THREE ESSAYS ON ACCOUNTING INFORMATION AND FINANCIAL DERIVATIVES

By

YUBIN LI

A dissertation submitted to the

Graduate School-Newark

Rutgers, The State University of New Jersey

In partial fulfillment of requirements

For the degree of Doctor of Philosophy

Graduate Program in Management

Written under the direction of

Professor Suresh Govindaraj

And approved by

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Suresh Govindaraj (Chair)

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Bharat Sarath

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Li Zhang

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N.K. Chidambaran

Newark, New Jersey

October, 2015

ABSTRACT OF THE DISSERTATION

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By YUBIN LI

Dissertation Director: Dr. Suresh Govindaraj

My dissertation comprises of three essays: 1) Accounting information and financial derivatives: a literature review 2) The Effect of Option Transaction Costs on Informed Trading in the Option Market around Earnings Announcements; and 3) The Effects of Credit Default Swaps trading on Analyst Forecast Properties.

The first essay surveys the previous researches on accounting information and financial derivatives. The financial derivate instruments we mainly focus on are stock option and credit default swaps. Then we also identify some research gaps for future research.

The second essay investigates the effect of transaction costs related to trading options on the directional and volatility informed trading in the option market. We find that both forms of informed trading are significantly stronger among firms with lower option bid-ask spread. Importantly, the effect of transaction costs is significant around earnings announcements, but not significant (on average) around randomly chosen dates with no events of consequence. This suggests that transaction costs play a particularly important role during information intensive periods. Trading strategies based on directional informed trading and option transaction costs earn monthly abnormal returns of 1.39% to 1.91%.

The third essay investigates whether the initiation of credit default swaps (CDSs) trading can affect analysts' forecast properties. Using a difference-in-difference research design, we find that the onset of CDS trading help analysts to increase forecast accuracy, which is consistent with notion that a new financial market facilitate information discovery and dissemination. This effect is more pronounced for firms with greater information asymmetry and higher leverage. We also find that CDS initiation can depress analysts' strategic forecast optimism. Relying on several proxies for analysts' strategic optimism, we find that the depressing effect is more pronounced for subsamples with higher optimism level. In addition, we find that the depressing effect is stronger when bad news is realized *ex post* in the earnings announcement date.

ACKNOWLEDGEMENTS

This dissertation would not have been possible without the help of professors in my dissertation committee. First of all, I would like to express my sincere gratitude to my advisor Prof. Suresh Govindaraj. You guide me to be a theoretical thinker and serious researcher. I really appreciate for your patience, motivation, trust and continuous support of My Ph.D study and related research. I also want to thank Prof. Bharat Sarath. You are such a nice Professor and encourage me a lot, and you are always very generous to give me some research idea. I really appreciate your kindness, smile and warm-hearted help. I also would like to thank Prof. Li Zhang and Prof. N.K. Chidambaran, for your insightful comments and encouragement, but also for the hard questions which lead me think about my research deeply and rigorously. I am also very grateful for the encouragement, trust and patient guidance from Prof. Zhaodong Zhong. You gave me valuable advice on research and life. Talking and working with you is such a pleasure. Finally, I also want to give special thanks to Prof. Jianming Ye. Thank you for introducing me to this doctoral program and all the efforts, time and energy you have devoted.

I also want to give special thanks to my classmate and girlfriend Dr. Chen Zhao. You bring me so much happiness during my Ph.D life and spiritually support me to finish this thesis. I'm very lucky to have your accompany and encouragement. Last but not the least, I would like to thank my family: my parents and my little sister for supporting me spiritually throughout writing this thesis and my life in general. Your love and care motivate me every day.

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ESSAY 1: Accounting Information and Financial Derivatives: a Literature Review

1. Introduction

In the popular review paper "Capital market research in accounting", Kothari (2001) reviews a lot of research on the relation between capital markets and accounting information. He find that most of research in this area include tests of market efficiency with respect to accounting information, fundamental analysis, and value relevance of financial reporting. But the capital markets he touches only include stock market and bond market. As well known fact, stock and bond are the most basic financial instrument in the capital market. However, according to Wikipedia, capital market includes financial markets for the buying and selling of debt or equity-backed securities. This is a very broad definition. The financial markets for the derivatives based on stock and debt also belong to the capital market. Thus, their review will focus on this gap: the researches on the relation between financial derivative markets and accounting information.

In a world of complete and competitive markets characterized by symmetric information, no transactions costs, and no restrictions on shorting, financial derivatives are redundant assets (Black and Scholes; 1973). However, such assumptions are often violated in reality, which also leave some functional space for derivatives, such as equity-based options and debt-based credit default swaps (CDSs). More specifically, compared to their underlying financial instruments, these derivatives are endowed with certain unique characteristics: such as lower trading cost, higher leverage, no short-selling restriction, and even less regulations from SEC. These unique features can also satisfy some investors' special needs, such as informed trading or even bypass regulation. More interestingly, we expect to find some unique and interesting research stories, which are different from those in the traditional stock or bond market research in accounting.

Our survey mainly focuses on two types of derivative. The first one is equity-based option. The accounting research about option market can be divided into three groups: the first group mainly includes research focus on the informed trading in the option market surrounding certain specific key events, such as earnings announcement (most frequently touched event), analyst forecast revisions, M&A, and shareholder meeting etc. Generally, the conclusion is that option trading activity can at least predict the stock market response for these events to some extent. The second group of research only objectively describes the response of option market trading activity to some specific event, such as the change of implied volatility, trading volume, open interest around earnings announcement. The third stream focus on the role of accounting fundamental information in the pricing of option. Some papers use the volatility of accounting numbers to derive theoretical models for option pricing. Other papers empirically argue that option market does not efficiently incorporate accounting information, which leave some risk-free arbitrage space for option trading strategies based on accounting information. After reviewing the literature, they identify some research gaps for future research: 1) the role of option transaction cost in the informed trading around earnings announcement; 2) the effect of option listing on firms' stock option incentive plan; 3) the response of option implied volatility for 10-K readability.

The second derivative is the debt-based credit default swaps. The accounting research in credit default swaps can be divided into four groups. Similar to option research, the first stream also focuses on the informed trading in the CDS market around some specific accounting event, such as earnings announcement, due to its high leverage, low trading cost and even less regulation. The second stream focuses on the role of accounting information in the pricing of CDS premia. For instance, some researches study whether internal control or the use of XBRL reporting format affect the pricing of CDS spread. The third stream studies the real effect of CDS on firms' accounting choice. For example, some papers find that CDS trading can decrease firms' conservatism level or increase firms' cash holding. The last group focus on the effect of the change of accounting regulation or standard on the CDS. After reviewing the literature, they also identify some research questions for future research: 1) the effect of CDS initiation on analyst forecast behavior; 2) the effect of CDS initiation on auditing; 3) whether audit risk is priced into the CDS premia.

The remainder of this article is organized as follows: Section 2 reviews the literature on option market and accounting information. Section 3 reviews the literature on credit default swaps market and accounting information. Section 4 concludes.

2. Stock options and accounting information

Compared to its long-lived underlying financial instrument, stock, option is relatively young. As they can see, Chicago Board Options Exchange (CBOE) is established in 1973. The first exchange to list standardized, exchange-traded stock options began its trading on April 1973. The accounting research about option market naturally follows the beginning of CBOE.

At first, I focus on the descriptive studies of option market trading activity around certain accounting events. Most of these studies are published in earlier stage. The first paper is Patell and Wolfson (1981), and they find that option implied volatility increases before earnings announcement and collapses immediately after earnings announcement.

Isakov and Perignon (2001) find similar results using Swiss market data. Whaley and Cheung (1982) find that the earnings information is fully incorporated in option prices by the end of the announcement week. Schachter (1988) documents a significant decline in open interest prior to announcements, which cannot be explained by the reactions of investors to good and bad news. While Donders, Kouwenberg and Vorst (2000) find that open interest increase immediately before earnings announcement, and they also find the effective spread increases on the event day and on the first two days following the earnings announcement. Levy and Yoder (1993) examines the option implied volatility around merger and acquisition announcements. The implied volatility of target firms increase significantly three days prior to the announcement, but the bidding firm implied standard deviations are not affected. Acker (2012) investigates volatility increases following annual earnings announcements and finds that bad news report and reports that are difficult to interpret delay the volatility increase. Truong et al. (2012) find that positive earnings surprises and positive profit announcements produce a larger uncertainty resolution in the option market than negative earnings surprises and loss announcements. These papers describe the interaction between accounting events and option market from different angles.

Next, I turn to the researches on informed trading in the option market. 1). Earlier studies focus on the response of stock market to earnings after option listing. Skinner (1990) documents that the information content of firms' accounting earnings releases is lower after exchange-traded options are listed on their stocks, implying that private information about earnings is revealed in the option market to some extent. Ho (1993) also finds that the price-earnings ratio is lower for firm with exchange-traded options. In contrast, Mendenhall and Fehrs (1999) find option listing may actually *increase* the stock-price response to earnings, but no evidence listing reduces the response. Arnold, Erwin, Nail and Nixon (2006) find that abnormal volume in the option market replaces abnormal volume in the stock market prior to cash tender offer announcements. Billings and Jennings (2011) find that an option based measure of anticipated information content positively correlates with the ex post magnitude of the stock market sensitivity to unexpected earnings. Truong and Corrado (2014) find that within the sample of firms with listed options stratified by options volume, they find that higher options trading volume reduces the immediate stock price response to earnings announcements.

2). More recently, researcher find that option market trading activity can predict stock market return or analyst forecast revision, which is consistent with informed trading in the option market. Amin and Lee (1997) show that the direction of this preannouncement trading foreshadows subsequent earnings news. Diavatopoulos et al. (2012) derive the implied skewness and kurtosis from option price and find that changes in implied skewness and kurtosis and are also associated with the mean and variability of the stock price response to the earnings announcement. Jin, Livnat and Zhang (2012) find that the option measures immediately before earnings announcements have higher predictive ability for short-term event returns than they do in a more dated window or before a randomly selected pseudo-event. They also find that option measures have predictive ability after information events. Johnson and So (2012) find that O/S (option trading volume divided by stock trading volume) also predicts future firm-specific earnings news, consistent with O/S reflecting private information. Atilgan (2014) finds that the predictability of equity returns by implied volatility spreads is stronger during earnings announcements. Hayunga and Lung (2014) demonstrate that options investors trade in the correct direction of the analysts' upcoming revision approximately 3 days prior to the announcement. Chan, Ge and Lin (2015) show that implied volatility spread predicts positively on the cumulative abnormal return (CAR), and implied volatility skew predicts negatively on the CAR. The predictability is much stronger around actual merger and acquisition (M&A) announcement days, compared with pseudo-event days. Lin and Lu (2015) show that the predictive power of option implied volatilities (IVs) on stock returns more than doubles around analyst-related events, indicating that a significant proportion of the options predictability on stock returns comes from informed options traders' information about upcoming analyst-related news.

3). Other studies show that option market enrich the information environment by reveal more information. Ho, Hasell and Swidler (1995) find that consensus analyst forecast accuracy improves after option listing. Chern, Tandon, Yu and Webb (2008) find that the prices of optioned stocks embody more information, diminishing the impact of the stock split announcement. Naiker, Navissi and Truong (2013) find that within firms that have listed options, firms with higher options trading volume are associated with lower implied cost of equity capital, which is consistent with the notion that options trading improves the precision of information and reduces information asymmetry problem.

Lastly, I focus on the researches on the role of accounting information in the option pricing. David and Veronesi (2002) shows that investor's uncertainty about a firm's fundamental affects option prices through its effect on stock volatility and the covariance between return and volatility. Sridharan (2012) finds financial statement information can predict future realized equity volatility incremental to market-based equity volatility forecasts and also demonstrates that the incorporation of accounting-based fundamental information into forecasting models yields lower forecast errors relative to models based solely on past realized volatility. Goodman et al. (2013) find that fundamental accounting signals exhibit incremental predictive power with respect to future option returns above and beyond what is captured by implied and historical stock volatility, suggesting that the options market does not fully incorporate fundamental information into option prices.

After reviewing the above literature, I identify some research gaps for future research: 1) the role of option transaction cost in the informed trading around earnings announcement; 2) the effect of option listing on firms' stock option incentive plan; 3) the response of option implied volatility for 10-K readability.

3. Credit default swaps and accounting information

Credit default swap (CDS) a swap agreement that the CDS seller will compensate the buyer in the event of a loan default (by the borrower) or other credit event. In other words, the seller of the CDS insures the buyer against some reference loan defaulting. In return, the buyer of the CDS makes a series of payments to the seller. It was invented by Blythe Masters from JP Morgan in 1994. Thus, CDS is very young financial derivatives from 90s of last century.

In a review paper, Richardson et al. (2011) make a call for paper on the relation between accounting information and credit market. Accounting information is useful to all investors, not just equity investors. A primary reason for this is the recent development of credit-default-swap (CDS) contracts and the significant increase in the

CDS market for publicly traded companies.

At first, I focus on the role of accounting fundamental information in the option pricing. Das et al. (2009) find that using accounting metrics performs comparably to market-based structural models of default in predicting the CDS spread. Callen, Livnat, and Siegal (2009) find that earnings (cash flows, accruals) of reference firms are negatively and significantly correlated with the level of CDS premia, consistent with earnings (cash flows, accruals) conveying information about default risk. Greatrex (2009) finds that CDS market have statistically significant reactions to earnings announcements. Baik et al. (2015) also find negative relation between earnings and CDS spread by using Korea data. Tang and Yan (2010) find that credit spreads generally rise with cash flow volatility. Batta (2011) finds that a larger indirect role for accounting information in pricing CDS, rather than direct effect. Shivakumar et al. (2011) document that credit markets react significantly to management forecast news and that the reactions to forecast news are stronger than to actual earnings news. Melgarejo (2012) shows that firms that beat analysts' earnings and revenue forecasts, and firms with less dispersed analysts' earnings and revenue forecasts have on average a reduction in their CDS premia around the earnings announcement date. De Franco et al. (2013) investigates the tone of sell-side debt analysts' discussions about debt-equity conflict events are associated with increases in credit spreads of CDS. Kim et al. (2013) find that greater comparability of financial reporting is associated with lower credit spreads for both bonds and five-year credit default swaps. Arora et al. (2014) find that asset reliability issues, attributable to SFAS 157 disclosures of Level 2 and, especially, Level 3 financial assets for a set of US financial institutions over the period of August 2007 to March 2009, are a significant determinant of short-term credit spreads and the shape of the general credit term structure. Tang, Tian and Yan (2015) companies experiencing internal control material weakness (MW) exhibit higher CDS spreads than companies with effective internal control. Bai and Wu (2015) find that firm fundamentals can explain the cross-sectional variation of credit default swap (CDS) spreads with average R-squared of 77%. Jenkins, Kimbrough and Wang (2014) examine the relation between previous earnings announcement and subsequent CDS market response, and finds that the CDS market is efficient during periods of relative economic stability but call into question its efficiency during less stable economic periods.

