

IMPLIED VOLATILITY OF S&P 500 COMPANIES  
DURING EARNINGS ANNOUNCEMENT : A  
STRUCTURED BAYESIAN APPROACH

TAN TEIK KHEONG

ASIA e UNIVERSITY

2015

**IMPLIED VOLATILITY OF S&P 500 COMPANIES  
DURING EARNINGS ANNOUNCEMENT: A  
STRUCTURED BAYESIAN APPROACH**

**TAN TEIK KHEONG**

**ASIA e UNIVERSITY  
2015**

AEU Library



\* 0 0 0 0 6 5 2 5 \*

IMPLIED VOLATILITY OF S&P 500 COMPANIES DURING  
EARNINGS ANNOUNCEMENT: A STRUCTURED  
BAYESIAN APPROACH

TAN TEIK KHEONG

A Thesis Submitted to Asia e-University in Fulfilment  
of the Requirements for the Degree  
of Industrial Doctorate

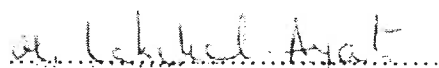
May 2015

## ABSTRACT

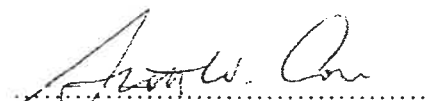
Can an earnings announcement provide a volatility arbitrage opportunity which allows an investor to profit from a sudden, sharp drop in implied volatility that triggers a similarly steep decline in an option's value? Tan, Merouane, and Connor (2015) developed a methodology that allows an investor to profit from this volatility crush phenomena in weekly options. In addition to managing the risk, this profitable strategy relies on a set of qualifying parameters including liquidity, premium collection, volatility differential, expected market move and market sentiment. While the effects of persistence and leverage have been thoroughly investigated in the literature, very little has been revealed thus far on the effects of market sentiment and liquidity. Building upon this framework, the effects of market sentiment and liquidity are investigated in the earnings event scenario to further reduce the risk associated with trading options during earnings announcements. The results of exploratory and confirmatory factor analyses of a four factor model on the dynamic of implied volatility during earnings announcement from the S&P 500 (N= 1060) supported by data collected for the past 15 years are presented. Structural equation modelling (SEM) is used to compare, confirm and refine the model. Bayesian analysis is used to further improve estimates of the model parameters. By comparing values derived from Bayesian and the Maximum Likelihood Estimates (MLE), one can verify the accuracy of the CFA model. Using Bayesian estimation and implied volatility differential to proxy for differences of opinion about term structures in option pricing, anomalous behaviour can be detected, if any.

## APPROVAL PAGE

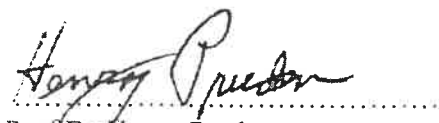
I certify that I have supervised /read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in quality and scope, as a thesis for the fulfilment of the requirements for the degree of Industrial Doctorate.



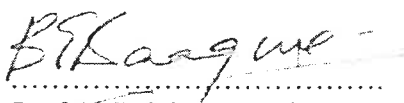
Prof Dr Merouane Lakehal-Ayat  
St. John Fisher College, New York  
Supervisor



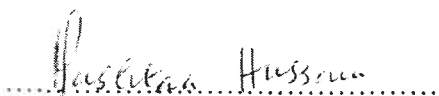
Mr Scott Connor  
Thinkorswim, TD AMERITRADE  
Co-Supervisor



Prof Dr Henry Pruden  
Golden Gate University, US  
External Examiner



Prof Dr Belal E Baaqui  
National University of Singapore  
External Examiner 2

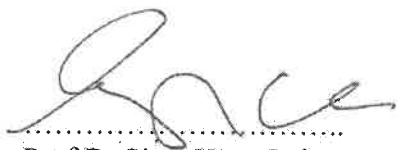


Prof Dato' Dr Sayed Mushtaq Hussain  
Asia e University  
Internal Examiner



Prof Dr Siow Heng Loke  
Asia e University  
Chairman, Examination Committee

This thesis was submitted to Asia e University and is accepted as fulfilment of the requirements for the degree of Industrial Doctorate.



