(29.205)**
StockSR	-0.001	0.017
	(-0.060)	(1.325)
StockSV	0.205	-0.109
	(8.732)**	(-2.550)*
VIX	-0.003	-0.001
	(-4.214)**	(-3.308)**
banned	0.061	-0.049
	(10.936)**	(-2.954)**
ban	0.045	-0.001
	(5.757)**	(-0.050)
postban	0.031	-0.069
	(4.016)**	(-3.161)**
banned x ban	-0.083	-0.080
	(-5.578)**	(-3.396)**
bannedx postban	-0.099	0.048
	(-6.940)**	(2.579)**
R-squared	0.010	0.017
AIC	-47337	-29096
Schwarz	-47265	-29029

Note: We report the t-stat in parentheses which are calculated based on White heteroskedasticity-corrected standard errors.

** indicates significance at the 1% level

* indicates significance at the 5% level

As for the first ban, we find that unbanned stocks experience a significant increase, at the 1% level of significance, in the information share of option trades during (after) the first ban. In contrast, the contribution of option trades to the price discovery of banned stocks deteriorates drastically relative to unbanned stocks during (after) the ban, as reflected by a statistically negative coefficient on the interaction term between the *banned* and *ban* (*postban)* dummy variables in the left column of Table 4.4. The net effect, it seems, is that less price discovery takes place in the option market for banned stocks, both during and after the first ban. As for the second ban, the negative coefficient on the *postban* dummy in the right column of Table 4.4 indicates that the information share attributable to option trades reduces for unbanned stocks after the second ban is lifted. On the contrary, the coefficient on the interaction term between the *banned* and *postban* dummy variables is statistically positive at 1% level of significance. This clearly indicates a greater contribution of option trades towards the price discovery for banned stocks relative to unbanned stocks after the second ban ends.

4.4.4. The impact of the bans on the option pricing

The next part of our empirical investigation examines the responses of option market makers to the trader migration effect indentified above. If market makers believe that option order flows come in part from investors with private information, then they will increase (decrease) option prices in response to the inflow (outflow) of informed traders. As the result, it is expected that the price impact of option trades will increase as there is an increase in the proportion of informed traders, and vice versa. In order to test for the impact of changes in trader composition on the option pricing, we employ the option implied volatility information to estimate the following cross-sectional regression

$$IV = \alpha_0 + \alpha_1\, Option\ Volume + \alpha_2\, Stock\ return + \alpha_3\, Stock\ volatility + \alpha_4\, VIX$$
$$+ \beta_1\, Banned + \beta_2\, Ban + \beta_3\,(Banned \times Ban) + \beta_4 PostBan + \beta_5\,(Banned \times PostBan)$$
$$+ [\delta_1\, Banned + \delta_2\, Ban + \delta_3\,(Banned \times Ban) + \delta_4 PostBan + \delta_5\,(Banned \times PostBan)] \times Option\ Volume + \varepsilon \qquad (7)$$

In the above specification, *IV* represents the daily average implied volatility of ATM options, converted from the market-observed call and put option prices and *Option Volume* represents the total number of option contracts traded each day. The corresponding slope coefficients δ_2.. δ_5, therefore, capture the changes in the average price impact of one-unit increase in option trading volume for each group of stocks (banned vs. unbanned) during and after the ban respectively[75], after controlling for potential variations in the implied volatility level driven by the market's pure expectation of future volatility.

Results of the option spread regression discussed in the previous section suggest there is an influx of uninformed option traders from banned stocks to unbanned stocks during and after the first ban, as reflected by a significant increase (decrease) in the bid-ask spread for banned (unbanned) stocks. It is generally expected therefore that this trader flow would have led to an increase in the information asymmetry in the option market for banned stocks relative to unbanned stocks. Given that market makers often adjust the option price to protect themselves from the increasing information asymmetry, we argue that the trader switching effect observed previously should directly translate into a significant increase (reduction) in the price impact of option trades for banned (unbanned) stocks during and after the first ban. In addition, we expect that the price impact of option trades on banned stocks should increase relative to unbanned stocks to reflect a greater information asymmetry manifested after the second ban.

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[75]It is important to point out here that changes in the price impact variable may potentially be driven by two different factors, i.e. one corresponding to information asymmetry and the other arising from pure demand pressure.

Table 4.5

Price impact of option trades during and after the ban

This table reports the results of the following cross-sectional regression

$$IV = \alpha_0 + \alpha_1 OptionVolume + \alpha_2 Stockreturn + \alpha_3 Stockvolatility + \alpha_4 VIX$$
$$+ \beta_1 Banned + \beta_2 Ban + \beta_3 (Banned \times Ban) + \beta_4 PostBan + \beta_5 (Banned \times PostBan)$$
$$+ [\delta_1 Banned + \delta_2 Ban + \delta_3 (Banned \times Ban) + \delta_4 PostBan + \delta_5 (Banned \times PostBan)] \times OptionVolume + \varepsilon$$

where IV refers to the implied volatility of at-the-money options; Option Volume is the natural logarithms of the daily option trading volume; Stock return and Stock volatility are the daily return and volatility of the underlying stock respectively; VIX is the daily closing value of the CBOE Volatility index; banned is the dummy variable which takes the value of one if the underlying stock is on the SEC list of banned stocks and zero otherwise; ban is the dummy variable which is assigned the value of one if the observation date is within the ban period and zero otherwise; postban is a dummy variable which is equal to one if the observation date is after the ban period and zero otherwise. This regression examines whether the price impact of option trades has changed as a result of SSR implemented during the ban. This sample set examined comprises of 51 optionable stocks, including 17 stocks which are subject to the first Emergency Order implemented on 21st July 2008 (ban 1), a matched sample of 17 stocks subject to the subsequent outright ban implemented on 19th September 2008 (ban 2) and another matched sample of 17 stocks not subject to short sale regulations. It is noticed that seperate regressions have been run for each ban period. The sample period for the first ban is between 2nd January 2008 and 18th September 2008 while it covers from 12th August 2008 to 26th December 2008 for the second ban.

Indepedent variables	Dependent variables	
	Ban 1	Ban 2
	IV-ATM	IV-ATM
Intercept	0.138	0.306
	(12.565)**	(36.115)**
Option volume	0.000	0.000
	(-18.055)**	(-11.839)**
StockSR	-0.001	-0.002
	(-0.131)	(-0.156)
StockSV	0.106	-0.003
	(5.014)**	(-0.101)
VIX	0.012	0.004
	(24.482)**	(13.234)**
banned	0.067	0.127
	(13.931)**	(14.500)**
ban	0.100	0.082
	(12.949)**	(7.569)**
postban	0.065	0.208
	(10.757)**	(14.271)**
banned x ban	-0.034	0.048
	(-2.139)*	(3.363)**
banned x postban	-0.032	-0.019
	(-2.211)*	(-1.660)
banned x Option volume	0.000	0.000
	(18.120)**	(10.764)**
ban x Option volume	0.000	0.000
	(-4.413)**	(-3.329)**
postban x Option volume	0.000	0.000
	(-2.767)**	(-5.654)**
banned x ban x Option volume	0.000	0.000
	(4.326)**	(2.629)**
banned x postban x Option volume	0.000	0.000
	(2.847)**	(2.736)**
R-squared	0.177	0.628
AIC	-27095	-12652
Schwarz	-26992	-12561

Note: We report the t-stat in parentheses which are calculated based on White heteroskedasticity-corrected standard errors.

** indicates significance at the 1% level

* indicates significance at the 5% level

This conjecture has been supported by the empirical results presented in Table 4.5, which basically show that a significantly positive coefficient, at 1% level of significance, has been found for the interaction term between the two dummy variables *banned*, *postban* and *option volume*. It is interesting to point out that our findings of the effect of the ban on option pricing documented thus far are perfectly aligned to changes in the degree of information asymmetry reflected by variations in the option bid-ask spread reported previously. The only noticeable difference is where we find (1) that unbanned stocks appear to experience a significant reduction in the degree information asymmetry pertained to their option trades both during and after the second ban; and (2) that option trades on banned stocks are subject to a greater degree of information asymmetry during the second ban. This occurs despite our earlier finding of insignificant changes in the option bid-ask spread in all those instances. A possible explanation for this disparity is that the option bid-ask spread may have been driven by factors other than the degree of information asymmetry between traders[76].

4.4.5. The impact of the bans on the speed of stock price adjustment and the probability of informed traders (PIN)

In this section, we analyze the impact of SSR on the pricing efficiency and the degree of information asymmetry in the stock market by estimating the cross-sectional regressions given below. Their specifications are very similar in feature to others previously used throughout this paper. Specifically,

$$\begin{aligned} Speed = {} & \alpha_0 + \alpha_1\, Stock\ return + \alpha_2\, Stock\ volatility + \alpha_3\, VIX \\ & + \beta_1\, Banned + \beta_2\, Ban + \beta_3\, (Banned \times Ban) + \beta_4 PostBan + \beta_5\, (Banned \times PostBan) + \varepsilon \qquad (8) \end{aligned}$$

$$\begin{aligned} PIN = {} & \alpha_0 + \alpha_1\, Stock\ return + \alpha_2\, Stock\ volatility + \alpha_3\, VIX \\ & + \beta_1\, Banned + \beta_2\, Ban + \beta_3\, (Banned \times Ban) + \beta_4 PostBan + \beta_5\, (Banned \times PostBan) + \varepsilon \qquad (9) \end{aligned}$$

[76] Refer to George and Longstaff (1993) and Anand (1990) for the empirical evidence of determinants of the option bid-ask spread (see also Stoll (1989) and Glosten and Harris (1988) for a basic a theoretical model of the bid-ask spread).

Where *Speed* and *PIN* refer to the speed of the stock price adjustments and the probability of informed traders respectively. As in our previous discussion in the variable construction section, we employ Hasbrouck's (1991) dynamic vector autoregression (VAR) model in order to estimate the *Speed* and employ Easley, Kiefer et al.'s (1996) model to calculate the *PIN*.

Once again, the key focus here is to detect if there is any change in *Speed* and *PIN* driven by the trader responses to SSR implemented during the two bans, as reflected by the terms *Ban*, *PostBan*, *Banned* x *Ban* and *Banned* x *PostBan*. It is first noted in the regression results presented in Table 4.6 that the speed of stock price adjustments significantly reduces for unbanned stocks during and after the first ban, reflecting the effect of relatively uninformed traders switching from banned to unbanned stocks as discussed previously. For the rest of the table, the coefficient estimates in both regressions of *Speed* and *PIN* have the expected but insignificant signs for all those special terms. For instance, the terms *Banned* x *Ban* and *Banned* x *PostBan* in the first regression of *Speed* have the positive signs, indicating a slight improvement of pricing efficiency for banned stocks relative to unbanned stocks both during and after the first ban. This once again consistently reflects the trader switching effect mentioned above. Similarly, the PIN for unbanned stocks tends to decrease slightly during and after the first ban, as shown by negative coefficients on the *Ban* and *PostBan* terms, whereas the opposite goes for banned stocks. In sum, all results are consistent with changes in trading activities reflected in the regressions of spread and volume reported previously.