Next, I turn to the informed trading in the CDS market. Batta, Qiu and Yu (2014) demonstrate that the strength of CDS price discovery prior to earnings announcements is related to the presence of private information. Gao et al. (2015) find that CDS credit spreads increase significantly in the months before the public discovery of frauds, and then spike upon the discovery date. Their results suggest that some credit investors may have superior information about suspected fraudulent activities prior to the public disclosure of frauds.

Then, I focus on the studies on the real effect of CDS trading initiation. Kim et al. (2014) find that managers are more likely to issue earnings forecasts when their firms have actively traded CDSs. Their results also suggest that liquid CDSs discipline managers to disclose bad news earnings forecasts, despite their career- and wealth-related incentives to withhold adverse information. Martin and Roychowdhury (2015) observe a decline in borrowing firms' reporting conservatism after CDS trade initiation.

Lastly, I focus on the researches on the effect of accounting regulation or standard change on CDS pricing. Andrade et al. (2014) show that corporate opacity and the cost of debt decrease significantly after SOX. The median firm in their sample experiences an 18 bp reduction on its five-year CDS spread as a result of lower opacity following SOX. Bhat, Callen and Segal (2014) find that the adoption of IFRS increases the credit risk informativeness of accounting variables and lower CDS spread. Similarly, Kraft and Landsman (2014) find that mean and median absolute percentage prediction errors of accounting based CDS model are larger for both financial and non-financial firms after mandatory IFRS adoption. Griffin et al. (2014) show a negative relation between these CDS spread and tier 1 and tier 2 XBRL adoptions.

After reviewing the above literature on accounting information and credit default swaps, they identify some research questions for future research: 1) the effect of CDS initiation on analyst forecast behavior; 2) the effect of CDS initiation on auditing; 3) whether audit risk is priced into the CDS premia.

4. Conclusion

In this paper I review the research on the relationship between accounting information and financial derivatives. I mainly focused on two types of derivatives, stock option and credit default swaps. I first review the accounting research in stock option and then review the accounting research in credit default swaps. I organize the papers in a chronological order to layout the development of the research stream. After the review the literature, I propose some research questions for future research. For option market: 1) the role of option transaction cost in the informed trading around earnings announcement; 2) the effect of option listing on firms' stock option incentive plan; 3) the response of option implied volatility for 10-K readability. For credit default swaps: 1) the effect of

CDS initiation on analyst forecast behavior; 2) the effect of CDS initiation on auditing; 3) whether audit risk is priced into the CDS premia.

ESSAY 2: The Effect of Option Transaction Costs on Informed Trading in the Option Market around Earnings Announcements

1. Introduction

In the last two decades, there has been an explosive growth in the volume of option contracts (specifically, stock options), traded in the United States and abroad.[1] In perfect, efficient, and frictionless financial markets, options would be redundant securities. In such ideal conditions, one would be hard pressed to explain the existence, the tremendous popularity, and the growth in derivative trading. However, the reality is that financial markets are neither perfect nor frictionless. Trading in the stock market involves frictions and imperfections such as transaction costs, constraints on short sales, and asymmetric information related issues. Therefore, the option market, with relatively less restrictions on short sales constraints, and higher leverage, becomes an attractive alternative to the equities market for investors, especially those with superior information (Black, 1975). This realization has spawned a number of research papers which have primarily focused on using the price discovery process in the option market to predict future stock returns and future stock volatility.

The focus of our study is the price discovery process around earnings announcements in the option market, and the role played by option transaction costs in this process. We focus on the earnings announcement because it is generally considered as an event of significance that should attract higher proportion of informed traders relative to normal times when there are no significant events. Consequently, the price

[1] The global option market size is 9.42 billion worth of contract for 2013. The information is extracted from the website: http://www.futuresindustry.org/volume-.asp.The US option market size is 4.1 billion contracts, with a total of $1.2 trillion in options premium exchanging hands in 2013: http://online.wsj.com/articles/SB10001424052702303870704579297050280237182.

discovery process in the option market is likely to be more intense during such major information events (Jin, Livnat, and Zhang, 2012; Atilgan, 2014).

It is to be expected that rational informed traders will weigh the benefits from their private information against the costs of trading, and rationally factor in the effect of transaction costs on trading profits. It is also expected that the impact of transaction costs on informed trading in the option market is more likely to be keenly felt, and carry more significance, around earnings announcements (when superior information is really valuable) relative to normal times. It is notable that while the fixed and variable costs involved with trades are roughly comparable across the option and stock market,[2] the relative bid-ask spread of options is much higher than that of the underlying stocks. For example, in our sample which includes about 5,000 firms during the period 1996 to 2011, the average bid-ask spread ratio of relatively liquid at-the-money options is as high as 20%; in contrast, the average bid-ask spread ratio of the underlying stocks is only 0.6%. Therefore we focus only on the transaction cost captured by the bid-ask spreads in the option market.

Specifically, we examine the impact of option transaction costs on two types of informed trading, namely, directional information trading and volatility information trading. By directional and volatility information trading we mean using option market related measures to predict future stock returns, and future stock return volatility, respectively. We depart from prior studies that have examined transaction costs (relative

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[2] The commission fee (fixed cost) for every stock trade (whatever this trading size) is usually less than $10 across many brokerage firms. For some brokerage firms, there is also variable trading cost. For example, TradeStation will charge 0.6 cents per share for the amount beyond 500 shares. But most of other brokerage firms do not have this variable charge. For option trading, the commission fee includes initial trade fee (less than $10) plus variable cost (less than $1 per contract).

bid-ask spreads) on the day of trading (an *ex post* measure), by measuring transaction costs at the close of a day prior to the actual trading day (an *ex ante* measure). Given the feedback effect between traded volume of options and the bid-ask spread, we believe this *ex-ante* measure of transaction costs is more appropriate for the purpose of our study, rather than the realized *ex post* bid-ask spread after the trading is completed. In other words, by using the *ex ante* measure, we correct for the fact that traders could not have known what the *ex post* bid-ask spread would have been before they had traded.

We first examine the effect of transaction costs (or the relative bid-ask spread for the option) on directional informed trading in the option market. Directional informed trading option market based predictors used in this analysis are implied volatility spread, and implied volatility skew (Cremers and Weinbaum (2010); Van Buskirk (2009); Xing, Zhang and Zhao (2010); Jin, Livnat, and Zhang (2012)), in the Pre window [-7, -1], relative to the earnings announcement day (designated as day 0). We document that the predictability of implied volatility spread (skew) for abnormal stock returns over the earnings announcement window [0, +2] is stronger among firms with relatively lower option bid-ask spreads. By contrast, the effect of the option bid-ask spread on the predictability of implied volatility spread (skew) is insignificant around random days when there are no events of consequence.

In addition, we also examine whether a hedged trading strategy incorporating the effects of transaction costs can significantly improve upon a trading strategy built solely on implied volatility spread (skew) around earnings announcements. That is, in each quarter, we assign stocks into four portfolios based on the option volatility spread (skew) quartile from the previous quarter. Our portfolio construction method ensures no look-ahead bias and is practically implementable. The baseline trading strategy that buys stocks in the highest (lowest) quartile of volatility spread (skew) and sells stocks in the lowest (highest) quartile earns monthly abnormal returns of 1.05% (1.17%). The hedge portfolio returns persist up to three months after the earnings announcement date. Particularly noteworthy is that, for our improved trading strategy conditional on the low option transaction costs, the hedge portfolio return is as high as 1.39% (1.91%) per month and statistically significant at the 5% (1%) level. By contrast, the corresponding hedge portfolio return in firms with high option transaction costs is only 0.42% (0.50%) per month and statistically insignificant. These results imply that informed trading will be higher for options with lower transaction costs. Hence, trading in these options carries economically stronger predictability for future stock returns and suggests a more profitable trading strategy.

Next, we investigate the effect of option transaction costs on volatility-based informed trading in the option market. Prior literature on volatility information trading suggests that both the implied volatility of at-the-money options, and the ratio of the option trading volume to stock trading volume (commonly referred to as the O/S ratio), can predict future stock return volatility (Harvey and Whaley, 1992; Canina and Figlewski, 1993; Jorion (1995); Christensen and Prabhala (1998); Roll, Schwartz, and Subrahmanyam (2010); Govindaraj et al. (2015)).[3] Our first predictor is the average implied volatility of short-term ATM call options in the Pre window (trading days) [-7, -1]. We find that the predictability of ATM implied volatility for absolute abnormal stock returns over the earnings announcement window (trading days) [0, +2] is stronger when the relative bid-ask spread of the ATM call option is lower. However, this effect is not

[3] The option trading volume is the total trading volume of all traded options for an underlying stock.

significant around randomly chosen (non-event) dates.

Our second predictor is the option O/S ratio (the ratio of the option trading volume to stock trading volume) in the Pre-window. For consistency, we also use the relative bid-ask spread of the underlying stock to scale the option relative bid-ask spread when measuring option transaction cost. Interestingly, the O/S ratio is a significantly stronger predictor of absolute abnormal returns over the earnings announcement window [0, +2] when the option bid-ask spread ratio is higher relative to the underlying stock bid-ask spread ratio. Since the O/S ratio is a response to the previous day's closing bid-ask spread, it can be viewed as an *ex post* measure of realized option trading activity conditioned on the knowledge of the transaction cost. In other words, the option trading volume is the result of a rational calculation between expected gains from private information and expected losses from transaction costs by informed traders. If an investor is willing to trade in the option market despite of the higher transaction costs, it is more likely that the investor has more accurate or more profitable private information. Higher transaction cost plays the role of a barrier and filter, and helps separate noise trading from informed trading. Therefore, we find that, for a given level of realized O/S ratio, the higher the transaction cost of options relative to that of the underlying stock prior to trading, the higher the absolute abnormal stock returns around the earnings announcements. This suggests that there is more informed trading in these options. Mirroring our results for the ATM implied volatility, the effect of transaction cost on the predictability of O/S ratio is not significant around randomly chosen dates.

A large body of recent research on the market microstructure of option market traces its roots to an influential paper by Easley, O'Hara, and Srinivas (1998), who proposed that the amount of informed trading in the option market should be related to the relative liquidity of the option market *vis à vis* the stock market, and the amount of leverage achievable with options. Since then, there have been a number of papers validating the propositions of the Easley, O'Hara, and Srinivas (1998). To cite a few, Chakravarty, Gulen and Mayhew (2004) find that option market price discovery tends to be greater when the option volume is higher relative to stock volume, and when the effective bid-ask spread in the option market is narrower relative to that in the stock market. With particular focus on predicting future stock returns, Cremers and Weinbaum (2010) document that the predictability of volatility spread for future stock returns is larger when option liquidity is high and stock liquidity is low. Xing, Zhang and Zhao (2010) find that the volatility skew predicts future stock returns better when stock market liquidity (stock turnover) deteriorates. Similar findings about the predictive power of option volatility skew and option volatility spread in predicting future stock returns have been recorded by Van Bursirk (2009), and more recently by Jin, Livnat, and Zhang (2012), and other authors (for example, Bali and Hovakimian, 2009; Chan, Chang and Lung, 2009). Some of the papers that have focused on predicting future stock volatility using the implied volatility of at-the-money options and the O/S ratio include Jorion (1995); Christensen and Prabhala (1998); Roll, Schwartz, and Subrahmanyam (2010); Govindaraj et al. (2015).

Our work differs from the prior studies in a number of ways. First, we focus on the effects of transaction costs on informed trading in the option market around a significant event, namely, the earnings announcement. There is little prior research on the effects of transaction costs with respect to any specific information event, and none with respect to earnings announcements. This is particularly important because the connection between private information and informed trading is most relevant around important information events; and it is our conjecture that transaction costs during these events can help shed light on informed and uninformed trading.

Second, in addition to informed trading on directional information, we also investigate how transaction costs affect the informed trading about the future volatility around earnings announcements. To the best of our knowledge, our study is the first one to examine the impact of transaction costs on volatility-related informed trading in the option market.

Third, as pointed out earlier, prior studies measure transaction costs and liquidity concurrently or after the trading volume is revealed, and show that options with higher trading volume or lower *ex post* bid-ask spread are more informative about future stock returns. Unlike these studies, we examine how the *ex ante* transaction costs of options affect the trading decisions of informed traders.

The remainder of this article is organized as follows: In Section II, we present our research design. Data and sample is presented in the Section III. Section IV presents empirical results on the effect of option transaction costs on the directional informed trading in the option market. The trading strategy based on volatility spread (skew) and transaction costs is described in Section V. In section VI, we investigate the effect of option transaction costs on the volatility-related informed trading. Section VII summarizes our results and presents suggestions for future research.

2. Research Design and Sample

2.1 Base and Pre Windows

It seems intuitive that option traders would have stronger incentives to acquire private information before information events, particularly before anticipated information events such as earnings announcements. Therefore, an informed trader's information advantage is presumably larger immediately before significant information events (Kim and Verrecchia, 1994, Skinner, 1997). Following this reasoning, we use the incremental predictive ability of the option market measures in a window close to and just prior to the announcement date (we refer to this window as the Pre window), relative to that of the same measures during a window before the Pre window (we refer to this as the Base window), to capture informed trading in option market. We first identify the event date (day 0). We then measure volatility spread/skew, implied volatility of ATM call options and O/S ratio over two windows: trading days [–30, –8] (Base window) and trading days [–7, –1] (Pre window)[4]. We attempt to predict abnormal returns and absolute abnormal return in the window [0, +2] (event window). Figure 2.1 below illustrates this graphically on a time line.

<INSERT FIGURE 2.1 HERE>

2.2 Measures of informed trading

We construct four measures of informed trading in the option market. Two of these measure directional informed trading, namely, implied volatility (IV) spread, and implied volatility (IV) skew. These are used for predicting future stock abnormal returns. The other two measures, namely, the implied volatility of ATM call options and option

[4] Our results are unaffected when using other windows such as (trading days) [-30, -11] for the Base window and (trading days) [-10, -1] for the Pre window.

trading volume to stock trading volume ratio (O/S ratio), are the volatility-related informed trading measures that we use to predict the absolute value of future stock abnormal returns.

IV spread is the implied volatility difference between call and put options with the same strike price and maturity (call-put parity deviation). We calculate volatility spread as the equal-weighted average of the difference in implied volatilities between all matched call and put option pairs over the Base and Pre window.[5] While the original Black-Scholes model predicts this spread should be zero, later work has shown this is not true in reality. As an example, it has been recorded that when option traders obtain information about a positive (negative) event, the demand for call (put) options increases relative to the demand for put options, and this results in deviations from zero for the IV spread. Ofek, Richardson, and Whitelaw (2004) and Cremers and Weinbaum (2010) show that this volatility spread can predict future stock returns, and Jin, Livnat and Zhang (2012) show that the volatility spread can predict abnormal stock returns around earnings announcement.