Prof Dr Siow Heng Loke  
Dean, School of Graduate Studies

## DECLARATION

I hereby declare that the thesis submitted in fulfilment of the Industrial Doctorate is my own work and that all contributions from any other persons or sources are properly and duly cited. I further declare that the material has not been submitted either in whole or in part, for a degree at this or any other university. In making this declaration, I understand and acknowledge any breaches in this declaration constitute academic misconduct, which may result in my expulsion from the programme and/or exclusion from the award of the degree.

Name: Tan Teik Kheong



Signature of the Candidate:

Date: 13 November 2015

**COPYRIGHT PAGE**

**Copyright by Asia e University**

## ACKNOWLEDGEMENTS

Firstly, I would like to express my sincere gratitude to my supervisors Prof. Dr. Merouane and Mr. Scott Connor for the continuous support of my Industrial Doctorate study and related research, for their patience, motivation, and immense knowledge. Their guidance helped me in all the time of research and writing of this thesis. I could not have imagined having a better team of advisors and mentors for my Industrial Doctorate study.

Besides my supervisors, I would like to thank the rest of my thesis committee: Prof. Dr. Siow Heng Loke, Prof. Dato' Sayed Mushtaq Hussain, Prof. Dr. Belal E Baaquie and Prof. Dr Henry O. Pruden for their insightful comments and encouragement, but also for the hard question which incited me to widen my research from various perspectives. A special thanks to Prof Dr. Barbara Byrne for her motivation to raise my inner game higher.

My sincere thanks also to Dr. Soon Seng Thah, Dr. Chang Lee Hoon, Dr. Lee Siew Eng and Prof. Dr. Chua Yan Piaw who provided me an opportunity to join their classes. I also wish to thank Ms. Swa Lee Lee, Ms. Siti Habsah, Dr. Sheila Cheng and Prof Dr. Mak Chai for the generous support behind the scenes, working tirelessly to ensure a smooth process throughout the journey. A heartfelt thanks to the staff of the AEU library and Ms Evelyn Tan for their generous support and guidance. Also, I thank my friends at AEU and IEEE conference committee members for all the fun we had in the last two and half years.

Last but not the least, I would like to thank my family and partner for supporting me spiritually throughout writing this thesis and my life in general.



## Table of Contents

	Page
<b>ABSTRACT</b>	<b>ii</b>
<b>APPROVAL PAGE</b>	<b>iii</b>
<b>DECLARATION</b>	<b>iv</b>
<b>ACKNOWLEDGEMENTS</b>	<b>vi</b>
<b>LIST OF TABLES</b>	<b>xii</b>
<b>LIST OF FIGURES</b>	<b>xii</b>
<b>LIST OF ABBREVIATIONS</b>	<b>xii</b>
 <b>CHAPTER</b>	
<b>1.0 INTRODUCTION</b>	<b>1</b>
1.1 Background of the Study	1
1.2 Problem statement	5
1.3 Research Objective	7
1.4 Research Questions	8
1.5 Research Hypothesis	14
1.6 Significance of Research	14
1.7 Research Gap	16
1.8 Limitations	17
1.9 Operational Definition of Terms	17
1.9.1 Market Sentiment	17
1.9.2 Liquidity	19
1.9.3 Leverage effect	21
1.9.4 Persistence effect	22
1.9.5 Implied Volatility	23
1.10 Organization of the Remainder of the Study	23
 <b>2.0 LITERATURE REVIEW</b>	 <b>25</b>
2.1 Introduction	27
2.2 Weekly Options	28
2.3 Trading Options during earnings	29
2.4 Applying Bayesian analysis to Options during Earnings	33
2.5 Conceptual Framework	35
2.5.1 Volatility Rank, Differential & Premium Concepts	36
2.6 Volatility Research	40
2.6.1 Option Implied Volatility versus Time series Model	41
2.6.2 Behavior of stock returns variance and the option market	45