Table 4.6

Summary statistics of changes in the speed of stock price adjustments (PA) and the probability of informed traders (PIN) in the stock market during and after the ban

This table reports the results of the following cross-sectional regressions

$$Speed = \alpha_0 + \alpha_1 Stock\,return + \alpha_2 Stock\,volatility + \alpha_3 VIX + \beta_1 Banned + \beta_2 Ban + \beta_3 (Banned \times Ban) + \beta_4 PostBan + \beta_5 (Banned \times PostBan) + \varepsilon$$

$$PIN = \alpha_0 + \alpha_1 Stock\,return + \alpha_2 Stock\,volatility + \alpha_3 VIX + \beta_1 Banned + \beta_2 Ban + \beta_3 (Banned \times Ban) + \beta_4 PostBan + \beta_5 (Banned \times PostBan) + \varepsilon$$

where Stock return and Stock volatility are the daily return and volatility of the underlying stock respectively; VIX is the daily closing value of the CBOE Volatility index; banned is the dummy variable which takes the value of one if the underlying stock is on the SEC list of banned stocks and zero otherwise; ban is the dummy variable which is assigned the value of one if the observation date is within the ban period and zero otherwise; postban is a dummy variable which is equal to one if the observation date is after the ban period and zero otherwise. Speed and PIN refer to the speed of the stock price adjustments and the probability of informed traders respectively. As per our previous discussion in the variable construction section, we employ (Hasbrouck 1991)'s dynamic vector autoregression (VAR) model in order to estimate the Speed and employ (Easley, Kiefer et al. 1996)'s model to calculate the PIN. These regressions examine the impact of SSR on the informational and pricing efficiency of stock trading for 51 optionable stocks. This sample set comprises of 17 stocks which are subject to the first Emergency Order implemented on 21st July 2008 (ban 1), a matched sample of 17 stocks subject to the subsequent outright ban implemented on 19th September 2008 (ban 2) and another matched sample of 17 stocks not subject to short sale regulations. It is noticed that seperate regressions have been run for each ban period. The sample period for the first ban is between 2nd January 2008 and 18th September 2008 while it covers from 12th August 2008 to 26th December 2008 for the second ban.

Indepedent variables	Dependent variables			
	Ban 1		Ban 2	
	Speed	PIN	Speed	PIN
Intercept	0.002	0.100	0.001	0.070
	(4.809)**	(8.648)**	(2.119)*	(5.481)**
StockSR	0.000	0.000	-0.001	0.000
	(-2.245)*	(0.000)	(-2.361)*	(0.000)
StockSV	0.000	0.000	-0.001	0.000
	(-1.922)	(0.000)	(-1.362)	(0.000)
VIX	0.000	0.000	0.000	0.000
	(-1.683)	(0.000)	(0.449)	(0.000)
banned	-0.001	0.006	0.000	0.023
	(-7.217)**	(0.213)	(1.355)	(1.386)
ban	-0.001	-0.010	0.000	0.026
	(-2.168)*	(-0.669)	(0.990)	(1.245)
afban	0.000	-0.022	0.000	0.030
	(-1.714)	(-1.382)	(0.150)	(1.095)
bannedban	0.000	0.002	0.000	0.005
	(1.466)	(0.068)	(-0.842)	(0.141)
bannedafban	0.000	0.004	0.000	-0.032
	(1.095)	(0.129)	(-0.300)	(-1.064)
R-squared	0.005	-0.032	-0.001	-0.002
AIC	-71892	-424	-36538	-388
Schwarz	-71830	-411	-36482	-374

Note: We report the t-stat in parentheses which are calculated based on White heteroskedasticity-corrected standard errors.

** indicates significance at the 1% level

* indicates significance at the 5% level

4.4.6. The impact of the bans on the lead-lag relations between stocks and options

The results we present so far indicate that traders migrate from one market to another in response to SSR implemented during the ban. Given the interrelation between the option and stock markets, we expect to observe some dynamic changes in the lead-lag relation between two markets driven by the trader switching effect. We examine this expression by estimating the following regressions:

$$\begin{aligned} SV = \; & \alpha_0 + \alpha_1 \, lag(IV) + \beta_1 \, Banned + \beta_2 \, Ban + \beta_3 \, (Banned \times Ban) + \beta_4 PostBan + \beta_5 \, (Banned \times PostBan) \\ & + \left[\delta_1 \, Banned + \delta_2 \, Ban + \delta_3 \, (Banned \times Ban) + \delta_4 PostBan + \delta_5 \, (Banned \times PostBan) \right] \times \; lag(IV) + \varepsilon \end{aligned} \tag{10}$$

$$\begin{aligned} Stock\ Volume = \; & \alpha_0 + \alpha_1 \, lag(Option\ Volume) + \beta_1 \, Banned + \beta_2 \, Ban + \beta_3 \, (Banned \times Ban) + \beta_4 PostBan + \beta_5 \, (Banned \times PostBan) \\ & + \left[\delta_1 \, Banned + \delta_2 \, Ban + \delta_3 \, (Banned \times Ban) + \delta_4 PostBan + \delta_5 \, (Banned \times PostBan) \right] \times \; lag(Option\ Volume) + \varepsilon \end{aligned} \tag{11}$$

where *SV* and *IV* refer to stock volatility and option implied volatility respectively. It is important to note that the current option literature suggests that any impact of the ban on the informational efficiency of the option market should manifest itself through dynamic changes in the lead-lag relations between (1) option implied volatility and stock volatility, and (2) option trading volume and stock volume. In the following discussion, we show that all regression results, also reproduced here, tend to reflect a similar effect to our previous findings.

4.4.6.1. The lead-lag relation between stock volatility and option volatility

Reasons for the lead-lag relation between stock volatility and option volatility have long existed in the literature: one of which relates to the degree of informed trading activities in the option market (Anthony, 1988). It is generally expected that lagged option implied volatility should be more informative of the expected changes in future stock volatility, if there is a greater proportion of informed traders entering the option market.

Table 4.7

Part A: Lead-lag Relation Between Stock Volatility and Option Implied Volatility (ATM)

This table reports the results of the following cross-sectional regression

$$SV = \alpha_0 + \alpha_1 lag(IV) + \beta_1 Banned + \beta_2 Ban + \beta_3 (Banned \times Ban) + \beta_4 PostBan + \beta_5 (Banned \times PostBan)$$
$$+ [\delta_1 Banned + \delta_2 Ban + \delta_3 (Banned \times Ban) + \delta_4 PostBan + \delta_5 (Banned \times PostBan)] \times lag(IV) + \varepsilon$$

where SV and IV refer to stock volatility and option implied volatility respectively; banned is the dummy variable which takes the value of one if the underlying stock is on the SEC list of banned stocks and zero otherwise; ban is the dummy variable which is assigned the value of one if the observation date is within the ban period and zero otherwise; postban is a dummy variable which is equal to one if the observation date is after the ban period and zero otherwise. This regression examines the impact of SSR on the lead-lag relation between the stock and option market of 51 optionable stocks. This sample set comprises of 17 stocks which are subject to the first Emergency Order implemented on 21st July 2008 (ban 1), a matched sample of 17 stocks subject to the subsequent outright ban implemented on 19th September 2008 (ban 2) and another matched sample of 17 stocks not subject to short sale regulations. It is noticed that seperate regressions have been run for each ban period, based on the implied volatility of different contract classifications including the average implied volatility of all ATM contracts (IV_ATM), of ATM Put options (IV_ATM Put) and of ATM Call options (IV_ATM Call). The sample period for the first ban is between 2nd January 2008 and 18th September 2008 while it covers from 12th August 2008 to 26th December 2008 for the second ban.

Indepedent variables	Stock volatility regressing on lagged option implied volatility					
	Ban 1			Ban 2		
	lag (IV_ATM)	lag (IV_ATM Put)	lag (IV_ATM Call)	lag (IV_ATM)	lag (IV_ATM Put)	lag (IV_ATM Call)
Intercept	-0.016	-0.012	-0.014	-0.003	-0.002	0.000
	(-3.621)**	(-2.856)**	(-3.104)**	(-0.528)	(-0.631)	(0.057)
lag(IV)	0.070	0.056	0.064	0.015	0.012	0.008
	(5.357)**	(4.655)**	(4.581)**	(1.177)	(1.499)	(0.647)
banned	0.029	0.013	0.032	0.031	0.001	0.029
	(2.624)**	(1.173)	(3.030)**	(1.783)	(0.085)	(1.812)
ban	-0.005	-0.014	0.005	0.017	0.010	0.008
	(-0.488)	(-1.175)	(0.562)	(0.913)	(0.817)	(0.463)
postban	0.002	-0.018	0.007	0.002	0.005	-0.003
	(0.170)	(-1.226)	(0.570)	(0.245)	(0.979)	(-0.451)
banned x ban	0.035	0.054	0.032	0.084	0.035	0.142
	(0.463)	(0.754)	(0.406)	(1.163)	(0.394)	(1.852)
bannedx postban	0.026	0.049	-0.070	-0.130	-0.158	-0.112
	(0.293)	(0.572)	(-0.886)	(-2.945)**	(-3.078)**	(-3.059)**
banned x lag(IV)	-0.041	-0.004	-0.048	-0.005	0.045	-0.007
	(-1.695)	(-0.178)	(-2.007)*	(-0.162)	(1.377)	(-0.217)
ban x lag(IV)	-0.004	0.021	-0.021	-0.030	-0.015	-0.014
	(-0.141)	(0.726)	(-0.943)	(-0.832)	(-0.674)	(-0.371)
postban x lag(IV)	0.004	0.046	-0.003	-0.004	-0.007	0.004
	(0.128)	(1.273)	(-0.102)	(-0.332)	(-0.742)	(0.314)
banned x ban x lag(IV)	-0.049	-0.106	-0.030	-0.095	-0.057	-0.164
	(-0.561)	(-1.273)	(-0.328)	(-1.199)	(-0.539)	(-1.915)
bannedx postban x lag(IV)	-0.068	-0.125	0.052	0.128	0.137	0.109
	(-0.675)	(-1.283)	(0.587)	(2.549)*	(2.286)*	(2.776)**
R-squared	0.011	0.014	0.010	0.022	0.024	0.023
AIC	-31586	-29174	-30511	-15288	-13643	-14277
Schwarz	-31504	-29094	-30430	-15216	-13573	-14206

Note: We report the t-stat in parentheses which are calculated based on White heteroskedasticity-corrected standard errors.