IV skew is the difference between the implied volatilities of out-of the money (OTM) put options and at-the-money (ATM) call options. To understand why there should be a difference, consider the case where option traders obtain information about a negative event. To protect themselves, they would trigger an excess demand for OTM put options relative to the demand for ATM call options, thereby increasing volatility skew. Consistent with volatility skews reflecting negative information, Xing, Zhang, and Zhao (2010) document that stocks with the largest volatility skews in their traded options underperform stocks with the smallest skews by 10.9% per year. Jin, Livnat and Zhang

[5] We also consider volume-weighted and open-interest weighted measures.

(2012) also find that volatility skew can (negatively) predict abnormal returns around earnings announcement dates. Following Jin, Livnat and Zhang (2012), for the Base and Pre windows, we select call options that have a delta in the range of [+0.4, +0.7], and choose the one closest to 0.5. Its implied volatility is the ATM implied volatility; and we then select all put options that have a delta in the range of [–0.45, –0.15][6]. We impose the conditions that the option expiration date should be between 10 and 60 days away and open interest should be positive. The volatility skew is the equal-weighted implied volatility of the OTM put options minus the implied volatility of the ATM call option over the Base and Pre window.[7]

The first measure of volatility informed trading in the option market is the implied volatility of ATM call options. Prior research shows that the implied volatility of an option can predict the ex-post realized stock return volatility over the remaining life of the option. For example, Christensen and Prabhala (1998) document that volatility implied by the S&P 100 index option price outperforms past volatility in forecasting future volatility. Ederington and Guan (2002) show that the implied volatility from S&P500 futures options has strong predictive power, and in general, subsumes the information in historical volatility. To measure the ATM implied volatility, we identify for each day all call options of a firm with time-to-maturity between 10 and 90 days, and expiring after the earnings announcements (or random event days as the case may be).

[6] We do not follow Jin, Livnat and Zhang (2012) by only choosing the put options with delta closest to -0.3. This is because the informed trader with negative information can also trade other options. Furthermore, when we apply the volume-weighted measure of IV skew, we need to consider the trading volume, and so we include all the options in the delta range [-0.45, -0.15]. We also try the method in Jin, Livnat and Zhang (2012) as a robustness check, and our results remain qualitatively similar.

[7] Once again, we also consider volume-weighted and open-interest weighted measures.

Then, from this set, we select call options that have a delta in the range of [+0.4, +0.7], and choose the one closest to 0.5. Its implied volatility is the ATM implied volatility.

O/S ratio is defined as the natural logarithm of the total daily option trading volume divided by the daily stock trading volume. Roll, Schwartz, Subrahmanyam (2010) show that the O/S ratio in pre-earnings announcement window can predict absolute abnormal returns in the earnings announcement window [0, +2]. This is consistent with the notion that at least a part of the increases in the O/S ratio occur just before earnings announcements is attributable to increased trading by the informed traders attempting to exploit their private knowledge of the upcoming unanticipated earnings surprise. In addition, since earnings surprises can be either negative or positive, and given that both long side and short side strategies can be conducted in the options market, the O/S ratio can reflect the private information about the magnitude of future earnings announcement abnormal return.

2.3 The measurement of option transaction cost

We measure option transaction cost using the option relative bid-ask spread, which is defined as the ask price minus the bid price and then divided by the average of the bid and ask price. In the absence of real time intra-day data on bid-ask spreads for the option market, we use the closing bid-ask spread from the previous trading day for call and put options to measure their transaction costs. Since we are interested in the volume of informed trading conditional on the transaction costs, it seems natural to document the next day traded volume, given the bid-ask spread before they trade (an *ex ante* measure). As mentioned earlier, this is distinct from prior studies that measure traded volume and the bid-ask spread concurrently at the closing time of the same trading day. Since the bid-ask spread and volume are jointly determined, the closing time bid-ask spread incorporates the volume traded; and in this sense it is an *ex-post* measure of transaction costs.

3. Data and descriptive statistics

3.1 Data

The sample period for our study is from 1996 to 2011. We obtain earnings announcement dates from Compustat, and data on stock returns as well as trading volume information from the Center for Research on Security Prices (CRSP) database. Our option data is obtained from OptionMetrics, which provides daily close bid and ask quotes, open interest, volume, implied volatilities, and option "greeks" for all put and call options listed and traded in the U.S. options market. OptionMetrics calculates the underlying implied volatilities of individual options using the binomial trees methodology that takes into account early exercise of individual stock options, and the dividends expected to be paid over the lives of the options.

3.2 Descriptive statistics

Table 1 presents the summary statistics. Panel A presents the descriptive statistics for the IV spread sample. The sample consists of 92,504 earnings announcements for 4,927 unique firms. The mean and standard deviation of the abnormal return over the earnings announcement window [0, +2] are 0.1% and 9.1%, respectively. The means of the IV spreads in the Base window [-30, -8] and the Pre window [-7, -1] are both about -

0.01, suggesting that put options are on average more expensive than call options.[8] The standard deviation of IV spread in the Pre window is 3.6%, which is about 20% larger than that in the Base window. The mean of option relative bid-ask spread in the Pre window [-7, -1] is as high as 31.7%. The firm size (i.e. market value of equity) is on average 1.5 billion dollars (similar to Johnson and So (2012)), the book to market ratio is on average 0.38, and the momentum (month t-12 to month t-1) is on average 18.1%. The annualized historical volatility of stock returns on the window [-70, -10] is 45% on average. This is similar to the findings in Xing, Zhang and Zhao (2010).

<INSERT TABLE 2.1 HERE>

Panel B presents the descriptive statistics in the IV skew regressions. The sample consists of 66,872 earnings announcements for 4,510 unique firms. The average IV skew in the Base window [-30, -8] is 0.030 and it increases to 0.035 in the Pre window [-7, -1]. Compared to call options, put options become more expensive in the period closer to earnings announcement. The average option relative bid-ask spread is 34.1%, with standard deviation of 29.3%. The firm size, book to market ratio and historical volatility are similar to those in the IV spread sample.

Panel C presents the descriptive statistics in the IV_ATM regressions. The sample consists of 92,474 earnings announcements for 5,293 unique firms from the year 1996 to 2011. The average implied volatility of ATM call options in the Pre window [-7, -1] is 0.515, which is slightly higher than that in the Base window [-30, -8] which is (0.50). This is consistent with the fact that option market incorporates more information about the uncertainty of the upcoming earnings release closer to the earnings event date (Roll,

[8] This is consistent with the notion that more jump risk premium is embedded in put options (e.g. Cummins, 1988; Pan, 2002).

Schwartz and Subrahmanyam, 2010). The average relative bid-ask spread of ATM call options is 20.1%, which is much lower compared to those in the IV spread and IV skew sample. This suggests that the relative bid-ask spread of ATM call options is lower than the average of all options or that of OTM put options. The annualized historical stock returns volatility is on average 0.467. It is lower than the option implied volatility. This is consistent with Bakshi and Kapadia (2003a, 2003b), who attribute the difference between option implied volatility and stock historical volatility to the negative volatility risk premium.

Panel D displays the summary statistics for O/S ratio sample. The sample consists of 81,237 earnings announcements of 4,752 unique firms from the year 1996 to 2011. The absolute value of abnormal returns in the 3-day earnings announcement window [0, +2] is on average 6.3% This is larger than the average absolute abnormal returns of 5.1% in the one-week Pre window [-7, -1] immediately before the earnings window). The O/S ratio in the Pre window [-7, -1] is smaller than zero, indicating that the total dollar trading volume across all options is less than the dollar trading volume of the underlying stock. More specifically, the option trading volume is on average only 3.4% of the stock trading volume in the Pre window. In the meantime, the relative bid-ask spread in the option market is about 550 times as high as that in the stock market, suggesting that the stock market is much more liquid than the option market.

Table 2 presents the Pearson and Spearman correlation coefficients. Panels A, B, C, and D show the correlation for the variables in the IV spread regressions, IV skew regressions, IV_ATM regressions and the O/S ratio regressions, respectively.

<INSERT TABLE 2.2 HERE>

In Panel A, the IV spread in the Pre window [-7, -1] is positively and significantly correlated with the abnormal stock returns in window [0, +2] (XRET02), with Pearson and Spearman correlation coefficients at 0.022 and 0.018 respectively. Although IV spread in the Base window is highly correlated with IV spread in the Pre window (Spearman 0.463 and Pearson 0.595), it is not significantly correlated with XRET02. This suggests that informed trading in the option market is stronger in the Pre window than in the Base window. The relative bid-ask spread in the Pre window is negatively correlated with firm size and positively correlated with book-to-market ratio, suggesting lower option transaction costs in larger firms, and firms with lower book-to-market ratios. Additionally, as expected, firm size is negatively correlated with historical volatility (Spearman -0.478 and Pearson -0.390). Panel B shows that IV skew in the Pre window is significantly and negatively correlated with the abnormal stock returns in window [0, +2] (XRET02), with Pearson and Spearman correlation coefficients at -0.015 and -0.019 respectively. However, the correlation between IV skew in the Base window and XRET02 is insignificant.

Panel C shows that the implied volatility of ATM call options in both the Pre window and the Base window are positively correlated with AXRET02. The Pearson and Spearman correlation coefficients are 0.359 and 0.357 and both are significant at 1% level. The implied volatility is negatively correlated with firm size and book-to-market ratio, and positively correlated with historical stock return volatility. In Panel D, the O/S ratio in the Pre window [-7, -1] is positively correlated with absolute abnormal returns in the window [0, +2] (AXRET02). The Pearson and Spearman correlation coefficients are 0.038 and 0.044 and both are significant at 1% level. The O/S ratio in the Base window, while somewhat smaller in magnitude, is also positively and significantly correlated with AXRET02 (Pearson 0.025 and Spearman 0.031). In addition, both the historical stock returns volatility and implied volatility of ATM call options are positively correlated with AXRET02 at the 1% significance level.

3.3 Options trading volume and implied volatility around earnings announcements

Figure 2 illustrates the option trading volume and implied volatility in the 60 trading days ([-30, +30]) around earnings announcements. Call options and put options show similar patterns. The implied volatility starts to increase from about 18 trading days before earnings announcements, peaks on 1 trading day before earnings announcements and then plunges to the previous level in about 7 trading days after earnings announcements. The option trading volume starts to increase from about 7 trading days before earnings announcement, peaks on the earnings announcement date and then plunges to the previous level in about 7 trading days after earnings announcements. Based on the change of options trading volume, we choose [-7, -1] as our prediction window and [-30, -8] as the Base window.[9]

<INSERT FIGURE 2.2 HERE>

Another interesting fact from Figure 2 is that the call option trading volume is larger than the put option trading volume. In the Base window period, the average daily trading volume is about 60 contracts for call options and 50 contracts for put options. In the earnings announcement period, the average daily trading volume is about 140 contracts for call options and 110 contracts for put options. Consistent with Lakonishok et al. (2007), Figure 2 suggests that call options trading is more active than put options trading.

[9] We also choose [-10,-1] as prediction window as a robustness test. The results remain qualitatively similar.

4. The effect of transaction costs on the directional informed trading

Table 3 reports the Fama–MacBeth statistics based on 64 quarterly regressions. The heteroscedasticity and autocorrelation in the time-series t-statistics are corrected according to the Newey and West (1987) procedure using four lags[10]. The sample includes all earnings announcements with data available from 1996 to 2011. The dependent variable is the stock excess return in the window [0, +2], with earnings announcement date designated as the trading day 0. Following Daniel and Titman (1997), we measure excess returns as the buy-and-hold return over the designated window minus the buy-and-hold return from a portfolio of stocks of similar size (market value of equity, two groups), book-to-market ratio (three groups), and 12-month momentum (three groups). Panel A presents the regression results for earnings announcement sample and Panel B presents the results for a randomly chosen date sample. To control for outliers, we winsorize each of these variables at the 1st and 99th percentiles.[11]

<INSERT TABLE 2.3 HERE>

We first discuss the results in Panel A. Equal-weighted IV spread is the predictor in Models 1to 3; equal-weighted IV skew is the predictor in Models 46. Model 1 is the base model and only includes IV spreads in the Base and Pre window (Jin, Livnat and Zhang, 2012). The coefficient of IV spread in the Pre window is 0.074, and is positively significant at the 1% level. From an economic point of view, our results show that one standard deviation increase of IV spread leads to 2.7% increase in abnormal stock returns in earnings announcement window. These results are consistent with previous literature

[10] We choose four lags because the seasonality of quarterly earnings. The earnings at quarter t is likely to be autocorrelated with earnings at quarter t-4, so is the abnormal return around earnings announcement.
[11] We also carried out regressions without winsorizing the variables, and the results remains qualitatively similar.

(Cremers and Weinbaum, 2010, Jin, Livnat and Zhang, 2012). Model 2 presents the effect of transaction costs on the predictability of IV spread. The interaction term between transaction costs and IV spread is significant at 1% level and the coefficient is -0.117, with opposite sign to the coefficient of IV spread. This indicates that, transaction costs impose a significant offsetting effect on informed trading in the option market. Additionally, after controlling for the effect of transaction costs, the predictability of IV spread increases. The coefficient of IV spread increases by 70%, from 0.074 to 0.126, and the t-value remains similar. This implies that the predictability of IV spread is largely influenced by option related transaction costs. In Model 3, to rule out the possibility that the result is sensitive to other determinants of abnormal stock returns, we control for size and book-to-market factors as in Fama and French (1993), a momentum factor as in Carhart (1997) and the historical volatility of stock return over [-70, -10] as in Xing, Zhang, and Zhao (2010). Additionally, we also control for the abnormal stock return in Pre window [-7, -1], due to the reversal pattern of stock returns (Jegadeesh, 1990). The predictability of IV spread is still highly significant. The effect of transaction costs still remains significant at the 5% level and also economically important.

Models 4-6 presents the results for IV skew. Model 4 is the base model (Jin, Livnat and Zhang, 2012) and only includes IV skew in the Base window [-30, -8] and in the Pre window [-7, -1]. The coefficient of IV skew in the Pre window is -0.036, and is significant at the 1% level. Our results show that one standard deviation increase in IV skew induces 2.6% lower stock excess returns in the earnings announcement window. We consider the effect of option related transaction costs in Model 5. The interaction term between transaction costs and IV skew is significant at 5% level and the coefficient is 0.068, with opposite sign to the coefficient of IV skew. Similar to IV spread, after controlling for the effect of transaction costs, the predictability of IV skew also increases: the magnitude of coefficient increases by 97%, from -0.036 to -0.071, and the t-value increases from 3.53 to 4.74. Therefore, the predictability of IV skew is also affected by option related transaction costs. In model 6, after controlling for size, book-to-market ratio, momentum and abnormal stock returns in the Pre window and historical volatility, the effect of transaction costs still remains significant at 5% level.