2.6.3	Differential implied volatility and premium collection	49
2.6.4	Danger of ignoring the effects of Vega.	49
2.6.5	Market's reaction to Corporate Earnings	56
2.7	Bayesian Framework	58
2.7.1	Mathematical Framework	63
2.7.2	Bayesian Analysis for implied volatility differential	69
2.7.3	Bayesian Structural Equation Modelling	70
2.8	Theoretical Framework	73
2.9	The Blacks-Scholes Option Pricing Model	74
2.10	The Options Greeks	81
2.11	The Leverage Effect	83
2.12	The Persistence Effect	84
2.13	The Seasonality Effect (Other Anomalies)	85
2.13.1	The Market Cycle	87
2.13.2	EBAY Historical Data	88
2.13.3	Google Historical data	95
2.14	Hypothesis development	99
2.15	Literature overview	101
2.16	Summary	104
<b>3.0</b>	<b>RESEARCH METHODOLOGY</b>	<b>105</b>
3.1	Introduction	105
3.2	Conceptual Framework	106
3.3	Variables Development – EBAY Case study	106
3.4	Variables Development – GOOGLE Case study	113
3.5	Bayesian Analysis	118
3.5.1	Bayesian Analysis of implied volatility differential	118
3.5.2	Bayesian Estimation using MCMC sampling	125
3.6	Main Quantitative research	126
3.7	Quantitative Research Framework	127
3.8	Alignment of Research Questions, Objectives and Hypotheses	128
3.9	Research Procedures	128
3.10	Research Tools	130
3.11	Sampling Procedures and Population	132
3.12	Multivariate outliers using Mahalanobis distance	134
3.13	Exploratory Factor Analysis	134
3.14	Transitioning from EFA to CFA	136
3.15	Structural Equation Modeling (SEM) methodology	136
3.15.1	Basis for SEM	139
3.15.2	Measurement model	143
3.15.3	Path model	146
3.15.4	Unobserved, exogenous variables	151
3.15.5	Observed, endogenous variables	153
3.16	Model Fit	157
3.17	Goodness-of-fit Statistics	159
3.18	Sample size and Data Selection	166
3.19	Summary	167
<b>4.0</b>	<b>RESEARCH FINDINGS</b>	<b>167</b>

4.1	Introduction	167
4.2	Test Results (Questions 1 – 3)	169
4.3	Multivariate Outliers	173
4.4	Normality Test	174
4.5	Reliability of Measurements	175
4.6	Exploratory Factor Analysis	176
4.6.1	Preliminary Analysis	176
4.6.2	Factor Extraction	179
4.6.3	Factor Rotation	182
4.6.4	Summary of EFA	184
4.6.5	Transitioning from EFA to CFA	185
4.7	Confirmatory Factor Analysis	187
4.7.1	SEM Findings	187
4.7.2	Model Fit	189
4.7.3	Measuring Model Validity	195
4.8	Bayesian Estimation Findings	196
4.8.1	Cross-Validation of the ML Estimation results	201
4.9	Summary of Hypothesis Testing and Research Objectives	202
4.10	Research Objectives and Hypothesis Testing Results	203
4.11	Results	203
<b>5.0</b>	<b>DISCUSSION, CONCLUSION AND RECOMMENDATIONS</b>	<b>205</b>
5.1	Overview of the Study	205
5.2	Statistical Analysis	206
5.3	Summary of Research Findings	208
5.4	Contribution of knowledge	209
5.5	Summary	212
5.6	Limitations	212
5.7	Suggestions for Further Research	216
5.8	Conclusion	217
5.9	Recommendations	218
	<b>REFERENCES</b>	<b>180</b>
	<b>APPENDICES</b>	
	Appendix A: Snapshot of Scanning Output	242
	Appendix B: Excel Visual Basic Data Mining Program	243
	Appendix C: Bayesian Analysis for IV Differential (Google)	244
	Appendix D: Paired T-Test results	245