** indicates significance at the 1% level

* indicates significance at the 5% level

Part B: Lead-lage Relation between Stock Volatility and Option Implied Volatility (Average)

This table reports the results of the following cross-sectional regression

$$SV = \alpha_0 + \alpha_1 lag(IV) + \beta_1 Banned + \beta_2 Ban + \beta_3 (Banned \times Ban) + \beta_4 PostBan + \beta_5 (Banned \times PostBan)$$
$$+ [\delta_1 Banned + \delta_2 Ban + \delta_3 (Banned \times Ban) + \delta_4 PostBan + \delta_5 (Banned \times PostBan)] \times lag(IV) + \varepsilon$$

where SV and IV refer to stock volatility and option implied volatility respectively; banned is the dummy variable which takes the value of one if the underlying stock is on the SEC list of banned stocks and zero otherwise; ban is the dummy variable which is assigned the value of one if the observation date is within the ban period and zero otherwise; postban is a dummy variable which is equal to one if the observation date is after the ban period and zero otherwise. This regression examines the impact of SSR on the lead-lag relation between the stock and option market of 51 optionable stocks. This sample set comprises of 17 stocks which are subject to the first Emergency Order implemented on 21st July 2008 (ban 1), a matched sample of 17 stocks subject to the subsequent outright ban implemented on 19th September 2008 (ban 2) and another matched sample of 17 stocks not subject to short sale regulations. It is noticed that seperate regressions have been run for each ban period, based on the implied volatility of different contract classifications including the average implied volatility of all contracts (IV mean), of Put options (IV mean Put) and of Call options (IV mean Call). The sample period for the first ban is between 2nd January 2008 and 18th September 2008 while it covers from 12th August 2008 to 26th December 2008 for the second ban.

Indepedent variables	Stock volatility regressing on lagged option implied volatility					
	Ban 1			Ban 2		
	lag (IV mean)	lag (IV mean Put)	lag (IV mean Call)	lag (IV mean)	lag (IV mean Put)	lag (IV mean Call)
Intercept	-0.013	-0.013	-0.009	0.001	0.012	0.001
	(-2.563)*	(-2.122)*	(-1.741)	(0.169)	(1.426)	(0.192)
lag(IV)	0.047	0.043	0.035	0.005	-0.021	0.005
	(3.505)**	(2.784)**	(2.618)**	(0.340)	(-1.033)	(0.470)
banned	-0.003	-0.031	-0.012	0.015	0.003	-0.006
	(-0.238)	(-2.332)*	(-0.960)	(0.716)	(0.134)	(-0.365)
ban	-0.014	-0.010	-0.003	-0.003	-0.023	-0.002
	(-1.008)	(-0.493)	(-0.273)	(-0.160)	(-1.606)	(-0.104)
postban	0.006	0.021	-0.008	-0.001	-0.012	-0.002
	(0.356)	(0.740)	(-0.609)	(-0.163)	(-1.105)	(-0.281)
banned x ban	0.080	0.147	0.083	0.102	-0.074	0.104
	(1.001)	(1.465)	(1.108)	(1.165)	(-1.374)	(1.087)
bannedx postban	-0.082	-0.061	-0.049	-0.147	-0.103	-0.093
	(-1.526)	(-1.234)	(-1.181)	(-3.762)**	(-2.974)**	(-2.572)*
banned x lag(IV)	0.020	0.060	0.041	0.012	0.028	0.038
	(0.799)	(2.058)*	(1.590)	(0.309)	(0.797)	(1.264)
ban x lag(IV)	0.032	0.019	0.009	0.008	0.050	0.005
	(1.006)	(0.428)	(0.360)	(0.206)	(1.640)	(0.185)
postban x lag(IV)	0.011	-0.021	0.032	0.004	0.029	0.004
	(0.289)	(-0.352)	(1.022)	(0.244)	(1.298)	(0.386)
banned x ban x lag(IV)	-0.136	-0.221	-0.139	-0.124	0.065	-0.132
	(-1.398)	(-1.804)	(-1.640)	(-1.206)	(0.921)	(-1.136)
bannedx postban x lag(IV)	0.031	0.022	-0.023	0.142	0.081	0.075
	(0.449)	(0.289)	(-0.444)	(2.929)**	(2.020)*	(1.709)
R-squared	0.016	0.029	0.018	0.018	0.006	0.017
AIC	-23588	-12676	-21674	-10975	-6691	-10295
Schwarz	-23510	-12607	-21598	-10908	-6631	-10229

Note: We report the t-stat in parentheses which are calculated based on White heteroskedasticity-corrected standard errors.

** indicates significance at the 1% level

* indicates significance at the 5% level

Part C: Lead-lage Relation between Stock Volume and Option Volume (Total Volume)

This table reports the results of the following cross-sectional regression

$$
\begin{aligned}
StockVolume = {} & \alpha_0 + \alpha_1 lag(IV) + \beta_1 Banned + \beta_2 Ban + \beta_3 (Banned \times Ban) + \beta_4 PostBan + \beta_5 (Banned \times PostBan) \\
& + \left[\delta_1 Banned + \delta_2 Ban + \delta_3 (Banned \times Ban) + \delta_4 PostBan + \delta_5 (Banned \times PostBan)\right] \times lag(OptionVolume) + \varepsilon
\end{aligned}
$$

where banned is the dummy variable which takes the value of one if the underlying stock is on the SEC list of banned stocks and zero otherwise; ban is the dummy variable which is assigned the value of one if the observation date is within the ban period and zero otherwise; postban is a dummy variable which is equal to one if the observation date is after the ban period and zero otherwise. Stock Volume and Option Volume refer to the natural logarithm of daily trading volume of option and stock respectively. This regression examines the impact of SSR on the lead-lag relation between the stock and option market of 51 optionable stocks. This sample set comprises of 17 stocks which are subject to the first Emergency Order implemented on 21st July 2008 (ban 1), a matched sample of 17 stocks subject to the subsequent outright ban implemented on 19th September 2008 (ban 2) and another matched sample of 17 stocks not subject to short sale regulations. It is noticed that seperate regressions have been run for different contract classifications in each ban period. The sample period for the first ban is between 2nd January 2008 and 18th September 2008 while it covers from 12th August 2008 to 26th December 2008 for the second ban.

Indepedent variables	Stock volume regressing on lagged option volume					
	Ban 1			Ban 2		
	lag(Option Volume)	lag(Put Volume)	lag(Call Volume)	lag(Option Volume)	lag(Put Volume)	lag(Call Volume)
Intercept	13.856	13.982	13.980	12.973	13.555	13.135
	(201.918)**	(222.424)**	(214.348)**	(77.554)**	(84.949)**	(79.290)**
lag (Option Volume)	0.134	0.137	0.125	0.241	0.180	0.244
	(12.459)**	(12.415)**	(10.965)**	(7.984)**	(5.633)**	(7.365)**
banned	-0.261	-0.192	-0.366	0.949	0.567	0.870
	(-2.320)*	(-1.851)	(-3.421)**	(6.299)**	(3.909)**	(5.863)**
ban	0.482	0.568	0.393	0.572	0.237	0.711
	(2.827)**	(3.869)**	(2.490)*	(1.974)*	(0.883)	(2.710)**
postban	-0.181	0.051	-0.152	1.133	0.842	1.081
	(-1.052)	(0.305)	(-0.869)	(6.022)**	(4.688)**	(5.734)**
banned x ban	-0.023	-0.031	-0.023	-0.068	-0.067	-0.080
	(-2.747)**	(-3.068)**	(-2.522)*	(-6.529)**	(-5.801)**	(-6.460)**
bannedx postban	-0.005	-0.010	-0.004	-0.040	-0.031	-0.046
	(-0.578)	(-0.926)	(-0.409)	(-6.342)**	(-3.710)**	(-6.339)**
banned x lag(Option Volume)	0.138	0.133	0.175	-0.050	0.002	-0.048
	(9.290)**	(8.828)**	(11.330)**	(-1.748)	(0.069)	(-1.510)
ban x lag(Option Volume)	-0.017	-0.031	-0.002	-0.036	0.005	-0.065
	(-0.688)	(-1.258)	(-0.088)	(-0.691)	(0.090)	(-1.236)
postban x lag(Option Volume)	0.025	-0.011	0.025	-0.129	-0.107	-0.137
	(0.997)	(-0.412)	(0.873)	(-3.554)**	(-2.730)**	(-3.426)**
banned x ban x lag(Option Volume)	0.002	0.003	0.002	0.007	0.007	0.009
	(3.055)**	(3.363)**	(2.818)**	(7.616)**	(6.912)**	(7.877)**
bannedx postban x lag(Option Volume)	0.001	0.001	0.001	0.005	0.004	0.006
	(0.728)	(1.236)	(0.482)	(10.011)**	(6.275)**	(10.576)**
R-squared	0.192	0.188	0.207	0.154	0.142	0.153
AIC	5130	4838	4730	3518	3191	3436
Schwarz	5212	4919	4811	3592	3263	3509

Note: We report the t-stat in parentheses which are calculated based on White heteroskedasticity-corrected standard errors.

** indicates significance at the 1% level

* indicates significance at the 5% level

Part D: Lead-lag Relation between Stock Volume and Option Volume (Total Trades)

This table reports the results of the following cross-sectional regression

$$StockVolume = \alpha_0 + \alpha_1 lag(IV) + \beta_1 Banned + \beta_2 Ban + \beta_3 (Banned \times Ban) + \beta_4 PostBan + \beta_5 (Banned \times PostBan)$$
$$+ \left[\delta_1 Banned + \delta_2 Ban + \delta_3 (Banned \times Ban) + \delta_4 PostBan + \delta_5 (Banned \times PostBan)\right] \times lag(OptionVolume) + \varepsilon$$

where banned is the dummy variable which takes the value of one if the underlying stock is on the SEC list of banned stocks and zero otherwise; ban is the dummy variable which is assigned the value of one if the observation date is within the ban period and zero otherwise; postban is a dummy variable which is equal to one if the observation date is after the ban period and zero otherwise. Stock Volume and Option Volume refer to the natural logarithm of daily number of trades of option and stock respectively. This regression examines the impact of SSR on the lead-lag relation between the stock and option market of 51 optionable stocks. This sample set comprises of 17 stocks which are subject to the first Emergency Order implemented on 21st July 2008 (ban 1), a matched sample of 17 stocks subject to the subsequent outright ban implemented on 19th September 2008 (ban 2) and another matched sample of 17 stocks not subject to short sale regulations. It is noticed that seperate regressions have been run for different contract classifications in each ban period. The sample period for the first ban is between 2nd January 2008 and 18th September 2008 while it covers from 12th August 2008 to 26th December 2008 for the second ban.