To compare the effect of transaction costs in different information environment, we replicate our analysis in a random day sample. The results are presented in Panel B. This day is a randomly selected trading day in the calendar day window of [+30, +60][12] relative to the earnings announcement date. Earnings announcement is a significant and anticipated information event, which triggers strong market reaction. More informed trading happens during this period (Kim and Verrecchia, 1994; Skinner, 1997). Because rational informed traders are expected to weigh the benefits from their private information against the costs of trading, they are likely to care more about option transaction costs than liquidity and noise traders. However, there is less informed trading on a randomly selected date, when no significant information is released. Therefore, we expect option transaction costs to have a much weaker effect on informed trading in the option market in this Pseudo event. In Models 1-3, we find the predictability of IV spread decreases but still remains significant, which is consistent with Cremers and Weinbaum (2010) and Jin, Livnat and Zhang (2012). However, the effect of option transaction costs

[12] We also try other windows: [+0, +30], and [+60, +90] relative to the earnings announcement date. The results remain qualitatively similar.

becomes insignificant in Models 2 and 3 for the Pseudo event. We find similar results in the regressions of IV skew, in Models 4-6.

As a robustness test, we also consider volume-weighted and open interest-weighted measures of IV spread (skew) and transactions costs, and find similar results. For brevity, the results are not tabulated. The above empirical findings are consistent with Easley, O'Hara, and Srinivas (1998): transaction costs play an important role in the informed trading in the option market. Additionally, these results also confirm the our predication about the effect of transaction costs: option trading costs play a more important role during major information events due to the more intense informed trading during these periods.

Chakravarty, Gulen and Mayhew (2004) have argued that the effect of option transaction costs is of secondary importance, compared with the effects of option leverage. However, this does not apply to the volatility spread in our study. We construct the volatility spread by a pair of call and put options, with the same strike price and maturity. The sum of the absolute values of their deltas will always be theoretically equal to 1. There is no cross-sectional and time series variation of leverage (delta) for different volatility spreads.[13] So the effect of leverage cannot substitute the effect of transaction costs for volatility spread. On the other hand, the leverage of volatility skew (the leverage of put option) is positively correlated with its relative bid-ask spread (transaction cost).[14] Therefore the options with higher transaction costs will attract less informed trading, but their higher leverage should attract more informed trading (Easley, O'Hara, and Srinivas;

[13] Empirical data show very small variation in the interval [+0.49, +0.51].
[14] We only consider the leverage of put option here, because call option is only used as a benchmark in the construction of IV skew. The OTM put's leverage is larger than the ITM put's leverage, because its delta-to-premium ratio is larger.

1998). This offsetting effect of transaction costs and leverage should make the statistical significance of option transaction costs weaker, and make it less likely that we will obtain significant results. Despite this offsetting effect of leverage, we still find significant effect of option transaction costs on informed trading, and adds to the strength of our findings.

We also note the differences between our study and the prior work by Amin and Lee (1997), Cremers and Weinbaum (2010) and Atilgan (2014). They also use option relative bid-ask spread to examine the relationship between option liquidity on the predictability of IV spread. In contrast to our study, they use the contemporaneous closing bid-ask spread ratio to measure liquidity and compare predictability of IV spreads with different liquidity. However, given that option trading affects liquidity and predictability simultaneously, it is difficult to make a causality argument between liquidity and predictability of IV spread. Another difference between our study and theirs is the intra-firm comparisons versus the inter-firm comparisons in our study. In their research, option volatility spreads are assigned to three groups according to their liquidity within every stock. The comparison of the predictability of volatility spread is within firm. In other words, their methodology captures the intra-firm variation of the predictability of option volatility spread. However, our methodology captures the inter-firm variation of the predictability of volatility spread. For every firm every quarter, we have one measure of option transaction costs. The Fama-Macbeth regression in our study compares the predictability of volatility spread across all firms in each quarter. Our methodology of inter-firm comparison can help construct an implementable trading strategy in the stock market.

5. Trading Strategy

The above results show that IV spread and IV skew can predict future abnormal stock returns. Our next goal is to construct a stock trading strategy based on these option informed trading measures, and investigate the effect of option transaction costs on the trading profit.

5.1 Base strategy

The base trading strategy is constructed as follows. In every quarter, all firms are assigned to four groups based on the average volatility spread or volatility skew in the pre-earnings announcement window [-7, -1]. Then we have three cutoff points determined by the quartile (25^{th}, 50^{th}, and the 75th percentile) of volatility spread or volatility skew. In quarter t+1, we buy (short) the stocks with volatility spread (skew) larger than the 75th percentile cutoff point of quarter t, and short (buy) the stocks with volatility spread (skew) smaller than the 25th percentile cutoff point in quarter t. From 1996 to 2011, we construct trading portfolios in 63 quarters (from 1996Q2 to 2011Q4). The reason that we only have 63 quarterly portfolios is that we use the first quarter of the sample period, 1996Q1, to construct the stock selection benchmark for the next quarter, and we continue with the same construction process for the following quarters. Therefore, our last stock selection benchmark is the 3rd quarter of 2011. This portfolio formation method is practically implementable and involves no look-ahead bias. Equally-weighted buy-and-hold abnormal returns for this long-short strategy are shown for three periods, [0, +2], [0, +7], and [0, +30].[15] As in Daniel and Titman (1997), the abnormal return is calculated as the return of a particular stock minus the return from a portfolio of stocks of

[15] Value-weighted buy-and-hold return shows qualitative similar results.

similar size (market value of equity, two groups), book-to-market ratio (three groups), and 12-month momentum (three groups. The reported t-statistics of the long-short strategy abnormal return are calculated over the time-series of 63 calendar quarters.

<INSERT TABLE 2.4 HERE>

Table 4 presents the abnormal returns for the implementable trading strategies. Panel A presents the results for volatility spread. As the rank of volatility spread becomes higher, the abnormal return becomes larger. This pattern is close to monotonic. For 3-day holding period, the long-short strategy produces 0.51% abnormal returns. For 1-week holding period, the abnormal return is 0.65%. For 1-month, 2-month and 3-month holding periods, the abnormal returns are 1.05%, 1.15% and 1.76%, respectively. The number of stocks in our portfolio ranges from 216 to 827 over the 63 calendar quarters. The portfolio returns are significant at 1% or 5% level. The magnitude of abnormal return increases as the holding period becomes longer. These results imply that the implied volatility spread can predict abnormal stock returns for up to 3 months after the earnings announcement. .

Panel B presents the results for volatility skew. As volatility skew becomes larger, the abnormal return becomes smaller monotonically. The abnormal returns for holding period [0, +2], [0, +7] and [0, +30] are 0.61%, 0.83%, and 1.17%, respectively. All of them are significant at 1% level over the 63 calendar quarters. And for 2-month and 3-month holding period, the abnormal returns are 1.50% and 1.75%, respectively. Both of them are significant at 5% level. The number of stocks in the portfolio ranges from 158 to 510 over the 63 calendar quarters. Similar to the findings for volatility spread, the abnormal return becomes larger as the holding period becomes longer. These results imply that the implied volatility skew can predict abnormal stock returns for up to 3 months after the earnings announcement.

It is important to note that our trading strategy and stock portfolio is constructed before the anticipated earnings announcement based on information solely from option market. This makes our trading strategy practically implementable. Our result is also in line with previous literature documenting that option market leads stock market in the price discovery process (Pan and Poteshman (2006), Ni, Pan and Poteshman (2008), Bali and Hovakimian (2009), Cremers and Weinbaum (2010), Xing, Zhang and Zhao (2010), Jin, Livnat and Zhang (2012), Johnson and So (2012), An et al. (2014)).

5.2 Improved strategy incorporating option transaction costs

As shown in Table 3, informed trading in the option market is stronger among firms with lower option relative bid-ask spread. Therefore, we next show that by incorporating transaction costs when constructing the trading portfolio, we can improve substantially the abnormal returns obtained from our Base strategy in subsection A.

Similar to the benchmark selection of volatility spread (skew), in quarter t, the average option transaction costs in the pre-earnings announcement window [-7, -1] is assigned to 4 groups. So we have 3 quartiles (25th, 50th, and 75th percentile) for quarter t. Then, in quarter t+1, we select stocks whose option transaction costs in the pre-earnings announcement window [-7, -1] fall into the highest and lowest quartile from quarter t. Within these two groups of stocks, we repeat the portfolio formation step in the above subsection A to construct the long-short trading portfolios. Our results are presented in table 5.

<INSERT TABLE 2.5 HERE>

Panel A of Table 5 presents the portfolio abnormal returns based on volatility spread and transaction costs. For low transaction costs group, abnormal returns increase monotonically with the rank of volatility spread. The abnormal portfolio returns of the low transaction costs group increase from 0.91% to 3.03% as the holding period increases from [0, +2] to [0, +90], and are statistically significant (except for the 2-month holding period). More importantly, for all holding periods, the abnormal portfolio returns are larger than the corresponding abnormal returns from the base strategy. The number of stocks in the portfolio ranges from 54 to 359 over the 63 calendar quarters, which provides a large enough stock pool for the trading strategy. It may be worth noting that while the new strategy incorporating transaction costs outperforms the base strategy across all 5 holding periods, the statistical significance (t-statistics) decreases. One possible reason is that, the standard error of abnormal returns now come from two sources, namely volatility spread and transaction costs, instead of just one source (only volatility spread) as in the base strategy. It is possible that introducing this extra dimension increases standard error and decreases the significance level of abnormal returns.

In the high transaction costs group, we do not find a monotonic relationship between the rank of volatility spread and abnormal stock returns. The abnormal portfolio returns are smaller than the abnormal returns from the base strategy and insignificant. This suggests that the predictability of volatility spread deteriorates when option transaction costs are high.

Panel B of Table 5 presents the portfolio abnormal return based on volatility skew and transaction costs. For low transaction costs group, abnormal returns decreases monotonically with the rank of volatility skew. The abnormal portfolio returns of the low transaction costs group increase from 0.65% to 2.46% as the holding period increases from [0, +2] to [0, +90], and are statistically significant. More importantly, for all holding periods, the abnormal portfolio returns are larger than the corresponding abnormal returns from the base strategy. The number of stocks in the portfolio ranges from 58 to 241 over the 63 calendar quarters. In the high transaction costs group, we do not find a monotonic relationship between the rank of volatility skew and abnormal stock returns. The abnormal portfolio returns are smaller than those from the base strategy and insignificant.

For the high transaction costs group, the abnormal returns for the 5 different holding periods are insignificant, and smaller than the corresponding abnormal returns from Base strategy. In a nutshell, the above results from panel A and Panel B show that incorporating option transaction costs effect can largely improve the performance of the implementable trading strategies based on volatility spread and volatility skew. More importantly, option transaction costs can still maintain its information-filtering function in this out-of-sample trading strategy analysis, in addition to the in-sample regression analysis in Section IV.

<INSERT FIGURE 2.3 HERE>

Figure 3 presents the quarterly time-series abnormal return of implementable trading strategies in Table 4 and 5. Abnormal portfolio returns for the 1-month ([0, +30]) holding period are displayed over 63 quarters (from 1996Q2 to 2011Q4). Figure 3a presents the quarterly abnormal return series for the base strategy of volatility spread. Figure 3b presents the abnormal return series for the improved strategy based on volatility spread and transaction costs. The green bar represents the abnormal return of low transaction costs group and the red bar represents the abnormal return of high transaction costs group. In 38 of the total 63 quarters (60%), the low transaction costs group produces higher abnormal returns than the high transaction costs group. Compared to abnormal return series in figure 3a, the two groups of abnormal return series in figure 3b become more volatile. This is consistent with the above result that adding one more dimension (transaction costs) into the trading strategy induces higher volatility of portfolio returns. Figure 3c presents the quarterly abnormal return series for the base strategy of volatility skew. Figure 3d presents the abnormal return series for the improved strategy based on volatility skew and transaction costs. Similarly, the green bar represents the low transaction costs group and the red bar represents high transaction costs group. In 39 of the total 63 quarters (62%), low transaction group produces higher abnormal returns than high transaction costs group.

6. The impact of option transaction costs on volatility-related informed trading

In this section, we investigate whether ex ante transaction costs affect volatility-related informed trading (second moment informed trading, namely, informed trading based on private information about the future volatility of the underlying stock return) in the option market. Specifically, we study the effect of option transaction costs on the predictability of implied volatility for the future absolute abnormal returns. It is worth noting that since we are predicting the future absolute returns, we cannot easily exploit the results to construct trading strategies that earn abnormal returns in the stock market.

6.1 The impact of option transaction costs on the predictability of implied volatility

Table 6 shows the impact of transaction costs on the predictability of implied volatility for future absolute abnormal returns. The dependent variables are the absolute abnormal returns in the window [0, +2]. Following previous literature(e.g., Harvey and Whaley, 1992; Canina and Figlewski, 1993; Jorion,1995; and Christensen and Prabhala, 1998), the predictor we use is the implied volatility of ATM call options. The models are estimated using the Fama–MacBeth regressions over 64 calendar quarters. Results for earnings announcement sample and Pseudo event sample are reported in Models 1 to 3, and Models 4 to 6, respectively.

<INSERT TABLE 2.6 HERE>

For the earnings announcement sample, we find that the implied volatility in the Base window and Pre window are both positively and significantly associated with absolute abnormal returns in the window [0, +2] (Model 1). However, the coefficient and statistical significance for the Pre window implied volatility are much larger than those for the Base window implied volatility, suggesting stronger informed trading in the Pre window. In Model 2, we add the proxy for *ex ante* transaction costs and its interaction with the implied volatility in the Pre window. The coefficient for the interaction is -0.065, significant at 1% level. This implies that investors with volatility information are more likely to trade options with lower transaction costs. In model 3, we add more control variables to check the robustness of our results. The control variables include firm size, book-to-market ratio, historical stock returns volatility, and absolute abnormal returns in the Pre Window. After controlling for these variables, we still find a negative and significant coefficient for the interaction between the option bid-ask spread and implied volatility.

We perform similar analysis for the sample of randomly chosen dates. We find that the implied volatility in Pre window also has predictability for future abnormal stock returns (Model 4). However, the coefficient for implied volatility in the Pre window is only half as large compared to the earnings announcement sample, suggesting a weaker predictability around random dates. The effect of *ex ante* transaction costs on the predictability of implied volatility is marginally significant in Model 5. After controlling for other variables, the effect becomes insignificant (Model 6). These results show consistent patterns with those in the directional informed trading from Section IV: option transaction costs play an important role in the informed trading, and its effect is only significant around information-intensive events.