## LIST OF TABLES

Table	Page
1.1 OPEN INTEREST ILLUSTRATION	20
2.1 PROBABILITY TRADEOFF - STRIKE SELECTION VERSUS STANDARD DEVIATION	31
2.2 VARIABLE DEPENDENCIES	32
2.3 RELATIONSHIP BETWEEN OBJECTIVES, QUESTIONS AND CONTRIBUTION	73
2.4 EBAY 15 YEAR HISTORICAL MONTHLY DATA RETURNS	88
2.5 EBAY 15 YEAR WEEKLY DATA	90
2.6 EBAY 10 YEAR MONTHLY DATA	91
2.7 EBAY 10 YEAR WEEKLY DATA	92
2.8 EBAY 5 YEAR MONTHLY DATA	93
2.9 EBAY 5 YEAR WEEKLY DATA	94
2.10 GOOGLE 10 YEAR MONTHLY DATA	95
2.11 GOOGLE 10 YEAR WEEKLY DATA	96
2.12 GOOGLE 5 YEAR MONTHLY DATA	97
2.13 GOOGLE 5 YEAR WEEKLY DATA	98
2.14 A CHRONOLOGY OF STUDY IMPACTING EARNINGS ANNOUNCEMENT	101
3.1 ACTUAL VERSUS ASSUMED IV FOR GOOGLE	122
3.2 ACTUAL VS ASSUMED IV FOR EBAY	123
3.3 RESEARCH QUESTION, OBJECTIVES AND STATISTICAL TECHNIQUES	128
3.4 CFA MEASUREMENT MODEL	143
3.5 SUMMARY OF VARIABLES SEM	147
3.6 SUMMARY OF ELEMENTS IN SAMPLE COVARIANCE MATRIX	149
4.1 SUMMARY IV TEST RESULTS	170
4.2 SUMMARY IV POST ANNOUNCEMENT	172
4.3 CRONBACH TEST	176
4.4 CORRELATION MATRIX AND SIGNIFICANCE TESTS	177
4.5 KMO AND BARTLETT'S TEST	178
4.6 TOTAL VARIANCE EXPLAINED	179
4.7 COMMUNALITIES	181
4.8 COMPONENT MATRIX (BEFORE AND AFTER ROTATION)	184
4.9 CFA MODEL SUMMARY PARAMETERS	188
4.10 SUMMARY OUTPUT OF THE MAXIMUM LIKELIHOOD ESTIMATES	189

4.11	GOODNESS OF FIT STATISTICS	190
4.12	HAIR ET AL. (2010) GUIDE TO THE INTERPRETATION OF GOF MEASURES	196
4.13	BAYESIAN ESTIMATION OUTPUT	198
4.14	COMPARATIVE ANALYSIS (MAX LIKELIHOOD (ML) AND BAYESIAN EST)	202
4.15	FINAL RESULTS	204