Indepedent variables	Stock volume regressing on lagged option volume					
	Ban 1			Ban 2		
	lag(Option Volume)	lag(Put Volume)	lag(Call Volume)	lag(Option Volume)	lag(Put Volume)	lag(Call Volume)
Intercept	8.737	8.874	8.891	8.281	8.681	8.470
	(202.266)**	(224.017)**	(224.697)**	(80.107)**	(83.444)**	(82.648)**
lag (Option Volume)	0.189	0.201	0.168	0.265	0.229	0.264
	(18.009)**	(18.154)**	(15.183)**	(9.829)**	(8.066)**	(8.636)**
banned	-0.202	-0.207	-0.291	0.727	0.521	0.611
	(-2.235)*	(-2.444)*	(-3.565)**	(6.845)**	(4.996)**	(5.874)**
ban	0.501	0.549	0.431	0.100	-0.049	0.179
	(3.617)**	(4.751)**	(3.596)**	(0.531)	(-0.258)	(0.995)
postban	0.065	0.256	0.079	0.589	0.482	0.555
	(0.535)	(2.128)*	(0.670)	(4.707)**	(3.958)**	(4.509)**
banned x ban	-0.074	-0.110	-0.079	-0.086	-0.079	-0.092
	(-4.710)**	(-5.590)**	(-4.070)**	(-6.062)**	(-4.397)**	(-5.240)**
bannedx postban	-0.045	-0.083	-0.048	-0.054	-0.038	-0.054
	(-2.475)*	(-3.757)**	(-1.941)	(-4.974)**	(-2.642)**	(-4.052)**
banned x lag(Option Volume)	0.149	0.157	0.205	-0.040	-0.013	-0.030
	(8.838)**	(8.835)**	(12.155)**	(-1.297)	(-0.411)	(-0.855)
ban x lag(Option Volume)	-0.027	-0.040	-0.005	0.034	0.042	0.001
	(-0.875)	(-1.348)	(-0.179)	(0.744)	(0.816)	(0.011)
postban x lag(Option Volume)	0.014	-0.032	0.016	-0.066	-0.077	-0.086
	(0.533)	(-1.078)	(0.553)	(-1.830)	(-1.965)*	(-2.088)*
banned x ban x lag(Option Volume)	0.010	0.016	0.011	0.011	0.012	0.013
	(5.089)**	(5.964)**	(4.333)**	(7.256)**	(5.461)**	(6.745)**
bannedx postban x lag(Option Volume)	0.006	0.012	0.006	0.009	0.009	0.010
	(2.506)*	(3.924)**	(1.886)	(8.134)**	(5.340)**	(7.239)**
R-squared	0.193	0.196	0.203	0.180	0.173	0.171
AIC	3584	3306	3336	2656	2370	2624
Schwarz	3666	3387	3417	2729	2442	2697

Note: We report the t-stat in parentheses which are calculated based on White heteroskedasticity-corrected standard errors.

** indicates significance at the 1% level

* indicates significance at the 5% level

Part A and Part B of Tables 4.7 present the regression results of the lead-lag relation between stock volatility and alternate measures of option implied volatility, ie the average implied volatility of all at-the-money (ATM) contracts and the average implied volatility of all available contracts respectively. It is clear that all coefficient estimates have the expected sign, consistent with the results reported previously in terms of changes in the information share between options and stocks during and after the ban. This applies to both the first and the second ban. In particular, the statistical significance of the term *Banned* x *PostBan* in the second regression indicates that after the second ban, the option implied volatility of banned stocks becomes significantly more informative of the future stock volatility. This highlights our previous finding that option trading on banned stocks seems to be more "informed" after SSR are lifted, and hence contributes better to the price discovery of the underlying stock. In particular, this result stays robust to different measures of implied volatility and subcategories of puts and calls.

4.4.6.2. The lead-lag relation between stock volume and option volume

Part C and Part D of Tables 4.7 present the regression results of the lead-lag relation between stock volume and option volume, using different measures of volume including total trading volume and total number of trades. Given our previous findings, we expect to observe that option trading volume should be more informative of expected changes in future stock volume if the option market is dominated by relatively more informed traders. Interestingly, our results indicate that option trading volume of banned stocks is more informative of future trading activities in the underlying stocks than that of unbanned stocks. This applies during and after the ban for both the first and the second bans, as reflected by significantly positive coefficient estimates for both terms *Banned x Ban x lag(OptionVolume)* and *Banned x PostBan x lag(OptionVolume)* found in both regressions. We interpret this result as consistent with our previous findings of increasing concentration of informed traders in the option market for banned stocks at least during (after) the first ban and after the second ban. Once again, this result stays robust to different measures of volume considered, and hence provides compelling evidence in support of our previous findings.

4.4.7. Discussion of the limitations and the robustness tests

Similar to many papers which have previously looked at the impact of 2008 SSB, our study is subject to some limitations. Firstly, given that the short-sale regulations were called for mainly due to SEC's attempt to circumvent the market collapse amidst the GFC, the introduction of these rules cannot be considered as "a perfect natural experiment". In fact, the fact that SSR were implemented in a time of extreme market conditions means that much of the change in the market quality found in our paper might have been driven by other economy-wide factors rather than the ban itself. While we have tried to control for other factors by employing a control sample in our analysis, there is not an obvious control group of unbanned stocks which have other characteristics closely matched to those of the banned stocks we examined. This issue emerges simply because the second ban covered nearly the entire financial sector. Hence, it remains a critical issue which potentially hinders the robustness of the results reported here. Secondly, the fact that the ban was centered on some major financial institutions which were considered as assets "in trouble" implies that part of the market reaction to those regulations might arise from an expectation of attempts by government to protect a specific set of securities. It is however impossible to disentangle the direct effect of the ban and the signaling effect discussed here. Thirdly, the timing and fashion with which these regulations were adopted also impose a challenging task for any attempt to distinguish the separate effects of the two bans. Not only is it difficult to unravel the after-ban effect of one from another, it is also unclear whether the market reactions observed had been solely in response to the ban itself. In fact, there was much uncertainty and conflicting expectations aroused during the period between the two bans, and even more confusion after the ban had been put in place[77]. All these factors might influence traders' attempts to pursue short-selling either for hedging/speculating purposes.

Even with these limitations in mind, we still seek to provide novel and descriptive evidence regarding both regulatory events. In particular, we employ a number of additional robustness tests to ensure the accuracy of our findings. Firstly, we perform all the analysis again after re-assigning the pre-ban period of the second ban to be the period preceding both regulatory changes. This is necessary to control for the effect of the first regulatory change in our analysis of the second ban[78]. Secondly, we examine different measures of volume in most regressions employed throughout this paper. Thirdly, we consider applying different filters on option contracts to those previously applied in our main analysis. Results of these tests, not being reproduced here, yield a very similar observation to previous findings.

[77] For instance, there was uncertainty regarding which stock will be listed/delisted from the ban list after SEC decides to pass this authority to the exchanges

[78]In our previous analysis, the pre-ban period of the second ban is defined as the period immediately after the first ban leading to the second ban. It can be argued that part of what happening during this period also reflects the effect of the first ban, which is meant to be excluded in our analysis of the second ban. In addition, Grundy et al (2010) point out that the market were in turmoil during this period. This has potential to spurious results, and hence needs to be accounted for.

4.5. CONCLUSION

The key focus of this paper centers around the effects of the two bans implemented during the GFC. The first Emergency order adopted in July 2008 prohibited naked short selling activities on a specific set of 19 stocks, which was soon followed after by the second outright ban of all short-sales on 797 financial stocks. More particularly, we aim to examine how regulatory changes ruling short-selling activities in one market affect the market microstructure of related markets. Consistent with the existing literature, we find that SSR result in a significant reduction in the liquidity of the underlying stock market, as measured by trading volume and spread. It is also clear that option trading activities are affected by those regulatory changes, as evidenced by significant changes in the liquidity and the informational efficiency of the option market measured in terms of trading volume, spread, price impact and contribution of option trades towards the price discovery of the underlying stock market. Most interestingly, the results presented throughout this paper suggest that many investors switch their option/stock trading from banned stocks to unbanned stocks during the first ban in the face of higher costs of short selling simply because substitute stocks are largely available. Though we find no significant shift of traders from the stock to the option market during the second ban, there is overwhelming evidence of traders migrating from the stock market to the option market after the second ban period ended, once it comes to realize that naked SSR are set permanently afterwards.

Given the distinctive features of the regulations considered, we further explore how the trader composition has been impacted differently in each ban, in order to scrutinize traders' different responses to regulatory changes. In fact, we have been able to elucidate the separate effects of the two bans by employing DV's theoretical arguments which exclusively distinguish between the SRE and the SPE of short-sale regulations. Specifically, we find that the SRE dominates in the first ban and leads to increasing information asymmetry in both stock and option markets for affected stocks and those which are close substitutes[79]. This evidence clearly indicates that uninformed traders are more sensitive to changes in trading costs in making their trading venue decisions. In contrast, we find that the trading dynamics around the second ban period seems to be driven by the SPE predicted in DV's model, given that no significant change in the trader composition has been detected in various diagnostics examined. In addition, we find significant evidence that a proportion of traders, mostly dominated by relatively more informed traders, switch their trading from the stock to the option market in response to a permanent naked SSB staying intact after the second ban is lifted. In general, the results mounted from the various diagnostics considered are supportive of the theoretical predictions by DV and of the hypothesis that synthetic option trading is of more practical use by sophisticated and relatively more informed traders in an attempt to mitigate SSR.

In conclusion, the results presented in this paper offer policy makers with useful practical implications based on many insights drawn from the effect of the 2008 SSB on the market quality of both stock and option markets. In fact, our findings of significant changes in the liquidity and the informational efficiency of the option market during and after the ban period clearly demonstrate that regulatory changes targeting a specific market also affect other related markets via the arbitrage link between them. By documenting the separate effects of two distinct sets of rules and how they are linked to

[79] While we acknowledge there are instances whereby some variables did not appear to be statistically significant to provide an utmost support to a notion that the flow of traders from banned to unbanned stock during (after) the first ban period might have been dominated by relatively uninformed traders, all the key variables of interest always yielded the expected signs in different regressions considered.

traders' different responses in each case, we further illustrate that investors trading behaviors must be carefully considered in future regulatory design. It also offers some significant contributions to the academic literature on short sales by providing additional evidence of the impact of SSR on option trading activities, in particular on the role of option trades in the price discovery of the underlying asset. Most importantly, it provides many insights into the asymmetric responses of informed and uninformed traders to SSR, which are useful to validate and further extend the theoretical arguments built upon DV's work.