6.2 The impact of option transaction costs on the predictability of O/S ratio

<INSERT TABLE 2.7 HERE>

Table 7 shows the impact of transaction costs on the predictability of O/S ratio for future absolute abnormal returns. The dependent variables are the absolute abnormal returns in the window [0, +2]. The models are estimated using the Fama–MacBeth regressions over 64 calendar quarters. Results for earnings announcement sample and random date sample are reported in Models 1 to 3 and Models 4 to 6, respectively.

We first discuss results for the earnings announcement sample. Consistent with Roll, Schwartz, and Subrahmanyam (2010), we find that O/S ratio in the Pre window can predict absolute abnormal returns in the earnings announcement window [0, +2] (Model 1). This indicates that the larger ratio of options trading volume to stock trading volume prior to an earnings announcement is, ceteris paribus, associated with a larger absolute price movement during the earnings announcement window. In Model 2, we add the proxy for transaction costs (relative bid-ask spread) and its interaction with the O/S ratio in the Pre window. For consistency, we use the relative bid-ask spread of the underlying stock to scale the option relative bid-ask spread when measuring option transaction cost. Interestingly, the O/S ratio is a significantly stronger predictor of absolute abnormal returns over the earnings announcement window [0, +2] when the option bid-ask spread ratio is higher relative to the underlying stock bid-ask spread ratio. Since the O/S ratio is a response to the previous day's closing bid-ask spread, it can be viewed as an *ex post* measure of realized option trading activity conditioned on the knowledge of the transaction cost. In other words, the option trading volume is the result of a rational calculation between expected gains from private information and expected losses from transaction costs by informed traders. If an investor is willing to trade in the option market despite of the higher transaction costs, it is more likely that the investor has more accurate or more profitable private information. Higher transaction cost plays the role of a barrier and filter, and helps separate noise trading from informed trading. Therefore, we find that, for a given level of realized O/S ratio, the higher the transaction cost of options relative to that of the underlying stock prior to trading, the higher the absolute abnormal stock returns around the earnings announcements. This suggests that there is more informed trading in these options. In Model 3, we add more control variables to check the robustness of our results. The control variables include firm size, book-to-market ratio, historical stock returns volatility, implied volatility of ATM options and absolute abnormal returns in the Pre window. After controlling for these variables, we still find a positive coefficient for the interaction between relative bid-ask spread and the statistical significance level increases from 10% to 5%.

For the Random date sample, we find O/S ratio in Pre window also has predictability for future abnormal stock returns (Model 4). However, the coefficient and statistical significance for O/S ratio in the Pre window are much smaller than those in the earnings announcement sample, suggesting a weaker predictability around Random date. More importantly, the effect of transaction costs on the predictability of O/S ratio becomes insignificant, as shown in Model 5 and Model 6.

Taken together, we find significant impact of ex ante transaction costs on the volatility informed trading in the option market around earnings announcements. Specifically, the implied volatility of ATM options is more informative about future abnormal returns when the relative bid-ask spread at the end of the previous trading day is lower. For a given level of O/S ratio, the higher the transaction costs of options relative to that of the underlying stock, the stronger the information revealed from O/S ratio about future abnormal returns. However, we find no significant role of transaction costs in the Random dates sample.

7. Conclusions

In this study, we investigate the effect of ex ante option transaction costs on the informed trading in the option market. We examine two forms of informed trading: directional-based and volatility-based informed trading. We find that both forms of informed trading in the option market are significantly stronger among firms with lower option relative bid-ask spread. We also document that option transaction costs have different effects in different information environments. It has significant effect around earnings announcements, but not around random days with no events of consequence. This suggests that transaction costs play a particularly important role during information intensive periods. We also build a trading strategy, which produces abnormal monthly return of 1.05% (1.17%) based on volatility spread (skew). After considering transaction costs, the performance increases to 1.39% (1.91%) per month at significance level of 5% (1%).

One limitation of our study is the data. As we do not have the transaction level data, we can only use the methodology of lead-lag relationship between option market and stock market to investigate the effect of transaction costs. It might also be interesting to use the transaction level data and apply methodology such as Hasbrouck's information share (Hasbrouck, 1991) to explore the effects of option transaction costs in the future.

Figure 2.1: Research design window

This figure shows research design window: Trading day [-30,-8] is the based window. Trading day [-7,-1] is the prediction window. Trading day [0,+2] is event window. Earnings announcement date is the trading day 0.

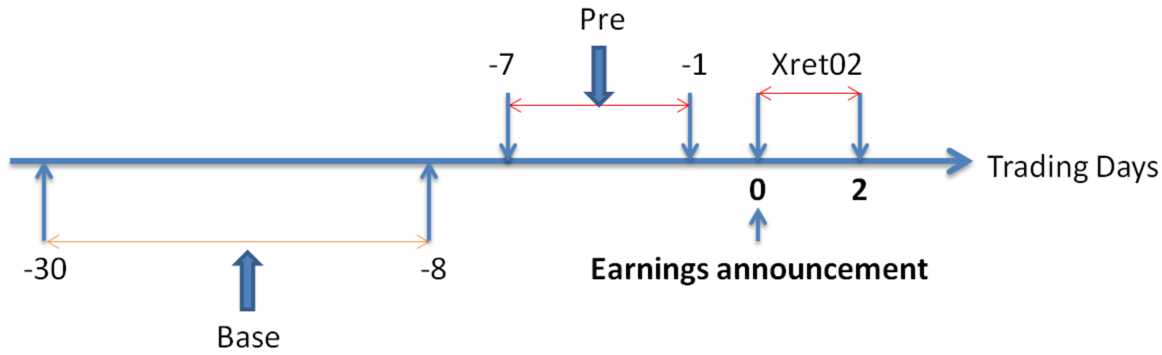
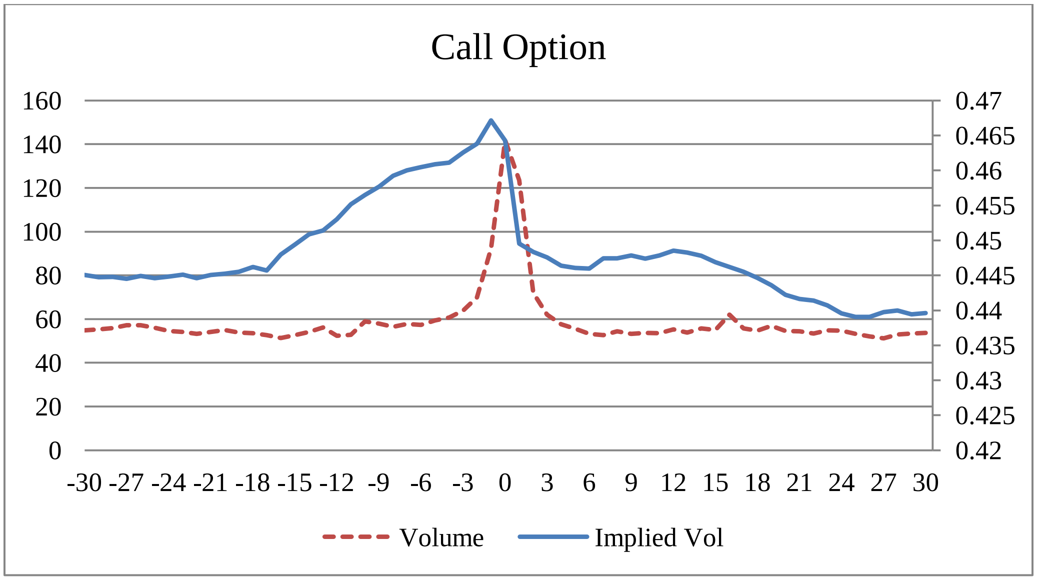


Figure 2.2: Options Trading Volume and Implied Volatility around Earnings Announcements

This figure shows the movement of option implied volatility and option trading volume around earning announcement in the trading day window [-30,+30], where earnings announcement is day 0. The solid blue line is the option implied volatility and the red dashed line is the option trading volume. Panel A presents the implied volatility and trading volume of call option, and Panel B presents put option. The sample period is from 1996 to 2011.

Panel A: Call option—volume and implied volatility around earnings announcements



Panel B: Put option—volume and implied volatility around earnings announcements

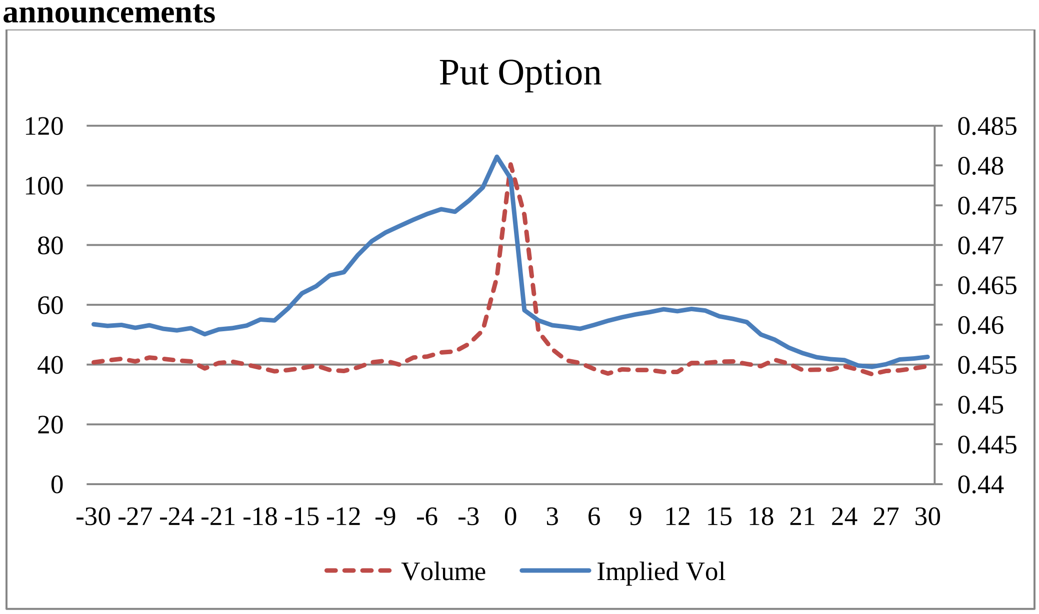


Figure 2.3: Trading Strategies and Abnormal Returns

This figure presents the quarterly time-series abnormal return of implementable trading strategy in Tables 4 and 5. Abnormal portfolio returns for the 1-month ([0, +30]) holding period are displayed over 63 quarters (from 1996Q2 to 2011Q4). Figure 3a presents the quarterly abnormal return series for the base strategy of volatility spread. Figure 3b presents the abnormal return series for the improved strategy based on volatility spread and transaction costs. The green (red) bar represents the abnormal return of low (high) transaction costs group. Figure 3c presents the quarterly abnormal return series for the base strategy of volatility skew. Figure 3d presents the abnormal return series for the improved strategy based on volatility skew and transaction costs. The green (red) bar represents the low (high) transaction costs group.

Figure 2.3a: IV Spread

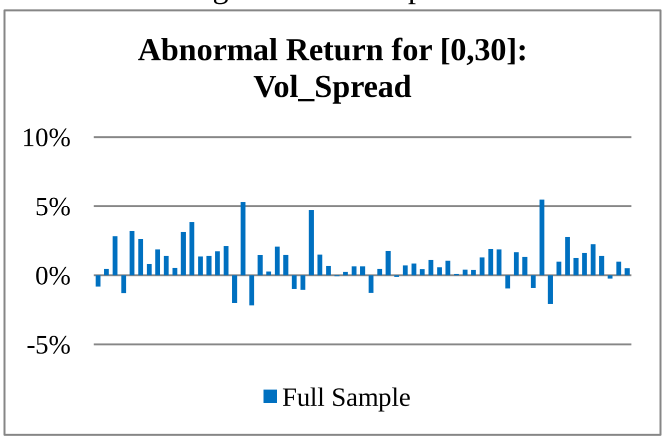


Figure 2.3b: IV Spread and Option Transaction Costs

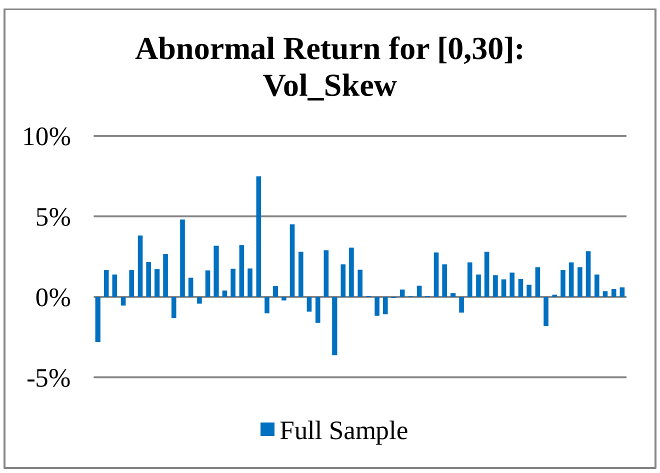


Figure 2.3c: IV Skew

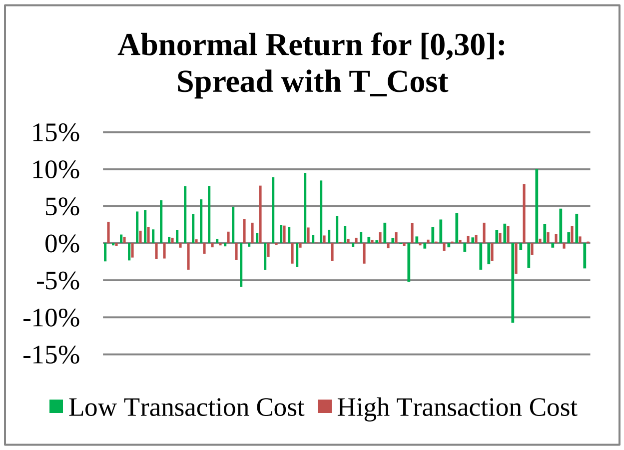


Figure 2.3d: IV Skew and Option Transaction Costs

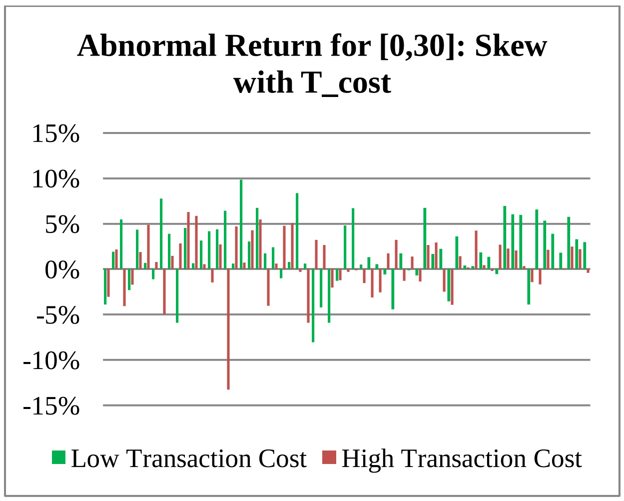


Table 2.1: Summary Statistic

This table presents the summary statistics of regression variables. Panel A presents the variables used in the implied volatility spread regression. Panel B presents the variables used in the implied volatility skew regression. Panel C presents the variables used in the O/S ratio regression. Size is the log of market capitalization and BM is the log of book to market ratio. The sample period is from the year 1996 to 2011. The 5th (P5), 25th (P25), 75th (P75) and 95th (P95) percentile are presented. See the appendix for definitions of the variables.