## LIST OF FIGURES

Figure	Page
2.1 CONCEPTUAL FRAMEWORK	36
2.2 IMPLIED VOLATILITY SURFACE	51
2.3 IMPLIED VOLATILITY BEFORE AND AFTER EARNINGS ANNOUNCEMENT	79
2.4 EBAY 15 YEAR MONTHLY DATA	89
2.5 EBAY 15 YEAR HISTORICAL WEEKLY DATA	91
2.6 EBAY 10 YEAR MONTHLY DATA	92
2.7 EBAY 10 YEAR WEEKLY DATA	93
2.8 EBAY 5 YEAR MONTHLY DATA	94
2.9 EBAY 5 YEAR WEEKLY DATA	95
2.10 GOOGLE 10 YEAR MONTHLY DATA	96
2.11 GOOGLE 10 YR WEEKLY CHART (WK 36 - WK 48 WITH EARNINGS ON WEEK 42)	97
2.12 GOOGLE 5 YEAR MONTHLY CHART	98
2.13 GOOGLE 5 YEAR WEEKLY CHART	99
3.1 LIQUIDITY CRITERIA FROM OPTIONS CHAIN FOR EBAY	108
3.2 IMPLIED VOLATILITY DIFFERENTIAL	109
3.3 HISTORICAL VOLATILITY FOR EBAY (1 YEAR PERIOD)	110
3.4 ALTERNATIVE MMM CALCULATOR	112
3.5 RISK PROFILE FOR SHORT STRANGLE ON EBAY	113
3.6 CREDIT FROM SELLING GOOGLE STRANGLE FOR \$8.30	114
3.7 CHANGING STRIKES INCREASES CREDIT AND RISKS	115
3.8 RISK PROFILE FOR SHORT STRANGLE ON GOOGLE	116
3.9 GOOGLE PRICE SPIKED AFTER THE CONFERENCE CALL.	117
3.10 BUYING POWER EFFECT.	117
3.11 BAYESIAN PROBABILITY DISTRIBUTIONS FOR GOOGLE IV DIFFERENTIAL.	122
3.12 BAYESIAN PROBABILITY DISTRIBUTIONS FOR EBAY IV DIFFERENTIAL.	124
3.13 QUANTITATIVE RESEARCH FLOW	127
3.14 MATRIX M	145
3.15 OVERALL SEM MODEL	150
4.1 IV PATH AROUND EARNINGS ANNOUNCEMENT	169
4.2 SCREE PLOT	182
4.3 MAPPING FROM EFA TO CFA	187
4.4 DIAGNOSTIC PLOT OF FIRST AND LAST COMBINED POLYGON	200
4.5 DIAGNOSTIC PLOT OF BAYESIAN SEM FOR VOLATILITY DIFFERENTIAL	200

## LIST OF ABBREVIATIONS

AMOS	Analysis of Moments Structures
AIC	Akaike's Information Criterion
ATM	At The Money
ATR	Average True Range
AVE	Average Variance Extracted
CAPM	Capital Asset Pricing Model
CBOE	Chicago Board of Options Exchange
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CS	Convergence Statistic
EGARCH	Exponential GARCH
ECVI	Expected Cross - Validation Index
EFA	Exploratory Factor Analysis
EPS	Earnings Per share
EXPMOVE	Expected Move
GARCH	Generalized AutoRegressive Conditional Heteroskedasticity
GFI	Goodness-of-fit index
HMO	Healthcare Maintenance Organizations
ITM	In The Money
IV	Implied Volatility
MCMC	Markov Chain Monte Carlo
MLE	Maximum likelihood Estimation
MMM	Market Maker Move
MSA	Measure of Sampling Accuracy
MVO	Mean Variance Optimization
NFI	Normed Fit Index
OCC	Options Clearing Corporation
OTC	Over the Counter
OTM	Out Of The Money
PNFI	Parsimonius Normed Fit Index
QE	Quantitative Easing
RMSEA	Root Mean Square Error of Approximation
RSI	Relative Strength Index
S&P 500	Standard & Poor's 500
SRMR	Standardized Root Mean Square Residual
SEM	Structural Equation Modeling
SPSS	Statistical Package for Social Sciences
TLI	Tucker-Lewis Index
VE	Variance Extracted
VIX	Volatility Index
VOLDIFF	Volatility Differential
VOLRANK	Volatility Rank