Appendix 4.A

List of stocks examined

This table lists the company names and tickers of 51 optionable stocks examined. Our stock sample can be categorised into three groups. Group 1 comprises of 17 stocks which are subject to the first Emergency Order implemented on 21st July 2008 (ban 1). Group 2 is the matched sample of 17 stocks which are subject to the subsequent outright ban implemented on 19th September 2008 (ban 2) while Group 3 is the second matched sample of 17 stocks which are not subject to the 2008 short sale regulations.

Group 1		Group 2		Group 3	
Ticker	Company Name	Ticker	Company Name	Ticker	Company Name
AZ	ALLIANZ SE	ALL	ALLSTATE	ANH	ANWORTH MGE.ASSET
BAC	BANK OF AMERICA CORP	AMP	AMERIPRISE FINL.	AVB	AVALONBAY COMMNS.
BCS	BARCLAYS PLC	AXP	AMERICAN EXPRESS	DIA	SPDR DJ.INDL.AVE.ETF
C	CITIGROUP INC.	BEN	FRANKLIN RESOURCES	DRE	DUKE REALTY
CS	CREDIT SUISSE GROUP	BLK	BLACKROCK	DVY	ISHARES TST.DJ.SLT.DIV. IDX.FD.
DB	DEUTSCHE BANK GROUP AG	CMA	COMERICA	EEM	ISHARES MSCI EMRG.MKTS. IDX.FD.
FNM	FRANNIE MAE	COF	CAPITAL ONE FINL.	EQR	EQUITY RESD.TST.PROPS. SHBI
FRE	FREDDIE MAC	ICE	INTERCONTINENTAL EX.	JLL	JONES LANG LASALLE
GS	GOLDMAN SACHS GP.	LNC	LINCOLN NAT.	JOE	ST.JOE
HBC	HSBC HOLDINGS PLC ADS	MBI	MBIA	KFN	KKR FINANCIAL HOLDINGS
JPM	JP MORGAN CHASE & CO.	PNC	PNC FINL.SVS.GP.	MMC	MARSH & MCLENNAN
LEH	LEHMAN BROTHERS HOLDING INC.	PRU	PRUDENTIAL FINL.	MPW	MEDICAL PROPS.TRUST
MER	MERRILL LYNCH AND CO. INC.	SLM	SLM	PCL	PLUM CREEK TIMBER
MFG	MIZUHO FINANCIAL GROUP INC.	SNV	SYNOVUS FINL.	PKY	PARKWAY PROPERTIES
MS	MORGAN STANLEY	STI	SUNTRUST BANKS	PPS	POST PROPERTIES
RBS	ROYAL BANK ADS	UTR	UNITRIN	SPG	SIMON PR.GP.
UBS	UBS AG	WFC	WELLS FARGO & CO	VNO	VORNADO REALTY TST.

CHAPTER 5

CONCLUSION

5.1. KEY FINDINGS

This research focuses on the issue of the role of options as a mechanism of information trading, with some particular interest in the practical implications of informed trading activities for the information content of option trades and the informational linkage between the option and stock markets. The key findings found in the three interrelated projects presented in chapters 2 to 4 jointly contribute to inform the two research questions and contribute to the two literature gaps formerly discussed in the first chapter.

In response to the first research question, the investigation into the relationship between option volume and stock volatility conducted in the first project (see Chapter 2) shows that a lead-lag relation of statistical significance exists after controlling for the information content reflected in option prices (implied volatility). Further examination of the forecast performance indicates that the information content extracted from option trading can be used to enhance predictions of future stock volatility. In addition, it is found that the importance of volume in forecasting volatility is shared between stock and option trading volume, with the latter possessing a better forecast quality. These findings indicate a slow diffusion of information into the market, particularly those relating to volatility news, via both stock and option trades, with the latter playing a more significant role in the price discovery process. In effect, the informativeness of options is thus proved to be directly related to those informed trading activities on options by which the volatility-related information is gradually disseminated into the market. This not only confirms the existence of informed traders in the option market, but also sheds light on the impact of their trading activities on the informational linkage between the option and stock markets. In relation to the existing literature, these findings not only support the notion that option trades are informative for the future dynamics of stock return volatility, as found in Easley, O'Hara et al. (1998), Chan, Chung et al. (2002), Pan and Poteshman (2006) and Ni, Pan et al. (2008), but also expand the empirical evidence for the forecasting applications which can be derived from the predictive power of trading volume.

The second project (see Chapter 3), which examines the relationship between option trading volume and the smile dynamics, reveals that the incorporation of option trading volume into the modelling of the smile dynamics also leads to better-quality forecasts of option prices (implied volatility), as it captures relatively well the changing dynamics of the smile over time. Evidence for the predictive power of option volume in forecasting the smile dynamics complements the previous project’s finding in asserting the existence and importance of informed trading in the option market. In effect, the significance of the lead-lag relation between option volume and price observed in this study once again supports the idea that informed trading in the option markets facilitates the information flow, which is disseminated into the market in a gradual fashion. In that sense, this project reaffirms the critical role of information-related trades in the process of incorporating new information into the option market. This viewpoint is in line with other empirical studies in the field, such as those of Bollen and Whaley (2004), Chan, Cheng et al. (2004), Ni, Pan et al. (2008) and Gârleanu, Pedersen et al. (2009), which advocate that option trades (demand) may have impacts on option pricing, as reflected by the changing behaviour of the IVS.

In response to the second research question, the empirical evidence found in the third project (see Chapter 4) indicates that increases in trading costs and trading restrictions induced by the imposition of the 2008 short-sale ban led to changes in the trader composition in both the option and stock markets, for the affected stocks. This happened because traders' decisions in relation to the trading venue in general might be heavily influenced by the trade-off of trading costs between related markets, and because uninformed traders in particular might be more responsive to changes in trading costs than uninformed traders. The net effect was reflected in significant changes in the degree of information asymmetry in both related markets and in the informational linkage between them during and after the ban period, as illustrated by the evidence presented in the paper. These findings suggest that trading cost is an important factor driving the trading behaviour of uninformed traders. Furthermore, these findings illustrate how informed traders respond differently to uninformed traders to changes in trading costs, and that trading restrictions imposed by regulations may ultimately influence the price formation process in related markets. In this sense, transaction costs and trading restrictions are thus proved to be important in determining the informational linkage between related markets. This finding is congruent with the theoretical argument of Diamond and Verrecchia (1987), with its prediction that short-sale restrictions, which have an effect of increasing trading costs, will result in changes in the trader composition in related markets, owing to the fact that uninformed traders are more sensitive to increasing trading costs.

In addition, the investigation into the role of trading volume in forecasting the stock volatility conducted in the first project (see Chapter 2) also indicates that the informativeness of trading volume varied across stocks with different levels of liquidity. This finding plays a critical role in showcasing the importance of liquidity in influencing the informational linkage between option and stock trades of individual stocks, given that liquidity appears to be the key factor which explains variations in the predictive power of volume among the cross-section of stocks examined. This viewpoint has generally been supported by the empirical evidence found in Chakravarty, Gulen et al. (2004), which shows that leverage, trading volume and spread might have influenced traders' decisions to trade across option contracts with different strike prices. It is also related to the traditional view that traders' decisions about the trading venue would depend on a trade-off of the relative trading costs between the option and stock markets, since they can trade in either market. This argument has been further developed by Easley, O'Hara et al. (1998) into the so-called "sequential-trade" model, which suggests that the degree of traders' participation in option trading is directly related to the leverage and liquidity of both the option and stock markets.

In summary, the results of this research confirm the predictive power of trading volume in forecasting the stock volatility and the smile dynamics. They provide evidence which indicates the existence of informed traders in the option market whose trading activities are related in part (but not limited) to information about the future volatility of the underlying stocks. In addition, it is found that (1) their trading behaviours might be affected by a number of factors including liquidity and trading costs; and (2) they responded differently to uninformed traders to changes in transactions costs and trading restrictions, suggesting some important implications for the informational linkage between the option and stock markets.

5.2. CONTRIBUTIONS OF THE THESIS

5.2.1. Contribution to Knowledge

From a theoretical perspective, this thesis satisfactorily addresses the gaps in the extant literature on option trading, particularly in the strand of empirical studies focusing on the role of options as a mechanism for trading on information about the underlying asset as discussed previously.

In particular, this research makes a significant contribution to the body of knowledge on the economic values of derivatives by investigating the critical role they play in the process of incorporating new information into the market. In fact, the examination of the role of the information content of option trading volume in forecasting future dynamics of the stock volatility and/or of the option implied volatility smile helps to address the fundamental economic question of how information gets incorporated into asset prices – a central issue to all information-based models. While the idea that option trades may play an important role in incorporating information into securities prices is not original to this research, this research presents some significant findings. These showcase the existence of informed traders in the option market and the implications this has for the price discovery in both related markets. Specifically, it is found that (1) option trades (as well as option prices) might first reflect new information before it is incorporated into stock prices, as illustrated by the information content of option volume (and implied volatility) in forecasting the stock volatility; and (2) option prices would adjust slowly to the private component of information in option trading, as evidenced by the information content of option volume in forecasting the smile dynamics. Since information-based models employed in Glosten and Milgrom (1985) and Easley, O'Hara et al. (1998) imply that prices only adjust slowly to the private information possessed by informed traders, the second finding also points to the existence of informed traders.

In addition, this thesis can significantly contribute to other areas in the finance literature. Firstly, it expands the empirical literature on the information linkage between the option and stock markets by providing evidence which clearly shows that the flow of information is not unidirectional as has been suggested in theory. In fact, a trader's preference for trading in the option market would cause option volume to convey new information before it is incorporated into stock prices, as reflected in the predictive power of option volume shown in our evidence. Further, this research shows that changes in the trading costs in related markets may have an effect on the trader composition and the direction of information flow, given the different trading responses of uninformed versus informed traders to these changes. Secondly, there are other issues of interest which have been addressed in the context of the consideration of three independent projects. Specifically, the analysis of the predictive power of volume in forecasting the stock volatility undertaken in the first project (see Chapter 2) contributes to the literature which focuses on examining the nature of the volume-volatility relation, particularly in regard to those studies which aim at improving modelling and forecasting the stock volatility. The investigation into the information content of option volume in forecasting the option smile in the second project (see Chapter 3) also helps to validate the economic explanations underlying the smile evolution, one of which is directly related to the flow of information into the market. This topic has captured much research interest in the option literature, since the existence of the smile and its time series dynamics exhibit fundamental departures from the option pricing theory built upon the influential Black and Scholes (1973) model. The final project which examines the market microstructure of the option and stock markets during the 2008 short-sale ban expands the empirical evidence in relation to the effect of short-sale restrictions – an issue which has been studied extensively in the finance literature. In particular, the empirical evidence presented in this project offers some support to Diamond and Verrecchia's (1987) theoretical predictions which exclusively distinguish between the short-restriction effect and the short-prohibition effect of short-sale restrictions.