	N	Mean	SD	P5	P25	Median	P75	P95
Panel A: IV Spread Sample								
XRET02	92,504	0.001	0.091	-0.140	-0.040	0.000	0.043	0.144
XRET71	92,504	0.003	0.062	-0.096	-0.029	0.001	0.031	0.108
_Base	92,504	-0.010	0.030	-0.059	-0.017	-0.007	0.000	0.028
_Pre	92,504	-0.010	0.036	-0.068	-0.020	-0.007	0.003	0.039
BAspd	92,504	0.317	0.199	0.103	0.180	0.265	0.392	0.718
Size	92,504	7.323	1.512	5.046	6.222	7.198	8.264	10.073
BM	92,504	-0.962	0.797	-2.420	-1.409	-0.885	-0.434	0.223
Momentum	92,504	0.181	0.626	-0.583	-0.186	0.087	0.382	1.261
Hvol	92,504	0.448	0.283	0.158	0.258	0.375	0.554	0.989
Panel B: IV Skew Sample								
XRET02	66,872	0.001	0.091	-0.142	-0.042	0.001	0.045	0.145
XRET71	66,872	0.004	0.070	-0.096	-0.029	0.002	0.034	0.110
_Base	66,872	0.030	0.059	-0.023	0.007	0.023	0.044	0.106
_Pre	66,872	0.035	0.073	-0.033	0.008	0.027	0.053	0.128
BAspd	66,872	0.341	0.293	0.077	0.155	0.254	0.421	0.902
Size	66,872	7.611	1.502	5.445	6.501	7.434	8.554	10.335
BM	66,872	-1.071	0.840	-2.503	-1.511	-0.990	-0.529	0.106
Momentum	66,872	0.265	1.169	-0.539	-0.158	0.117	0.436	1.408
Hvol	66,872	0.453	0.272	0.169	0.270	0.383	0.556	0.976

Panel C: IV_ATM Sample

AXRET02	92,474	0.064	0.068	0.003	0.019	0.043	0.086	0.194
AXRET71	92,474	0.053	0.061	0.003	0.015	0.035	0.068	0.161
_Base	92,474	0.500	0.240	0.213	0.329	0.446	0.618	0.962
_Pre	92,474	0.515	0.254	0.216	0.335	0.458	0.637	1.000
BAspd	92,474	0.201	0.198	0.050	0.095	0.147	0.234	0.515
Size	92,474	7.414	1.529	5.196	6.305	7.244	8.348	10.191
BM	92,474	-1.041	0.860	-2.525	-1.489	-0.953	-0.488	0.162
Hvol	92,474	0.467	0.291	0.168	0.271	0.390	0.576	1.032

Panel D: O/S ratio Sample

AXRET02	81,237	0.063	0.067	0.004	0.019	0.043	0.085	0.191
AXRET71	81,237	0.051	0.060	0.003	0.015	0.034	0.066	0.156
_Base	81,237	-3.604	1.231	-5.596	-4.474	-3.618	-2.741	-1.580
_Pre	81,237	-3.386	1.310	-5.611	-4.275	-3.333	-2.447	-1.339
OS_BAspd	81,237	5.512	5.955	0.196	0.820	3.975	7.861	16.733
Size	81,237	7.410	1.510	5.221	6.321	7.248	8.321	10.157
BM	81,237	-1.029	0.850	-2.489	-1.469	-0.942	-0.484	0.154
Hvol	81,237	0.455	0.282	0.164	0.265	0.380	0.559	1.001
IV_ATM	81,237	0.503	0.246	0.211	0.330	0.449	0.621	0.972

Table 2.2: Correlation Analysis

This table shows the correlation matrix of variables in the IV Spread sample, IV Skew sample and O/S Ratio sample, respectively. Spearman correlations are reported above the main diagonal and Pearson correlations are reported below the main diagonal. * denotes significance at 1% level. See appendix for variable definitions.

Panel A: IV Spread Sample

	XRET02	*XRET71*	*_Base*	*_Pre*	*BAspd*	*Size*	*BM*	*Momentum*	*Hvol*
XRET02	1	-0.060*	0.003	0.0217*	0.004	0.033*	0.004	0.001	-0.029*
XRET71	-0.060*	1	0.010*	-0.0807*	-0.039*	0.008	-0.015*	0.020*	0.002
_Base	0.005	0.012*	1	0.4628*	-0.001	-0.016*	0.043*	-0.024*	-0.057*
_Pre	0.018*	-0.059*	0.595*	1	-0.011*	-0.010*	0.025*	0.007	-0.053*
BAspd	0.005	-0.037*	-0.038*	-0.042*	1	-0.396*	0.297*	-0.120*	-0.085*
Size	0.017*	-0.017*	0.023*	0.015*	-0.358*	1	-0.243*	0.229*	-0.478*
BM	0.011*	-0.009*	0.045*	0.029*	0.252*	-0.238*	1	-0.382*	0.034*
Momentum	-0.019*	0.014*	-0.010*	0.008	-0.114*	0.114*	-0.385*	1	-0.250*
Hvol	-0.020*	0.044*	-0.082*	-0.077*	-0.054*	-0.390*	0.043*	-0.093*	1

Panel B: IV Skew Sample

	XRET02	*XRET71*	*_Base*	*_Pre*	*BAspd*	*Size*	*BM*	*Momentum*	*Hvol*
XRET02	1	-0.062*	-0.007	-0.019*	-0.003	0.024*	0.009	-0.012*	-0.022*
XRET71	-0.061*	1	-0.013*	0.036*	-0.002	-0.009	-0.006	0.015*	0.010*
_Base	-0.005	-0.013*	1	0.390*	-0.057*	-0.053*	0.037*	-0.100*	0.240*
_Pre	-0.015*	0.011*	0.383*	1	-0.014*	-0.036*	0.041*	-0.109*	0.190*
BAspd	-0.001	0.001	0.051*	0.089*	1	-0.487*	0.262*	-0.107*	-0.034*
Size	0.014*	-0.028*	-0.067*	-0.049*	-0.372*	1	-0.180*	0.135*	-0.456*
BM	0.015*	-0.001	0.034*	0.034*	0.201*	-0.172*	1	-0.374*	-0.008
Momentum	-0.018*	0.010	-0.034*	-0.035*	-0.059*	0.011*	-0.255*	1	-0.197*
Hvol	-0.014*	0.050*	0.187*	0.147*	-0.066*	-0.366*	0.002	0.027*	1

Panel C: IV_ATM Sample

	AXRET02	*AXRET71*	*_Base*	*_Pre*	*BAspd*	*Size*	*BM*	*Hvol*
AXRET02	1	0.164*	0.345*	0.357*	0.017*	-0.211*	-0.032*	0.302*
AXRET71	0.192*	1	0.394	0.404	0.049*	-0.227*	-0.023*	0.384*
_Base	0.340*	0.429*	1	0.963*	0.097*	-0.553*	-0.012*	0.885*
_Pre	0.359*	0.444*	0.944*	1	0.089*	-0.541*	-0.026*	0.868*
BAspd	0.011*	0.021*	0.068*	0.079*	1	-0.567*	0.296*	0.078*
Size	-0.206*	-0.216*	-0.481*	-0.463*	-0.379*	1	-0.194*	-0.458*
BM	-0.023*	-0.030*	-0.037*	-0.049*	0.209*	-0.184*	1	-0.016*
Hvol	0.298*	0.410*	0.843*	0.813*	0.027*	-0.362*	-0.029*	1

Panel D: O/S Ratio Sample

	AXRET02	*AXRET71*	*_Base*	*_Pre*	*Os_BAspd*	*Size*	*BM*	*Hvol*	*IV_ATM*
AXRET02	1	0.159*	0.031*	0.044*	-0.092*	-0.217*	-0.023*	0.302*	0.359*
AXRET71	0.185*	1	0.048*	0.038*	-0.246*	-0.234*	-0.012*	0.384*	0.405*
_Base	0.025*	0.042*	1	0.834*	-0.059*	0.193*	-0.236*	0.091*	0.124*
_Pre	0.038*	0.035*	0.834*	1	-0.021*	0.197*	-0.230*	0.058*	0.101*
OS_BAspd	-0.140*	-0.215*	-0.054*	-0.039*	1	0.336*	0.055*	-0.442*	-0.433*
Size	-0.213*	-0.227*	0.242*	0.231*	0.332*	1	-0.209*	-0.461*	-0.542*
BM	-0.011*	-0.013*	-0.233*	-0.220*	0.036*	-0.199*	1	0.005	-0.007
Hvol	0.298*	0.412*	0.067*	0.042*	-0.362*	-0.369*	0.001	1	0.866*
IV_ATM	0.359*	0.445*	0.109*	0.089*	-0.395*	-0.465*	-0.024*	0.812*	1

Table 2.3: The Effect of Option Transaction Cost on the Predictability of IV Spread and IV Skew

This table shows the impact of option bid-ask spread on the predictability of IV Spread and IV Skew for future abnormal returns around earnings announcements and randomly selected days. The dependent variables in Panels A and B are 3-day ([0,+2]) abnormal returns around quarterly earnings announcements and Pseudo event day, respectively. The Random day is a randomly selected trading day in the calendar window of [+30,+60] relative to the earnings announcement date. Models 1-3 show the effect of transaction costs on the predictability of IV Spread and Models 4-6 show the effect of transaction cost on the predictability of IV Skew. The coefficients are estimated with Fama-MacBeth regressions. The t-statistics are adjusted using Newey and West (1987) procedures with four lags. ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively, based on two-tailed t-tests. See appendix for variable definitions.

Panel A: Earnings Announcements

	Dependent Variable: XRET02					
	IV Spread			**IV Skew**		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
_Base	-0.033**	-0.037***	-0.029**	-0.007	-0.006	-0.003
	(-2.40)	(-2.73)	(-2.12)	(-0.65)	(-0.58)	(-0.30)
_Pre	**0.074*** **	0.126***	0.103***	**-0.036*** **	-0.071***	-0.060***
	(5.60)	(5.24)	(4.43)	(-3.53)	(-4.74)	(-4.25)
BAspd		0.003	-0.001		0.000	-0.003
		(1.53)	(-0.60)		(0.01)	(-1.44)
*BAspd*_Pre*		**-0.117*** **	**-0.091** **		**0.068** **	**0.053** **
		(-2.69)	(-2.13)		(2.37)	(2.08)
Size			0.000			-0.000
			(0.49)			(-0.16)
BM			0.000			0.001
			(0.62)			(1.51)
Momentum			-0.001			-0.001
			(-1.27)			(-1.50)
XRET71			-0.079***			-0.074***
			(-9.18)			(-7.94)
Hvol			-0.014***			-0.012***
			(-5.15)			(-4.74)
Constant	0.002***	0.001	0.008**	0.002***	0.002**	0.011***
	(2.79)	(1.38)	(2.09)	(2.74)	(2.23)	(2.88)
N	92,504	92,504	92,504	66872	66872	66872
Adj.R-Squared	0.002	0.004	0.015	0.004	0.007	0.019

Panel B: Random Days

	Dependent Variable: XRET02					
	IV Spread			**IV Skew**		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
_Base	-0.019*	-0.020*	-0.018	0.004	0.005	0.003
	(-1.79)	(-1.75)	(-1.55)	(0.54)	(0.59)	(0.45)
_Pre	**0.023*****	0.033**	0.031**	**-0.014****	-0.008	-0.006
	(2.71)	(2.40)	(2.25)	(-2.39)	(-0.91)	(-0.68)
BAspd		0.001	0.001		0.001	0.001
		(0.24)	(0.33)		(0.87)	(0.88)
*BAspd*_Pre*		**-0.014**	**-0.013**		**-0.008**	**-0.010**
		(-0.79)	(-0.74)		(-0.69)	(-0.82)
Size			-0.001			0.002
			(-0.07)			(0.05)
BM			-0.002			0.001
			(-0.34)			(0.28)
Momentum			0.001			0.001
			(0.73)			(1.01)
XRET71			-0.024***			-0.020***
			(-5.37)			(-3.66)
Hvol			-0.008***			-0.007***
			(3.35)			(3.22)
Constant	0.001	-0.002	-0.002	-0.000	-0.001	-0.001
	(0.00)	(-0.02)	(-0.03)	(-0.54)	(-0.83)	(-0.38)
N	94,557	94,557	94,557	67,333	67,333	67,333
Adj.R-Squared	0.003	0.006	0.014	0.005	0.009	0.019

Table 2.4: Trading Strategies based on IV Spread or IV Skew

This table shows the equal-weighted buy-and-hold abnormal returns for each volatility spread portfolio (Panel A) or volatility skew portfolio (Panel B). All returns are shown in percentage. Every quarter, firms are assigned to four groups based on the average volatility spread or volatility skew in the pre-earnings announcement window [-7,-1]. The cutoff point is determined by the quartile (25th, 50th and 75th percentile) of volatility spread or volatility skew from the previous quarter, which ensures that there is no look-ahead bias in the portfolio construction. Buy-and-hold abnormal returns are shown for five periods: [0,+2], [0,+7], [0,+30], [0,+60] and [0,+90]. Following Daniel and Titman (1997), the abnormal return is calculated as the return on a particular stock minus the return from a portfolio of stocks of similar size (market value of equity, two groups), book-to-market ratio (three groups), and 12-month momentum (three groups). Reported t-statistics are based on the difference in high and low portfolios over the time-series of calendar quarters.

Panel A: Portfolios based on IV Spread

IV Spread	Holding Period				
	[0,+2]	[0,+7]	[0,+30]	[0,+60]	[0,+90]
Low	-0.31	-0.44	-0.31	-0.69	-1.11
2	0.14	0.10	0.35	0.12	0.11
3	0.24	0.26	0.56	0.41	0.44
High	0.20	0.21	0.74	0.45	0.65
High-Low	0.51***	0.65***	1.05***	1.15**	1.76***
t-stat	(3.98)	(3.77)	(2.88)	(2.23)	(2.82)

Panel B: Portfolios based on IV Skew

IV Skew	Holding Period				
	[0,+2]	[0,+7]	[0,+30]	[0,+60]	[0,+90]
Low	0.33	0.33	0.77	0.42	0.45
2	0.29	0.28	0.56	0.38	0.60
3	-0.05	-0.17	0.01	0.18	0.22
High	-0.28	-0.50	-0.40	-1.08	-1.30
Low-High	0.61***	0.83***	1.17***	1.50**	1.75**
t-stat	(3.82)	(4.06)	(2.77)	(2.60)	(2.37)

Table 2.5: Improved Trading Strategies

This table shows the impact of transaction cost and leverage on volatility spread or volatility skew portfolio returns. All returns are shown in percentage. Firms are sorted into four groups each quarter based on the average option bid-ask spread in the Pre window [-7,-1]. Firms in the first (fourth) group have the lowest (highest) bid-ask spread or low (high) transaction costs. The cutoff point is determined by the quartile (25th, 50th and 75th percentile) of bid-ask spread from the previous quarter, which ensures that there is no look-ahead bias in the portfolio construction. Then we show the volatility spread or volatility skew portfolio returns for firms with high and low transaction costs separately. The volatility spread or volatility skew portfolio returns are calculated in the same way as described in Table 4.