## CHAPTER 1

### INTRODUCTION

#### 1.1 Background of the Study

There is an old saying on Wall Street that the market is driven by just two emotions: fear and greed. Although this is an oversimplification, it can often be true. Succumbing to these emotions can have a profound and detrimental effect on investors' portfolios and the stock market. Ultimately, the manifestation of fear and greed relates to the volatility inherent in the stock market. When investors lose their comfort level due to losses or market instability, they become vulnerable to these emotions, often resulting in very costly mistakes. For years, researchers tried to quantify these emotional forces via complex forecasting models such as GARCH (General Auto regressive Conditional Heteroskedasticity) as a way to predict future volatility. These models however have limited utility especially in today's highly dynamic options landscape. The introduction of weekly options has completely changed the options landscape. In 2005, the Chicago Board Options Exchange introduced "weeklys" to the public but it wasn't until 2009 that the volume of this burgeoning product took off. Currently weeklys have become one the most popular trading products the market has to offer. According to the CBOE, about 30% of all options volume in the SPX – the S&P 500 cash index – is done with weeklys. Estimates from options traders point towards north of 35% of options volume is of the weekly variety. The addition of weeklys has significantly changed the volatility forecasting industry. Before weeklys were introduced, the volatility change that resulted from an earnings announcement is subjected to anywhere between 10 to 20



days before the expiration cycle ends. With weeklys, the window has shrunk to at most 5 days. This contraction in expiration window creates more opportunities as well as risk before the next cycle begins. Because of their short shelf life, weeklys options positions require close monitoring, as they can be subject to significant volatility. Profits can disappear quickly and can even turn into losses with a very small movement of the underlying asset. The theoretical basis for this contraction supports the view from analytical solutions insofar as the crush in volatility is concerned. However, due to the nature of a shorten option expiration for weeklys, the explanations for the crush stemming from the effects of persistence and leverage alone are insufficient R. F. Engle and Patton (2001). Empirical studies conducted by Tan et al. (2015) indicate the presence of other forces such as liquidity and market sentiment that impact the degree of the crush for weeklys. This is the basis of the contribution to the body of knowledge related to volatility forecasting for equity options. The results from that study were substantiated by the use of Bayesian analysis with informative priors.

Coupled with the introduction of weekly options is the concept of volatility differential (term structure), volatility rank and high probability trades. The introduction of weekly options alone has created a myriad of strategies that take advantage of high volatility and selling the premium associated with it. There is hardly any research done on premium selling strategies for weekly options. When selling options, the amount of money we get (our credit we receive for selling the option) is the most we can make on the trade. As a result, we are limiting our profitability, since we can't make any more than the initial amount we receive, but in doing so we're able to increase our theoretical probability of success. We can

improve our chances of success by choosing to sell strikes at our desired probability of expiring out of the money. Selling options as part of a premium collection strategy works extremely well in a highly volatile stock. Sometimes stocks move a lot very unexpectedly and other times we can predict this volatility. One of these predictable periods of volatility immediately follows earnings announcements. These happen every quarter and the news can affect a stock's price dramatically. One of the more popular premium selling strategies during earnings is the short strangle. A short strangle gives one the obligation to buy the stock at strike price A and the obligation to sell the stock at strike price B if the options are assigned. As an options writer, you are predicting the stock price will remain somewhere between strike A and strike B, and the options you sell will expire worthless. By selling two options, you significantly increase the income you would have achieved from selling a put or a call alone. But that comes at a cost. You have unlimited risk on the upside and substantial downside risk. Greed however takes over and option traders will still run this strategy (albeit unlimited risk) to take advantage of a decrease in implied volatility once the earnings results are released. If implied volatility is abnormally high due to a binary event such as earnings announcement, the call and put will likely be overvalued. After the sale, the idea is to wait for volatility to drop and close the position at a profit. Conceptually, this strategy sounds logical and fairly easy to accomplish. Many things could go awry. Firstly, selling a naked call or put carries unlimited risk and puts considerable burden on the buying power on the account. Traders governed by greed will execute these unlimited risk strategies and watch their account blow up. This situation is further exacerbated by the introduction of weekly options. Weekly options are like a double edged sword. It gives the investor more opportunities to profit but also more unlimited risk with higher potential of wiping out the investor's