In sum, the evidence presented in this thesis not only extends our understanding of informed trading activities in the option market but also contributes to the existing literature by providing both theoretical insights and empirical evidence into many important research topics. However, it is important to note that the key focus of this thesis has been to highlight some practical implications of informed trading on the information linkage between the stock and option markets. In addition, it is important to note that this thesis has been structured to encompass three independent projects which were conducted on different samples and in different settings. This allows for an inclusive examination into different aspects of informed trading in the option market and ensures that its implications for the informational linkage between the option and stock markets are fully explored. Indeed, it can be argued that the validity of our findings has been enhanced significantly, since the key research questions have been empirically examined through various data sets employed in the three projects constituting this thesis.

5.2.2. Contribution to Practice

Due to the nature of the analysis conducted in the first two projects, which was to some extent focused on improving the modelling and forecasting of the stock volatility and the option smile, some important forecasting applications can also be developed from the results produced by these projects. The findings presented in those projects indicate that trading volume contains useful information about the time variations of stock volatility and option implied volatility (prices). In addition, they suggest that modelling the time-series dynamics of stock volatility or of option implied volatility smile may benefit from expanding the information set of traditional time-series models when including additional factors such as trading volume. In fact, the forecast models developed in these papers deliver a simple yet effective mechanism which proved to bring about beneficial improvements in forecasting the stock volatility or option implied volatility (prices). Since volatility plays such a central role in the practice of derivatives trading, risk analysis and portfolio management, better forecasts of these quantities are clearly important and highly regarded by practitioners.

The third project, which illustrates how the short-sale restrictions imposed on equity trading would also affect option trading activities, provides many valuable insights into the question of how regulations targeting a specific market may affect related markets. The flow of traders switching from stock to option trades exhibited during the ban period as found in the third project also points to the important role of options in mitigating short-sale restrictions applied to equity trading. In addition, it indicates that a policy which has an effect of changing the relative costs of option and stock trading will lead to changes in the market microstructure of both markets and the direction of information flow between them. Further, it suggests some important issues that need to be considered from the policy making perspective to better anticipate the full-scale effect of new regulations, especially those in relation to short-sale restrictions, in the real context of the arbitrage link existing between the option and stock markets. In particular, it should be realised by regulators that government interventions may have mixed consequences which need to be fully accounted for before being enacted. In fact, in light of the current knowledge of how traders respond to changes in transaction costs and trading restrictions, it is important to acknowledge that regulatory changes which impact on the trading costs may result in radical changes in other aspects of trading, including the liquidity of related markets and the informational linkage between them.

5.3. LIMITATIONS

While each chapter discusses in great details the limitations pertaining to each project, this section is devoted to discussing some of the key limitations of this research as a whole.

Firstly, the major limitation of this research largely lies in the limited number of stocks/indices examined in the projects involved, a factor which somewhat impairs the generalisation of key findings reported previously. While this is a pertinent issue in most option research due to the intensity of transaction data involved, it may be worthwhile to attempt to expand the scale of the analysis to include a broader cross-section of stocks to examine whether these findings continue to hold for those which are less liquid. In a similar vein, while it has been found that the information content of option volume varies across the stock sample, it is unclear whether liquidity is the only factor driving this cross-sectional variation. In fact, it can be argued that the informativeness of option volume may have been related to other market conditions and/or stock characteristics which are excluded from the existing analysis. In order to examine this aspect with some degree of confidence a fairly large sample is necessary. This, however, goes beyond the scope of the current research.

Secondly, it is important to acknowledge that though the key findings reported in this research help to shed light on the informational linkage between the option and stock markets and to enhance our understanding of the price discovery in the option market, the mere evidence of the information content of option trading volume may not be sufficient to show that informed traders participate in the option market. Arguably, some or all information reflected in option trades could be information that has been revealed publicly, despite not yet being incorporated into stock prices due to temporary mispricings or order imbalances. In addition, another limitation may be that some of the proxies employed may not perfectly capture the quantity or information content intended. For instance, the market microstructure measurements employed in the last project, to analyse the impact of short-sale restrictions on the trader allocation across related markets, tend to lump together the information component of option trading with other liquidity-related-measures. Alternatively, some are unable to distinguish between the permanent price change which is directly driven by the new content of information and the temporary price change component which merely reflects the temporary mispricings. All of these concerns raise the need for using a more direct and effective measurement of informed trading. This issue, however, in itself presents another critical research question which goes beyond the scope of the current research.

5.4. AREAS FOR FUTURE RESEARCH

Other than contributing to the existing finance literature by addressing the many important research issues previously emphasised, the key findings reported in this thesis suggest several directions for future research, with some directions highlighted below.

5.4.1. Informed trading in the option market

As discussed previously, there are some important research questions in relation to the issue of informed trading in the option market which have not yet been addressed within the scope of this research. For example, the evidence that option volume has some information content in relation to the future dynamics of stock volatility and the option implied volatility smile is particularly interesting. The scale of the current analysis is, however, limited to the small sample of stocks and indices examined. Perhaps it will be beneficial therefore to employ a larger sample size to further explore both the cross-sectional and time-series variations in the informativenesss of option trades. This is important to verify whether the degree of informed trading in the option market is a function of firm characteristics and/or market conditions. It may be considered as a future research endeavour also to investigate whether the informativeness of option trades varies across option strike prices. Past research, such as that of Chakravarty, Gulen et al. (2004), suggests that the contribution of option trades to the price discovery varies for options of different strike prices, indicating that informed traders are distributed unevenly across options with different strike prices. This may have some implications for how to best identify the informed component of trading volume and/or how to develop a better measure which captures the information content reflected in option trades. In addition, further empirical examination is needed to shed light on the nature of the information set captured by option trades. While the key findings in this research show that option trades have some information content of the future stock volatility and of the dynamics of the option smile, the analogous question of what types of information reflected by option trades has not been systematically addressed. In fact, it is still unclear whether traders use options to trade on information other than those related to future stock volatility. For instance, the fact that option trades can somehow predict the future dynamics of the option smile is particularly intriguing. This basically suggests the multi-dimensionality of information captured by option trades, since it can be expressed in terms of predictions of not just the implied volatility level, but also of the shape of the smile. While the former is solely related to the market expectation of future stock volatility, the latter is to some extent reflective of the characteristics of the stock return distribution, reflecting the relevance of a broader information set which informed traders may have been acting on. This issue is worth further investigation in order to enhance our understanding of traders' different motivations to trade in the option market and to gain insight into how their trading activities affect the option pricing.

5.4.2. Volatility forecasting

Volatility forecasting is an important area of research in finance which has received increasing attention from both academics and practitioners for its many practical applications in derivative pricing, risk analysis and portfolio management. The question of whether volume can be forecasted falls within the vast literature on the predictability of asset prices and market efficiency. Given the key findings previously reported, future research opportunities in this area could be explored from two aspects. Firstly, the research into the role of trading volume in forecasting volatility highlights that volatility forecasts can be improved by expanding the traditional information set of the GARCH model to include other factors such as trading volume and option implied volatility. While this evidence to some extent supports the multi-factor modelling approach, the forecasting improvement generated from the appropriate incorporation of multiple factors may not be limited to the GARCH framework in volatility forecasting. Hence, an investigation into the incorporation of information reflected in option prices and volume into other model structures is likely to offer some practical benefits in terms of improving both modelling and forecasting the stock volatility. As an extension of this discussion, research into the relevance of other factors related to modeling the stock volatility would potentially offer a forecast improvement. Secondly, as mentioned previously, the scale of the current analysis has been limited to a small sample of the most liquid stocks and index. It would be interesting therefore to investigate how useful trading volume is as a tool of forecasting volatility when the stocks being examined have options that are far less liquid. As it has been pointed out in previous research, such as that of Mayhew and Stivers (2003), that the market liquidity may be an important determinant of the informed traders' decisions to trade in the option market, the question of how this would affect the forecast quality of trading volume deserves further attention. In sum, further examination into different model structures and/or the use of a more inclusive set of data is needed to ascertain the practical applications generated from employing trading volume in volatility forecasting.

5.4.3. Option implied volatility smile

The existence of the option implied volatility smile has long received attention from researchers as it depicts option price departures from the Black and Scholes' model (1973). Despite the extensive literature which aims at explaining the existence of the smile, there has been a scarcity of interest in investigating its time-series dynamics. It is important to note that this research illustrates that the smile dynamics is forecastable on the basis of the information reflected by option trading volume. In regard to opportunities for future research, two important aspects arise from this finding. Firstly, it confirms that the shape of the option smile would have been determined by the trading process which incorporates new information. While this offers indirect evidence of the existence of informed trading in the option market, it also gives rise to a new line of inquiry which aims at further assessing the information content reflected by the time-varying dynamics of the smile. For instance, it may be worthwhile to investigate whether the changing shape of the smile reflects specific information regarding changes in the market conditions and/or the distribution of the underlying asset. Secondly, this research illustrates that modelling the IVS dynamics may benefit from expanding the traditional VAR information set by including other factors such as trading volume. It is important to note however that our results have solely been based on index options for which the Black-Scholes model pricing errors are minimal. Empirical evidence also documents that the smile of index options has a distinctive shape, different to that of stock options. Bollen and Whaley (2004) and Gârleanu, Pedersen et al. (2009) further suggest this difference may partly be driven by different demands for index and stock options, reflecting that different trader composition participates in the index and stock option markets. This implies that stock option trades and index option trades may reflect different sets of information and/or that their trading activities would impose different impacts on the smile dynamics. Hence, it would be interesting to examine whether the strength of the link between volume and the smile dynamics found in this paper would continue to hold for individual stocks, with some particular attention to the forecasting implication. It may also be worthwhile as a future research endeavor to investigate whether trading volume still plays an important role in modelling and forecasting the smile dynamics for stock options, especially those which are far less liquid, knowing that the efficiency of the option market, which determines how quickly new information is incorporated into the trading prices, has a great influence on the information content of volume. On a separate line of enquiry, it is noteworthy that findings of the forecasting power of trading volume also impose important implications for portfolio and risk management, asset pricing and policy making which are worth further investigation. For instance, one potential practical application which can be derived from this information set is the development of an indicator of the market condition based on the characteristics of the smile. Towards this end, the development of the VIX index by the Chicago Board of Exchange (CBOE), which has now been widely used by practitioners as an indicator of investors' uncertainty about the market condition, showcases an important application derived from the information captured by the option smile. However, the focus has been placed solely on the level of the smile which centres on the set of at the money options only, and hence the rich information content across strike prices has largely been ignored. Future research can therefore benefit from a more in-depth examination into this issue.