Panel A: Portfolios based on IV Spread and Transaction Costs

Holding Period	[0,+2]		[0,+7]		[0, +30]		[0, +60]		[0, +90]	
	Transaction Costs		Transaction Cost		Transaction Costs		Transaction Costs		Transaction Costs	
IV Spread	Low	High	Low	High	Low	High	Low	High	Low	High
Low	-0.66	-0.03	-1.05	-0.01	-1.01	0.19	-1.72	-0.03	-2.39	-0.32
2	-0.05	0.27	-0.26	0.40	-0.02	0.92	-0.31	0.48	-0.10	0.21
3	0.04	0.15	-0.04	0.15	0.19	0.46	-0.27	0.67	-0.08	0.88
High	0.25	0.21	0.09	0.23	0.38	0.61	-0.00	0.48	0.64	0.65
High-Low	0.91***	0.24	1.13***	0.24	1.39**	0.42	1.72	0.51	3.03**	0.97
t-stat	(3.06)	(1.44)	(3.36)	(1.06)	(2.01)	(1.19)	(1.58)	(1.00)	(2.11)	(1.61)

Panel B: Portfolios based on IV Skew and Transaction Costs

Holding Period	[0, +2]		[0, +7]		[0, +30]		[0, +60]		[0, +90]	
	Transaction Cost		Transaction Cost		Transaction Cost		Transaction Cost		Transaction Cost	
IV Skew	Low	High	Low	High	Low	High	Low	High	Low	High
Low	0.18	0.24	0.14	0.28	0.87	0.77	0.24	0.41	0.18	0.54
2	0.13	0.41	-0.01	0.59	0.24	0.67	-0.14	0.96	0.36	1.24
3	-0.23	0.10	-0.44	0.02	-0.36	0.22	-0.67	0.10	-0.49	0.08
High	-0.47	-0.14	-0.86	-0.28	-1.03	0.25	-2.00	0.18	-2.28	-0.65
Low-High	0.65**	0.38	1.00***	0.55**	1.91***	0.50	2.24**	0.59	2.46**	1.19
t-stat	(2.32)	(1.62)	(3.01)	(2.06)	(2.81)	(0.96)	(2.33)	(0.90)	(2.02)	(1.50)

Table 2.6:The Impact of Transaction Costs on the Predictability of IV_ATM for Future Absolute Abnormal Returns

This tables shows the impact of transaction costs (option relative bid-ask spread) on the predictability of implied volatility of ATM call options for absolute abnormal returns over the 3-day window [0,+2] around earnings announcements and Random dates. The Random date is a randomly selected trading day in the calendar window of [+30,+60] relative to the earnings announcement date. AXRET02 and AXRET71 used in the following regressions are in percentage. The coefficients are estimated using Fama–MacBeth regressions over 64 calendar quarters. T-statistics reported in parentheses are based on Newey and West (1987) adjusted standard errors using four lags. ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively, based on two-tailed t-tests. See appendix for variable definitions.

	Earnings Announcement Sample			**Pseudo Event Sample**		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
_Base	0.012**	0.005	-0.004	0.015***	0.012**	0.005
	(2.16)	(1.35)	(-0.89)	(2.73)	(2.36)	(1.01)
_Pre	**0.092*** **	0.115***	0.100***	**0.047*** **	0.054***	0.045***
	(13.84)	(21.21)	(15.94)	(7.08)	(9.12)	(7.82)
OS_BAspd		0.026***	0.008		0.007***	0.002
		(5.41)	(1.59)		(2.78)	(0.77)
*OS_BAspd*_Pre*		**-0.065*** **	**-0.049*** **		**-0.011* **	**-0.002**
		(-5.83)	(-4.41)		(-1.70)	(-0.35)
Size			-0.004***			-0.001***
			(-7.32)			(-4.81)
BM			-0.001***			-0.001***
			(-3.78)			(-4.88)
Hvol			0.000			0.007***
			(0.05)			(6.82)
AXRET71			0.035***			0.042***
			(4.43)			(9.90)
Constant			0.040***	0.002***	0.000	0.006***
			(7.08)	(4.72)	(0.20)	(3.71)
N	92,474	92.474	92,474	88,616	88,616	88,616
Adj.-R squared	0.112	0.118	0.129	0.122	0.130	0.142

Table 2.7:The Impact of Transaction Costs on the Predictability of O/S Ratio for Future Absolute Abnormal Returns

This tables shows the impact of transaction costs (option bid-ask spread relative to stock bid-ask spread) on the predictability of O/S ratio for absolute abnormal returns over the 3-day window [0,+2] around earnings announcements and Random dates s. The Random date is a randomly selected trading day in the calendar window of [+30,+60] relative to the earnings announcement date. AXRET02 and AXRET71 used in the following regressions are in percentage. The coefficients are estimated using Fama–MacBeth regressions over 64 calendar quarters. T-statistics reported in parentheses are based on Newey and West (1987) adjusted standard errors using four lags. ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively, based on two-tailed t-tests. See appendix for variable definitions.

	Earnings Announcement Sample			**Pseudo Event Sample**		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
_Base	-0.049	-0.084	-0.218***	0.118**	0.112**	0.034
	(-0.68)	(-1.22)	(-6.13)	(2.54)	(2.49)	(1.47)
_Pre	**0.363*** **	0.334***	0.205***	**0.096*** **	0.104***	0.009
	(9.43)	(5.26)	(4.35)	(4.66)	(2.88)	(0.37)
OS_BAspd		-0.246	0.167**		-0.246	-0.026
		(-1.20)	(2.02)		(-1.63)	(-0.59)
*OS_BAspd*_Pre*		**0.072* **	**0.045** **		**-0.001**	**-0.009**
		(1.84)	(2.02)		(-0.02)	(-0.68)
Size			-0.332***			-0.107***
			(-6.16)			(-8.61)
BM			-0.194***			-0.105***
			(-3.95)			(-3.88)
Hvol			0.211			0.950***
			(0.66)			(7.16)
IV_ATM			7.955***			4.222***
			(16.36)			(13.34)
AXRET71			0.029***			0.040***
			(3.49)			(10.88)
Constant	7.366***	8.322***	4.216***	4.013***	4.589***	1.370***
	(20.55)	(27.10)	(5.67)	(11.90)	(17.78)	(6.78)
N	81,237	81,237	81,237	77,050	77,050	77,050
Adj.-R squared	0.007	0.035	0.127	0.007	0.033	0.139

ESSAY 3: The Effects of Credit Default Swaps trading on Analyst Forecast Properties

1.Introduction

This paper investigates the effects of a financial instrument innovation on analyst forecast properties. The financial instrument innovation we focus is the credit default swaps, which are widely used by lenders to manage credit risk and speculators to arbitrage mispricing profit. In the last two decades, there has been an explosive growth in the credit default swaps market, with the notional amount increasing from $300 billion in 1998 to $57 trillion at the end of June 2008 and decreasing to 19.4 trillion at June 2014[1]. Given the large size of credit default swaps market, it's crucial to identify and quantify the potential effects of this new market on different groups in the capital market. In this paper, we focus on the group of equity analysts. Our primary goal is to examine whether and how the initiation of credit default swaps (hereafter CDS) trading affect the analyst forecast accuracy and analyst forecast optimism (bias).

CDS is a swap agreement that the seller of the CDS will compensate the buyer in the event of a loan default (by the debtor) or other credit events. The buyer of the CDS makes a series of payments to the seller and, in exchange, receives a payoff if the loan defaults.

Why would CDS trading affect analyst forecast properties? CDS contracts are traded over the counter by large financial institutions, including banks, insurance companies and hedge funds etc. In particular, some bank creditors also serve as dealers in this market, by supplying CDS spread quotes for firms to which they have loan exposure. Acharya and Johnson (2007) and Qiu and Yu (2012) show that the CDS market dominates the equity market in terms of price discovery when a CDS reference entity has a relative high

[1] BIS reports the notional amount of CDS: http://www.bis.org/statistics/dt1920a.pdf.

number of ongoing banking relationships. Blanco et al.(2005) find that CDS market also leads the bond market and Berndt and Ostrovnaya (2014) also find that CDS market leads equity option market before bad news. The above evidence are consistent with informed trading by informed lenders, which often results in the revelation of a substantial amount of private information through CDS pricing (Glantz, 2003, and Whitehead, 2012)[2]. On the other side, equity analysts gather, acquire and process information, and then disseminate information by announce earnings forecast and other forecasts. Given the superior private information revelation in the CDS market, we conjecture that the initiation of CDS trading can help analyst to improve forecast accuracy.

On the other hand, we conjecture that the initiation of CDS trading can depress the analysts' strategic forecast optimism. Lim (2001) and Jackson (2005) propose theoretical models to analyze analysts' incentive and constraint. They find that optimistic forecast is a rational and optimal choice for analysts, after trading off reputation, management access and trading commission. The real effect of CDS on analysts' strategic optimism lies in two aspects. On one hand, optimism can help analysts to improve management access to get more private information, which help analyst to increase accuracy in the future (Lim, 2001). However, after the introduction of CDS trading: 1). More private information is revealed in the CDS market. 2). According to Kim et al. (2015), management is also forced by CDS market to do more voluntary information disclosure. Either way, analysts' demand for management access is decreased after CDS trading. Rationally. They will be less intentional optimistic to pleasure management, which can also increase forecast accuracy to build reputation. On the other hand, analysts also have

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[2] Anecdotal evidence also implies that CDS reflects information ahead of other markets (e.g., The Wall Street Journal, 2006, 2007, Bloomberg, 2006, and The New York Times, 2007).

concern about their reputation when issuing optimistic forecasts. The introduction of CDS market makes the information environment more transparent, which increases analyst reputation concern when issue optimistic forecast. Imagine that, given CDS market already reveals certain bad news about earnings in the near future, certain analysts still announce blatantly optimistic forecasts. Their clients, such as institutional investors, could treat their optimistic forecasts as obviously misleading signals. This is a huge cost to their reputation, especially when the voting rights of "All Star" analysts and even the future job offers from buy-side are controlled by these stakeholders. Thus, the rational choice for analysts is become more conservative or more honest in a more transparent information environment.

Our CDS transaction data is from Markit. Markit includes CDS composite and contributor level data on approximately 3,000 individual entities. It receives contributed CDS data from market makers from their official books and records. Our dataset covers 888 North American firms with a CDS trading history during period from 2001 to 2008. After eliminating the firms without available data for the control variables, we identify 503 CDS firms over our sample period. The major empirical exercise involves the identification of CDS trading initiation date.

A potential concern with any study of the impact of CDS trading on other variables of interest is the endogeneity issue (Ashcraft and Santos,2009; Saretto and Tookes, 2013; Subrahmanyam, Tang, and Wang, 2014; Kim et al.,2015; Martin and Roychowdhury,2015). Two important sources of endogeneity are simultaneity and omitted variables. First, we try to control for as many observable variables as possible: 23 determinants of analyst forecast properties suggested by previous literature (Bhushan, 1989; Barth et al, 2001; Duru and Reeb, 2002; Gu and Wu, 2003; Nagar et al.,2003; Gu and Wang, 2005; Cotter et al, 2006; Frankel et al., 2006; Cowen et al., 2006; Lehavy et al., 2011; Hilary and Hsu, 2013; and Liang and Riedl, 2013). Second, following Saretto and Tookes (2013), we control for firm fixed effect to account for time-invariant unobservable differences between firms, whether or not they have CDS contracts trading on their debt. However, this method assumes that the timing of CDS introduction is exogenous. To address the potential concern that the introduction of CDS trading is simultaneously determined with unobservable variables related to analyst forecast behavior, we also employ three different method of propensity score matching to do the difference-in-difference analysis (Subrahmanyam, Tang, and Wang,2014; Martin and Roychowdhury, 2015; Kim et al.,2015). Our sample period is from 1996 to 2012.

Firstly, we find that the initiation of CDS trading can help analyst increase their forecast accuracy, which is consistent with notion that the introduction of CDS trading enriches the information environment and help analyst to increase forecast accuracy. In addition, we conduct a series of cross-sectional analysis to investigate when the impact of CDS initiation is more pronounced. On the one hand, we expect that an increase in analyst forecast accuracy after CDS trading is more likely when the CDS reference entities are more informationally opaque. Among these firms, the introduction of CDS trading can produce larger marginal effect in terms of information revelation. Consequently, analyst can increase their forecast accuracy more. The empirical evidence confirm our conjecture: the increase of forecast accuracy after CDS trading is only significant for: smaller firms (market value is below the sample median), more volatile firms (historical earnings volatility or stock return volatility is above the sample median), less transparent firms (the number of management earnings forecast is below the sample median) and for less experienced analysts. On the other hand, we expect that the effect of CDS trading on forecast accuracy is stronger when the underlying firm is more leveraged. Because CDS is a derivative instrument written on the firm's liability. If a firm's debt occupy larger weight in its capital structure, CDS trading can also gather and convey relative more information about this firm. Indeed, we find that the increase in analyst forecast accuracy is only significant for high leveraged firms.

Secondly, we find that the introduction of CDS trading can depress analysts' strategic optimism in the whole sample for the three matching methods. Furthermore, we investigate when the depressing effect is stronger. We expect that it is stronger when the original optimism level is higher before CDS introduction. But strategic optimism is an inner subjective behavior, which is relatively difficult to observe, define and measure. Thus, we select three different proxies to measure it from different angles following prior literature. The first proxy is analyst following experience. Because analysts who follow a company for long periods develop a close relationship with management. This reduced objectivity is likely to be reflected in relatively more optimistic forecasts and recommendations (Francis and Philbrick, 1993; Das et al., 1998; Lim, 2001; Cowen et al., 2006). The second proxy is the stock trading volume. Because brokerage firms’ primary source of income is commissions from client trade execution. So these firms typically link analyst compensation to commission from trading volume. This is likely to encourage analysts to provide optimistic research that encourages investors to trading more frequently (Hayes, 1998; Gu and Wu,2003; Irvine, 2004; Jackson, 2005, Cowen et al., 2006; Agrawal and Chen, 2012). The third proxy is the analysts' brokerage firm size.