capital. A solution to this specific problem of shorting strangles with unlimited risk was addressed by a methodology proposed by Tan and Bing (2014). Returning to the sword analogy, the methodology provides a way to use the blade to cut out losses quickly, leaving the profits room to grow. Subsequently a more generic solution covering premium selling strategies involving Bayesian analysis and factor analysis was proposed by Tan et al. (2015). As a burgeoning industry, the options market is relatively young compared to the forex, commodities or futures market. Yet, countless of options traders are taking on these low probability, unlimited risk strategies in the pursuit of quick profit especially so in weekly options. A solution is needed to change the parameters of these trades from low to high probability and in doing so, re-define the risk parameters such that if certain criteria are not met, the execution of premium selling trades will not be recommended. The risk is further mitigated by allowing more time to manage the trade especially in weekly options. For example, if a trade is deemed risky for the front cycle (cycle could be a week or a month), by understanding the volatility differential behaviour and volatility rank of the underlying, a less risky trade could be put on for the back cycle instead. This has the added benefit of theta decay and providing a more emotional-free zone to manage the trade for profitability (or even breakeven if the trade goes horribly wrong).

The study on information disclosures (earnings) and their associated risks have been a topic of extensive research since the pioneering work of Ball and Brown (1968). Some of these risks however can be mitigated by qualifying the trade appropriately. The dynamic of option price discovery and earnings news dissemination has been documented extensively in K. I. Amin and Lee (1997) and Berkman and Truong (2009). Since the volatility crush is the key determinant for profitability, I

modelled the crush between the implied volatility of the front and next earliest expiration using Bayesian statistics. The accuracy of the Bayesian model is quantified using examples from the tech sector, such as Google and EBAY - Tan and Bing (2014). A similar research using Bayesian was also conducted by Schmitt-Grohé and Uribe (2012) where they focussed on anticipated and unanticipated shocks affecting US economy during the various business cycles. This research investigates theoretically and empirically the dynamics of the implied volatility around earnings announcements dates. In order to do this, I present a theoretical framework for the change dynamics in implied volatility (IV) resulting from two established theories as well as two relatively untapped but increasingly important features. These features are known as persistence, leverage, market sentiment and liquidity respectively. From empirical evidence, it has been observed that the volatility tends to drop after the earnings results. The characteristic of the drop depends on several influences. These influences include the overall market sentiment, nature of the earnings, and historical pattern of earnings behavior for the particular underlying. In other words, there are no specific criteria that can reliably predict the post-event IV path. The only effect that is certain is the drop in volatility once the earnings results alongside an increase in volume for options traded as reported in Chiang (2010) and Kim and Verrecchia (1994). An empirical investigation is conducted on the selected S&P 500 stocks over the period 2000-2015.

## **1.2 Problem statement**

The goal of this research is to investigate the dynamics of implied volatility (IV) around binary events such as earnings announcement. The dynamics of the volatility implied in options prices will be analyzed. In particular this research investigates the forces that shape the outcome of the post-event IV. The focus is on

the relationship between persistence effect, leverage effect, market sentiment and liquidity risk on volatility crush after the earnings announcement date. A natural outcome of this understanding allows the investor to profit from the rise and fall of implied volatility (volatility crush) via writing strangles and other option premium selling strategies while reducing the risk associated with selling naked puts and calls. Understanding the degree of volatility crush is essential to the success of any premium selling strategy. The two established theories of persistence and leverage in volatility alone are not enough to protect the premium seller. Does the degree of volatility crush after earnings announcement dependent solely on the effects of persistence and leverage? Establishing the effectiveness of a volatility forecast is not straightforward since volatility itself is not observable. However, the effects of the volatility crush after earnings announcement are dependent not just on the effects of persistence and leverage, but the market sentiment and liquidity as well. Understanding the effects of persistence and leverage together with liquidity and market sentiment results in a high probability, risk defined trade.

The problem of this research is formulated below:

*Premium selling strategies in weekly options that rely on volatility crush during earnings announcement can be dangerous due to the unlimited risk and low probability of success. Due to the shortened expiration cycle of weeklys, new investigations of factors that influence the dynamics of implied volatility for weeklys need to be conducted in order to create high probability and managed risk opportunities.*

In order to answer the formulated research question, two sets of sub-questions need to be answered first. The first set of sub-questions, based on prior research

conducted concerning this topic, needs to promote the understanding of the framework used in this research. These questions focus on the state of IV leading up to the earnings date. The second set of sub-questions addresses the nature of IV after the earnings have been announced .