5.4.4. Short-sale restrictions

The effect of short-sale restrictions on market efficiency has captured increasing research interest, especially because of what happened recently during the course of the global financial crisis. This study expands the academic literature on short-sales by offering empirical evidence of the effect of short-sale restrictions on option trading activities, particularly on the role of option trades in the price discovery of the underlying asset. The results in this paper, however, have been limited to the small number of stocks considered, while the focus has been solely on the US market.

Previous studies which document the effect of short-sale restrictions on the liquidity and price efficiency of the underlying stock on the global markets, such as those of Beber and Pagano (2011) and Saffi and Sigurdsson (2011), take notice of some significant differences existing across markets. Therefore, it may be worthwhile as a future research endeavour to expand the scale of the analysis to include a more comprehensive data set or to conduct the investigation in different countries to see how the effect of a short-sale ban on option trading may differ across markets, knowing that there are considerable variations in short-sale regimes across countries. In addition, an investigation into the role of option trades in mitigating short-sale restrictions imposed in different markets is likely to build a more complete understanding of the mechanism through which a short-sale ban affects asset pricing. In particular, variations in the degree of option trading liquidity between international markets may partly explain the different effects of the short-sale ban observed across countries.

5.5. CONCLUDING REMARKS

In conclusion, this research makes a valuable contribution to the field of option research by investigating the role of options as a mechanism for trading on information about the underlying asset. A series of independent research projects undertaken as part of this research jointly reveal important findings in relation to the characteristics of informed traders' behaviours, and highlight some key impacts of informed trading on asset pricing and forecasting. They collectively show that (1) option volume has some information content which is useful for forecasting the future stock volatility and the future dynamics of the option smile and (2) that the allocation of informed traders across the option and stock markets appears to depend on the trade-off of transaction costs and trading opportunities between the two markets.

From the theoretical perspective, this thesis helps to address the gaps in the existing literature and extends our understanding of informed trading activities in the option market. In particular, it contributes to the body of knowledge on the economic value of derivatives by investigating the critical role they played in the process of incorporating new information into the market. From the practical perspective, it proposes a simpleyeteffective technique which employs trading volume to improve forecasts of the underlying stock volatility and the option implied volatility (price) respectively. Since volatility plays such a central role in the practice of derivatives trading, risk analysis and portfolio management, better forecasts of these quantities are clearly important and highly valued by practitioners.

REFERENCES

Abu Hassan Shaari Mohd, Nor, and Cheong Chin Wen 2007. An empirical study of realized volatility and trading volume dynamics. *International Research Journal of Finance & Economics,* 160-166.

Anand, Amber, and Sugato Chakravarty 2007. Stealth trading in options markets. *Journal of Financial and Quantitative Analysis,* 42: 167-187.

Anand, M. Vijh 1990. Liquidity of the cboe equity options. *The Journal of Finance,* 45: 1157-1179.

Andersen, T. G., and T. Bollerslev 1998. Answering the sceptics: Yes, standard volatility models do provide accurate forecasts. *International Economics Review*, 39: 885-905.

Andersen, T. G., T. Bollerslev, F. X. Diebold, and P. Labys 2001. The distribution of realized exchange rate volatility. *Journal of the American Statistical Association,* 96: 42-55.

Andersen, T. G., T. Bollerslev, and S. Lange 1999. Forecasting financial market volatility: Sample frequency vis-a-vis forecast horizon. *Journal of Empirical Finance,* 6: 457-477.

Andersen, Torben G. 1996. Return volatility and trading volume: An information flow interpretation of stochastic volatility. *Journal of Finance,* 51: 169-204.

Anderson, Healther M., and Farshid Vahid 2007. Forecasting the volatility of australian stock returns: Do common factors help? *Journal of Business & Economic Statistics*, 25.

Anthony, Joseph H. 1988. The interrelation of stock and options market trading-volume data. *Journal of Finance,* 43: 949-964.

Bakshi, Gurdip, Charles Cao, and Zhiwu Chen 1997. Empirical performance of alternative option pricing models. *The Journal of Finance,* 52: 2003-2049.

Bates, David S. 1991. The crash of '87: Was it expected? The evidence from options markets. *The Journal of Finance,* 46: 1009-1044.

Battalio, Robert H., and Paul H. Schultz 2010. Regulatory uncertainty and market liquidity: The 2008 short sale ban's impact on equity option markets. *The Journal of Finance, forthcoming*.

Battalio, Robert, and Paul Schultz 2006. Options and the bubble. *The Journal of Finance,* 61: 2071-2102.

Beber, Alessandro, and Marco Pagano 2011. Short-selling bans around the world: Evidence from the 2007-09 crisis. *Journal of Finance, forthcoming*.

Becker, R. 2008. Are combination forecasts of s&p 500 volatility statistically superior? . *International journal of forecasting,* 24: 122.

Black, Fischer 1975. Fact and fantasy in the use of options. *Financial Analysts Journal,* 31: 36-72.

Blake, Phillips 2011. Options, short-sale constraints and market efficiency: A new perspective. *Journal of Banking and Finance,* 35: 430-442.

Boehmer, Ekkehart, Charles M. Jones, and Xiaoyan Zhang 2008. Which shorts are informed? *The Journal of Finance,* 63: 491-527.

Boehmer, Ekkehart, Charles M. Jones, and Xiaoyan Zhang 2009. Shackling short sellers: The 2008 shorting ban. *Working paper, Columbia Business School*.

Bollen, Nicolas P. B., and Robert E. Whaley 2004. Does net buying pressure affect the shape of implied volatility functions? *Journal of Finance,* 59: 711-753.

Bollerslev, T., and J. M. Wooldridge 1992. Quasi-maximum likelihood estimation and inferene in dynamic models with time-varying covariances. *Econometric Reviews,* 11: 143-72.

Boulton, Thomas J., and Marcus V. Braga-Alves 2010. The skinny on the 2008 naked short-sale restrictions. *Journal of Financial Markets*, 13: 397-421.

Brailsford, T. J., and R. W. Faff 1996. An evaluation of volatility forecasting techniques. *Journal of Banking and Finance,* 20: 419-438.

Bris, Arturo, William N. Goetzmann, and Ning Zhu 2007. Efficiency and the bear: Short sales and markets around the world. *The Journal of Finance,* 62: 1029-1079.

Brock, W. A., and B. D. LeBaron 1996. A dynamic structural model for stock return volatility and trading volume. *Review of Economics and Statistics,* 78: 94-110.

Brooks, C. 1998. Predicting stock index volatility: Can market volume help? *Journal of Forecasting,* 17: 59-80.

Cao, Charles, John M. Griffin, and Zhiwu Chen 2005. Informational content of option volume prior to takeovers. *Journal of Business,* 78: 1072-1109.

Cao, H. Henry, and Hui Ou-Yang 2009. Differences of opinion of public information and speculative trading in stocks and options. *Review of Financial Studies,* 22: 299-335.

Chakravarty, Sugato, Huseyin Gulen, and Stewart Mayhew 2004. Informed trading in stock and option markets. *Journal of Finance*, 59: 1235-1257.

Chan, Kalok, Y. Peter Chung, and Wai-Ming Fong 2002. The informational role of stock and option volume. *Review of Financial Studies,* 15: 1049-1075.

Chan, Kalok, Y. Peter Chung, and Herb Johnson 1995. The intraday behavior of bid-ask spreads for nyse stocks and cboe options. *The Journal of Financial and Quantitative Analysis,* 30: 329-346.

Chan, Kam C., Louis T. W. Cheng, and Peter P. Lung 2004. Net buying pressure, volatility smile, and abnormal profit of hang seng index options. *Journal of Futures Markets,* 24: 1165-1194.

Chang, Eric C., Joseph W. Cheng, and Yinghui Yu 2007. Short-sales constraints and price discovery: Evidence from the hong kong market. *The Journal of Finance,* 62: 2097-2121.

Chen, Crystal Xiaobei, and S. Ghon Rhee 2010. Short sales and speed of price adjustment: Evidence from the hong kong stock market. *Journal of Banking & Finance,* 34: 471-483.

Chiang, Raymond, and P. C. Venkatesh 1988. Insider holdings and perceptions of information asymmetry: A note. *The Journal of Finance,* 43: 1041-1048.

Chordia, T., R. Roll, and A. Subrahmanyam 2001. Market liquidity and trading activity. *Journal of Finance,* 56: 501-530.

Chordia, Tarun, Sahn-Wook Huh, and Avanidhar Subrahmanyam 2009. Theory-based illiquidity and asset pricing. *Review of Financial Studies,* 22: 3629-3668.

Christensen, B. J., and N. R. Prabhala 1998. The relation between implied and realized volatility. *Journal of Financial Economics,* 50: 125-150.

Christoffersen, Peter, and Kris Jacobs 2004. The importance of the loss function in option valuation. *Journal of Financial Economics,* 72: 291-318.

Clark, Peter K. 1973. A subordinated stochastic process model with finite variance for speculative prices. *Econometrica,* 41: 135-155.

Clemen, Robert T. 1989. Combining forecasts: A review and annotated bibliography. *International Journal of Forecasting*, 5: 559-583.

Copeland, Thomas E. 1976. A model of asset trading under the assumption of sequential information arrival. *Journal of Finance,* 31: 1149-1168.

Copeland, Thomas E., and Daniel Friedman 1987. The effect of sequential information arrival on asset prices: An experimental study. *Journal of Finance,* 42: 763-797.

Copeland, Thomas E., and Dan Galai 1983. Information effects on the bid-ask spread. *The Journal of Finance,* 38: 1457-1469.

Corrado, C. J., and T. W. Miller 2005. The forecast quality of cboe implied volatility indexes. *Journal of Futures Markets,* 25: 339-373.

Danielsen, Bartley R., and Sorin M. Sorescu 2001. Why do option introductions depress stock prices? A study of diminishing short sale constraints. *The Journal of Financial and Quantitative Analysis,* 36: 451-484.

Day, T., and C. Lewis 1992. Stock market volatility and the information content of stock index options. *Journal of Econometrics*, 52: 267-287.

Day, Ted E. 1993. Forecasting futures market volatility. *Journal of Derivatives*, 1: 33-50.

Diamond, Douglas W., and Robert E. Verrecchia 1981. Information aggregation in a noisy rational expectations economy. *Journal of Financial Economics,* 9: 221-235.

Diamond, Douglas W., and Robert E. Verrecchia 1987. Constraints on short-selling and asset price adjustment to private information. *Journal of Financial Economics,* 18: 277-311.

Diebold, F. X., and A. Inoue 2001. Long memory and regime switching. *Journal of Econometrics,* 105: 131-159.

Diebold, F. X., and R. S. Mariano 1995. Computing predictive accuracy. *Journal of Business and Economic Statistics,* 13: 253-263.

Diebold, Francis X., and Canlin Li 2006. Forecasting the term structure of government bond yields. *Journal of Econometrics,* 130: 337-364.

Ding, Z., C. W. J. Granger, and R. F. Engle 1993. A long memory property of stock market returns and a new model. *Journal of Empirical Finance,* 1: 83-106.

Donaldson, R. G., and M. J. Kamstra 2005. Volatility forecasts, trading volume, and the arch versus option-implied volatility trade-off. *Journal of Financial Research,* 28: 519-538.

Dumas, Bernard, Jeff Fleming, and Robert E. Whaley 1998. Implied volatility functions: Empirical tests. *The Journal of Finance,* 53: 2059-2106.

Easley, D., M. O'Hara, and P. S. Srinivas 1998. Option volume and stock prices: Evidence on where informed traders trade. *J. Finance,* 53: 431-465.

Easley, David, Nicholas M. Kiefer, Maureen O'Hara, and Joseph B. Paperman 1996. Liquidity, information, and infrequently traded stocks. *The Journal of Finance,* 51: 1405-1436.

Engle, R. F., H. Hong, Alex Kane, and Jaesun Noh 1993. Arbitrage valuation of variance forecasts with simulated options. *In advances in Futures and Options Research.*

Figlewski, Stephen 1981. The informational effects of restrictions on short sales: Some empirical evidence. *Journal of Financial and Quantitative Analysis,* 16: 463-476.

Figlewski, Stephen, and Gwendolyn P. Webb 1993. Options, short sales, and market completeness. *The Journal of Finance,* 48: 761-777.

Fleming, J., B. Ostdiek, and R. E. Whaley 1995. Predicting stock market volatility: A new measure. *Journal of Futures Markets,* 15: 265-302.

Garcia, René, Richard Luger, and Eric Renault 2003. Empirical assessment of an intertemporal option pricing model with latent variables. *Journal of Econometrics,* 116: 49-83.

Gârleanu, Nicolae, Lasse Heje Pedersen, and Allen M. Poteshman 2009. Demand-based option pricing. *Review of Financial Studies,* 22: 4259-4299.

George, Thomas J., and Francis A. Longstaff 1993. Bid-ask spreads and trading activity in the s&p 100 index options market. *Journal of Financial and Quantitative Analysis,* 28: 381-397.

Geweke, J., and S. Porter - Hudak 1983. The estimation and application of long memory time series. *Journal of Time Series Analysis,* pp. 221-238.

Glosten, L., and P. Milgrom 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics,* 14: 71-100.

Glosten, Lawrence R., and Lawrence E. Harris 1988. Estimating the components of the bid-ask spread. *Journal of Financial Economics,* 21: 123-142.

Glosten, Lawrence R., and Paul R. Milgrom 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics,* 14: 71-100.

Gonçalves, SÃ-lvia, and Massimo Guidolin 2006. Predictable dynamics in the s&p 500 index options implied volatility surface. *Journal of Business,* 79: 1591-1635.

Gordon, Gemmill 1996. Did option traders anticipate the crash? Evidence from volatility smiles in the u.K. With u.S. Comparisons. *Journal of Futures Markets,* 16: 881-897.

Gospodinov, N., A. Gavala, and D. Jiang 2006. Forecasting volatility. *Journal of Forecasting,* 25: 381-400.

Grundy, BD, and M McNichols 1989. Trade and the revelation of information through prices and direct disclosure. *Review of Financial Studies,* 2: 495-526.

Grundy, Bruce D., Bryan Lim, and Patrick Verwijmeren 2010. Do option markets undo restrictions on short sales? Evidence from the 2008 short-sale ban. *The Journal of Finance, forthcoming*.

Guidolin, Massimo, and Allan Timmermann 2003. Option prices under bayesian learning: Implied volatility dynamics and predictive densities. *Journal of Economic Dynamics and Control,* 27: 717-769.

Guo, Dajiang 2000. Dynamic volatility trading strategies in the currency option market. *Review of Derivatives Research,* 4: 133-154.

Harris, Lawrence, Ethan Namvar, and Blake Phillips 2009. Price inflation and wealth transfer during the 2008 sec short-sale ban. *Working paper, University of Southern California*.

Harris, M, and A Raviv 1993. Differences of opinion make a horse race. *Review of Financial Studies,* 6: 473-506.

Harvey, C. R., and R. E. Whaley 1992. Market volatility prediction and the efficiency of the s & p 100 index option market. *Journal of Financial Economics,* 31: 43-73.

Hasbrouck, Joel 1991. Measuring the information content of stock trades. *The Journal of Finance,* 46: 179-207.

Hasbrouck, Joel 1995. One security, many markets: Determining the contributions to price discovery. *The Journal of Finance,* 50: 1175-1199.

Hodrick, Robert J., and Edward C. Prescott 1997. Postwar u.S. Business cycles: An empirical investigation. *Journal of Money, Credit & Banking,* 29: 1-16.

Hong, Harrison, and Jeremy C. Stein 2003. Differences of opinion, short-sales constraints, and market crashes. *Review of Financial Studies,* 16: 487-525.

Iori, G. 2002. A microsimulation of traders activity in the stock market: The role of heterogeneity, agents' interactions and trade frictions. *Journal of Economic Behavior and Organization,* 49: 269-285.

Jones, Charles M., and Owen A. Lamont 2002. Short-sale constraints and stock returns. *Journal of Financial Economics,* 66: 207-239.

Kang, Jangkoo, and Hyoung-Jin Park 2008. The information content of net buying pressure: Evidence from the kospi 200 index option market. *Journal of Financial Markets,* 11: 36-56.

Kim, Oliver, and Robert E. Verrecchia 1994. Market liquidity and volume around earnings announcements. *Journal of Accounting and Economics,* 17: 41-67.

Kolasinski, Adam C., Adam V. Reed, and Jake Thornock 2010. Can short restrictions result in more informed short selling? Evidence from the 2008 regulations. *Working paper, University of Washington and University of North Carolina*.

Konstantinidi, Eirinin, George Skiadopoulos, and Emilia Tzagkaraki 2008. Can the evolution of implied volatility be forecasted? Evidence from european and us implied volatility indices. *Journal of Banking and Finance,* 32: 2401-2411.

Lamoureux, C. G., and W. D. Lastrapes 1990. Heteroskedasticity in stock return data: Volume versus garch effects. *Journal of Finance,* 45: 221-229.

Lamoureux, C. G., and W. D. Lastrapes 1990. Persistence in variance, structural change and the garch model. *Journal of Business and Economic Statistics,* 8: 225-234.

Lamoureux, C., and W. Lastrapes 1993. Forecasting stock-return variance: Toward an understanding of stochastic implied volatilities. *Review of Financial Studies,* 6: 293-326.

Le, Van, and Ralf Zurbruegg 2010. The role of trading volume in volatility forecasting. *Journal of International Financial Markets, Institutions and Money,* 20: 533-555.

Lee, C., and M. Ready 1991. Inferring trade direction from intraday data. *J. Finance,* 46: 733-746.

Lee, CMC, B Mucklow, and MJ Ready 1993. Spreads, depths, and the impact of earnings information: An intraday analysis. *Review of Financial Studies,* 6: 345-374.

Lee, Jason, and Cheong H. Yi 2001. Trade size and information-motivated trading in the options and stock markets. *Journal of Financial and Quantitative Analysis,* 36: 485-501.

Mayhew, Stewart, and Vassil T. Mihov 2005. Short sale constraints, overvaluation, and the introduction of options. *Working paper, Securities and Exchange Commission*.

Mayhew, Stewart, Atulya Sarin, and Kuldeep Shastri 1995. The allocation of informed trading across related markets: An analysis of the impact of changes in equity-option margin requirements. *The Journal of Finance,* 50: 1635-1653.

Mayhew, Stewart, and Chris Stivers 2003. Stock return dynamics, option volume and the information content of implied volatility. *Journal of Futures Markets,* 23: 615-646.

Miller, Edward M. 1977. Risk, uncertainty, and divergence of opinion. *The Journal of Finance,* 32: 1151-1168.

Milton, Harris, and Artur Raviv 1993. Differences of opinion make a horse race. *The Review of Financial Studies,* 6: 473-506.

Ni, S. X., J. Pan, and A. M. Poteshman 2008. Volatility information trading in the option market. *Journal of Finance,* 63: 1059-1091.

Ni, Sophie X., J. U. N. Pan, and Allen M. Poteshman 2008. Volatility information trading in the option market. *The Journal of Finance,* 63: 1059-1091.

Nilsson, Roland 2008. The value of shorting. *Journal of Banking and Finance,* 32: 880-891.

Ofek, Eli, and Matthew Richardson 2003. Dotcom mania: The rise and fall of internet stock prices. *The Journal of Finance,* 58: 1113-1138.

Ofek, Eli, Matthew Richardson, and Robert F. Whitelaw 2004. Limited arbitrage and short sales restrictions: Evidence from the options markets. *Journal of Financial Economics,* 74: 305-342.

Pan, Jun, and Allen M. Poteshman 2006. The information in option volume for future stock prices. *Review of Financial Studies,* 19: 871-908.

Poon, Ser-Huang, and Clive W. J. Granger 2003. Forecasting volatility in financial markets: A review. *Journal of Economic Literature,* 41: 478.

Saffi, Pedro A. C., and Kari Sigurdsson 2011. Price efficiency and short selling. *Review of Financial Studies,* 24: 821-852.

Seungmook, Choi, and Mark E. Wohar 1992. The performance of the gph estimator of the fractional difference parameter: Simulation results. *Review of Quantitative Finance & Accounting,* 2: 409-417.

Sorescu, Sorin M. 2000. The effect of options on stock prices: 1973 to 1995. *The Journal of Finance,* 55: 487-514.

Stephan, Jens A., and Robert E. Whaley 1990. Intraday price change and trading volume relations in the stock and stock option markets. *Journal of Finance,* 45: 191-220.

Stoll, Hans R. 1989. Inferring the components of the bid-ask spread: Theory and empirical tests. *The Journal of Finance*, 44: 115-134.

Tauchen, G., and M. Pitts 1983. The price variability-volume relationship on speculative markets. *Econometrica,* 51: 485-505.

Wagner, N., and T. A. Marsh 2005. Surprise volume and heteroskedasticity in equity market returns. *Quantitative Finance,* 5: 153-168.