### **1.3 Research Objective**

The objective of the study is to develop an empirical substantiated implied volatility model that can be utilized by the investment and trading community during earnings season. By way of the methodology outlined in Tan et al. (2015), it will demonstrate the soundness of the Bayesian model when deployed as a trading strategy during earnings season in the US market. As such, it will contribute to the options trading/investment community and will significantly contribute to the knowledge of volatility rank and term structure as key indicators for improving the probability of success during binary events. Specifically the objective of this study is:

1. To determine if the dynamics of implied volatility are a function of the effects of persistence, leverage, market sentiment and liquidity

In order to meet the broad objective outlined, 3 sub-objectives are identified:

- a) To identify how implied volatility increases before earnings announcement.
- b) To identify if the volatility crush is consistent with current literature findings.
- c) To confirm if market sentiment also impacts volatility crush besides the effects of persistence and leverage

#### 1.4 Research Questions

From the research objective above, the basis for the following research questions are derived:

- 1. Does implied volatility increase progressively before earnings announcement?*

Since the pioneering work from Ball and Brown (1968), it has been well established that there is a correlation between earnings announcement and stock returns. They discovered the post earnings announcement drift from samples gathered from the S&P 500 and Dow Jones Industrial. It wasn't until 1973 when the Black Scholes equation was formalized that the concept of implied volatility became an important criteria for the research community. The awareness of the rise in volatility before binary event was documented as early as 1986 by Jennings and Starks (1986). The behavior of implied volatility became mainstream only in the late 1990s and the notion of weekly options implied volatility hasn't really caught on in the research literature hitherto.

In order to answer this research question, it is essential to understand the concept of liquidity, volatility rank, volatility differential and expected market maker move. What is the threshold of volatility rank before considering a premium selling strategy? In earlier research by Ding (2009), Dušan Isakov and Perignon (2001), (M. Donders, Kouwenberg, and Vorst (2000); M. W. Donders and Vorst (1996); M. W. Donders and Vorstb (2008)), the findings indicated that implied volatility increases progressively before earnings, but none have really concluded how far back in advance (number of days) before the announcement and how many days thereafter. The closest towards pinpointing the relationship between pre and post event volatility increase came from Dušan Isakov and Perignon (2001), who studied the Swiss market

from 1989 – 1998, using regular monthly options (albeit a less diverse and less liquid market). This makes the question significant from two perspectives: the introduction of weekly options and the diversity of the market accorded by the S&P 500. These two aspects were noticeably missing from prior research papers. A third and increasingly important aspect that this research question addresses is the use of volatility differential (term structure) and volatility rank as indicators for probability of success in selling premium. Finally the notion of increase in volatility before earnings really is driven by greed and fear. These two emotion as documented by Truong and Corrado (2014) manifest themselves extremely well in a highly liquid underlying. Similar observations were made in earlier papers by Baker and Stein (2004) and M. Donders et al. (2000).

2. *Does implied volatility decrease sharply after the announcement date, once the uncertainty is removed?*

In most of the research literature covered on this topic, it is well established that the IV decreases sharply after the earnings announcement is made. This stems from multiple theories chief amongst which is the effects of leverage and persistence. However, the context of selling premium requires the trade to be closed within a fairly short time. Since the work of Berkman and Truong (2009), there has been increasing uncertainty to the real causes of volatility drop. Theoretically, it is well documented in David and Veronesi (2000), M. W. Donders and Vorst (1996), Govindaraj, Liu, and Livnat (2012), Dušan Isakov and Perignon (2001), Ni, Pearson, and Poteshman (2005), Jones (2003), Xing and Zhang (2013) and others that persistence and leverage account for the volatility drop post earnings. However, several papers have challenged this finding, indicating that perhaps other factors such as macro-economic news and other sentiments are also responsible for the degree of