Ljungqvist et al. (2007) find that brokerage firms size is positively related to analyst optimism. Because analysts bear the greater pressure from their employers to stimulate trading volume when they are in larger brokerage firms.

The empirical results confirm our expectation: the depressing effect of CDS trading is only significant in the subsamples with higher likelihood of analysts' strategic optimism: more experienced analysts, more liquid stocks, and larger brokerage houses. However, Hong and Kubik (2003) find a negative correlation between forecast accuracy and optimism. Thus, one concern is that the depressing effect of CDS initiation on analysts' strategic optimism is probably driven by the positive effect of CDS introduction on forecast accuracy. If this is the case, CDS introduction should only significantly increase forecast accuracy in the subsamples of more experienced analysts, more liquid stocks, and larger brokerage houses, while do not affect the analyst accuracy of the opposite subsample. However, empirical results show that CDS trading even increases analyst forecast accuracy more for opposite subsample. These results confirm that the effects of CDS trading on forecast accuracy and optimism are not substitutes for each other. Accuracy and optimism measures two different dimensions of analyst forecast property. Accuracy is more closely related with information asymmetry, but optimism is more closely related with analysts' strategic behavior.

Lastly, we also split the full sample based on whether bad news is indeed announced in the earnings announcement date. Previous literature implies that informed trading, especially those related with bad news, exists in the CDS market (Acharya and Johnson, 2007; Qiu and Yu 2012). If the forthcoming bad news is really preemptively revealed in CDS market, we expect the depressing effect of CDS trading on analysts' *ex ante* optimism is more pronounced because analysts can observe this signal from CDS market. Indeed, we find that the depressing effect of CDS trading on analyst optimism is stronger when earnings turns out to be negative, when EPS change from the same quarter of last year turn out to be negative, and when the 3-month momentum return before earnings announcement is negative.

Our primary contribution is to systematically document the real effect of CDS trading on analyst forecast properties. In particular, the information dissemination function of CDS market help analyst to increase accuracy. And the quicker revelation of bad news in the CDS market also disciplines strategically optimistic analysts to be more conservative due to greater reputation concern in a more transparent information environment. This complements the previous studies focusing on the impact of CDS initiation (Ashcraft and Santos,2009;Saretto and Tookes, 2013; Subrahmanyam, Tang, and Wang, 2014; Kim et al.,2014; Martin and Roychowdhury,2015). This also improves our understanding of this huge but relative opaque derivative market. Although prior literature criticize its existence for exacerbating the recent financial crisis (e.g. Bank of England, 2008; Stanton and Wallance, 2011), for increasing bankruptcy risk (Subrahmanyam et al., 2014) and for decreasing lenders' monitoring incentive (Ashcraft and Santos, 2009; Martin and Roychowdhury, 2015), we do find its positive externalities in terms of information discovery and discipline effect on strategically optimistic analysts. This is similar to Kim et al. (2014) who find the positive externality of CDS market in terms of discipline effect on management voluntary disclosure.

This paper is structured as follows. Section 2 surveys the prior literature and formulate the hypotheses. Section 3 presents the data, sample and descriptive. Section 4 describes the research design. Section 5 presents the empirical results on analyst forecast accuracy. Section 6 presents the empirical results on analyst forecast optimism. Section 7 concludes.

2. Related literature and hypothesis formulation

Hypothesis 1: The introduction of a new market for CDS can enrich firms' information environment, which can help analysts to increase their earnings forecast accuracy.

The major players in this market are major banks, insurance companies and other financial institutions. They use CDS to hedge their loan default risk. Because of their lending activities with the CDS reference entities, they can access material non-public information. These include more timely financial disclosure, future investment project, covenant compliance information, acquisition or mergers, which are usually reported to the lenders before public announcement (Standard and Poor's, 2007). In addition, these lenders are not just the end-user of CDS, but also play the role of dealers in the market. Given the absent effective isolation between loan officer and CDS trading desk in these big banks, material non-public information is frequently traded on the lightly regulated CDS market (e.g., The Economist, 2003; Financial Times, 2005; Kim et al. 2015)

In addition, CDS market also leads other markets in terms of price discovery in some cases. Acharya and Johnson (2007) and Qiu and Yu (2012) show that the CDS market dominates the equity market in terms of price discovery when a CDS reference entity has a relative high number of ongoing banking relationships. Blanco et al.(2005) find that CDS market also leads the bond market. Berndt and Ostrovnaya (2012) also find that CDS market leads equity option market before bad news. The above evidence are consistent with informed trading by informed lenders, which often results in the revelation of a substantial amount of private information through CDS pricing (Glantz, 2003, and Whitehead, 2012)[3]. In a nutshell, the introduction of a new market for CDS trading can enrich firms' information environment. On the other side, equity analysts gather, acquire and process information, and then disseminate information by announce earnings forecast and other forecasts. Thus, they could rely on the introduction of CDS market to make more accurate forecast.

Hypothesis 1a: The increase in analyst forecast accuracy after CDS trading is greater for CDS firms with greater information asymmetry or greater leverage.

On the one hand, we expect that the increase in analyst forecast accuracy after CDS trading is more significant when the CDS reference entities are more informationally opaque. Among these firms, the CDS market can produce larger marginal effect in terms of information dissemination. Then, analysts following these firms can increase their forecast accuracy relatively more. On the other hand, we conjecture the CDS introduction can increase analyst forecast accuracy more for higher-leverage firm. Because CDS is a derivative instrument written on the firm's liability. If a firm's debt occupy larger weight in its capital structure, CDS trading can also gather and convey relative more information about this firm.

Hypothesis 2: The initiation of CDS trading can depress analysts' strategic optimism due to analysts' greater reputation concern in a more transparent information

[3] Anecdotal evidence also implies that CDS reflects information ahead of other markets (e.g., The Wall Street Journal, 2006, 2007, Bloomberg, 2006, and The New York Times, 2007).

environment and smaller demand for the personal access to management for private information.

Hypothesis 2a: The depressing effect of CDS trading on analysts' strategic optimism is stronger for subsamples with higher original optimism level.

Lim (2001) and Jackson (2005) theoretically derive that optimistic forecast is a rational and optimal choice for analysts, after trading off reputation, management access and trading commission. However, after the introduction of CDS trading: 1). More private information is revealed in the CDS market. 2). According to Kim et al. (2015), management is also forced by CDS market to do more voluntary information disclosure. Either way, analysts' demand for management access is decreased after CDS trading. Rationally. They will be less intentional optimistic to pleasure management, which can also increase forecast accuracy to build reputation. On the other hand, analysts also have concern about their reputation when issuing optimistic forecasts. The introduction of CDS market makes the information environment more transparent, which increases analyst reputation cost when issue optimistic forecast. In addition, CDS trading should produce larger marginal effect on optimism when the original optimism level is higher.

Hypothesis 2b: The depressing effect of CDS market on analysts' *ex ante* optimism should be stronger when bad news is indeed announced in the earnings announcement date.

If informed trading related with bad news indeed exists in the CDS market and if bad news is indeed announced in the earnings announcement date, we expect the depressing effect of CDS trading on analysts' *ex ante* optimism is more pronounced. Because analysts and other investors can observe these signals in the CDS market before announcement, analysts will suffer large reputation loss if they still issue overly optimistic forecast.

3. Data, Sample and Summary Statistics

3.1 Data source and sample selection

We collect information on CDS contracts from Markit. Markit includes CDS composite and contributor level data on approximately 3,000 individual entities. It receives contributed CDS data from market makers from their official books and records. There are 888 North American CDS firms during period from 2001 to 2008. After eliminating the firms without available data for the control variables, we identify 503 CDS firms from 2001 to 2007[4]. The major empirical exercise involves the identification of CDS trading initiation date.

The analyst forecast data is retrieved from I/B/E/S Detail database. The financial data and stock data are obtained from Compustat and CRSP, respectively. The data on management voluntary disclosure is from First Call database. The data on institutional holding is from Thomson-Reuters Institutional Holding (13F) database.

3.2 Matched control firms

CDS contract is a tool for credit risk transfer between CDS buyer and CDS seller. The introduction of CDS contract is not randomly assigned to the whole firms sample. It's based on firms' certain specific characteristics, such as credit rating, firm size etc. To address the potential concern that the introduction of CDS trading is simultaneously determined with unobservable variables related to analyst forecast behavior, we follow

[4] The CDS firms from 2008 is very few and they are deleted due to lack of data for required control variables.

previous literature to estimate a probit model to predict the CDS initiation. (Ashcraft and Santos,2009; Saretto and Tookes,2013; Subrahmanyam et al., 2014; Kim et al.,2014; Martin and Roychowdhury,2015). We combine the observable determinant variables from Subrahmanyam, Tang, and Wang (2014) and Martin and Roychowdhury (2015). The model is as follows:

$$\begin{aligned} Prob(CDS_t = 1) = \phi(&\beta_0 + \beta_1 InvestmentGrade_{t-1} + \beta_2 Rating_{t-1} + \beta_3 Leverage_{t-1} + \beta_4 Profit\ Margin_{t-1} \\ &+ \beta_5 Size_{t-1} + \beta_6 Return\ Volatility_{t-1} + \beta_7 MB_{t-1} + \beta_8 Log(Asset)_{t-1} + \beta_9 ROA_{t-1} \\ &+ \beta_{10} \frac{Sales}{Total\ \text{Asset}}_{t-1} + \beta_{11} \frac{EBIT}{Total\ \text{Asset}}_{t-1} + \beta_{12} \frac{PPENT}{Total\ \text{Asset}}_{t-1} \\ &+ \beta_{13} \frac{RE}{Total\ \text{Asset}}_{t-1} + \beta_{14} \frac{WCAP}{Total\ \text{Asset}}_{t-1} + \beta_{15} \frac{CAPX}{Total\ \text{Asset}}_{t-1}) + \varepsilon_t \end{aligned} \qquad (1)$$

Where *CDS* is an indicator variable equal to one for firms with CDS trading during 2001 to 2007, and zero otherwise; *InvestmentGrade* is an indicator variable equal to 1 if a firm has an S&P rating above BB+, and 0 otherwise; *Rating* is an indicator variable equal to 1 if a firm has an S&P rating, and 0 otherwise; *Leverage* is firm's total debt (short-term debt plus long-term debt) scaled by total asset; *Profit Margin* is the net income scaled by sales; *Size* is the natural logarithm of market value of equity; *Return Volatility* is standard deviation of daily stock return within the last 3 month; *MB* is the ratio of market value to book value of equity; *Ln(Assets)* is the logarithm of the firm's total asset value; *ROA* is the firm's return on asset; *Sales/Total Asset* is the ratio of sales to total assets; *EBIT/Total Asset* is the ratio of earnings before interest and tax to total assets; *PPENT/Total Asset* is the ratio of property, plant, and equipment to total assets; RE/Total Asset is the ratio of retained earnings to total assets; *WCAP/Total Asset* is the ratio of working capital to total assets; *CAPX/Total Asset* is the ratio of capital expenditure to total assets. These variables is chosen based on their role in capturing the hedging demand, credit risk and firm characteristics. We use the variables in the last quarter, t-1, to predict the onset of CDS trading in current quarter, t. And we use all Compustat firms with available data during period 1997-2008.

<Insert Table 3.1 Here>

Table 1 reports the regression result of Equation 1. Our regression is based on the data at firm-quarter level. As we can see, the model specification for the onset of CDS trading is good. The ratio of concordant pairs is as high as 89.9% and the ratio of discordant pairs is as low as 6.3%. Specifically, we find that CDS trading initiation is more likely for firms with higher credit rating, leverage, profit margin, earnings ratio, book value and market value. This is consistent with Martin and Roychowdhury (2015). Based on adverse selection explanation, given CDS buyer, such as banks, possess superior private information about the underlying bond or loan of CDS, the CDS seller, such as insurance companies, will only provide CDS contract on the safer firms (higher credit rating and profit margin) and more transparent firms (larger firms). Because CDS contract is written on debt, the hedging demand for CDS is larger for firm with higher leverage. The likelihood of CDS trading is positively related with stock return volatility, which is consistent with Subrahmanyam et al. (2014). Probably this is due to the hedging demand through debt-based derivative. In addition, we find that the ratio of working capital, the ratio of retained earnings and the ratio of capital expenditure is negatively related to the CDS introduction.

Next, we employ propensity score matching method to select the non-CDS control firm. As noted by Roberts and Whited (2012), the key advantage of propensity score matching to address endogeneity is that it does not rely on a clear source of exogenous variation for identification. The propensity score is the estimated probability from

Equation 1. For each CDS firm, we use three methods to select matched non-CDS firms. The first method is the repeated "nearest neighbor one" matching, selecting only one matching non-CDS firm with the nearest propensity score. This method produced 273 non-CDS matching firms for 503 CDS firms. The second method is the 0.5% radius matching, selecting the matching non-CDS firms whose propensity scores is neither greater than 1.005 times of the propensity score of a CDS firm nor smaller than 0.995 times of propensity score of that firm. This method produced 638 non-CDS matching firms. The third method is the 1% radius matching, which produces 869 non-CDS matching firms. The matching of estimated likelihoods is made in the calendar year of the fiscal quarter prior to the CDS-trade-initiation date [5]. Following Martin and Roychowdhury (2015), we require a non-CDS firm enters the sample only once every year[6], even if it can serve as a match for more than one treatment (i.e., CDS) firm; thus, every control firm-year observation is unique.

3.3 Descriptive Statistics

<Insert Table 3.2 Here>

Table 2 Panel A presents the sample distribution based on the CDS-trade-initiation year for the CDS sample and matched non-CDS sample. As we can see, most of CDS introduction in our final sample happened in 2001, which is 172. There is a decreasing trend of CDS initiation as time goes on. This may also reflecting the forthcoming of financial crisis. Risk becomes larger and larger, and CDS contract provider becomes

[5] For example, if a firm's CDS is initiated in the middle of third quarter, then its' predicted propensity score for CDS trading is estimated from second quarter. The non-CDS firms' propensity score from the whole same year can be matched to this CDS firm (regardless that it's estimated from the first, or the fourth quarter of the same year).

[6] As a robustness check, we also require the matching is based on the same fiscal quarter and a non-CDS firm enters the sample only once every quarter, which produces qualitatively similar results.

more conservative. Only 27 firms' CDS is initiated in 2007, the pre-financial crisis period. Among the three samples of matching non-CDS firms, we find similar time trend in repeated nearest neighbor matching method. But the other two radius matching methods produces most matching non-CDS firm in the middle of time period, 2003-2005. Table 2 Panel B reports the sample distribution by industry. Most CDS firms are in the industry of food, apparel, petroleum refining, and paper and printing (26.04%). Following is Rubber, stone, computer, transportation equipment(25.45%), the third industry is transportation, communication, electric, gas and sanitary services(17.10%). The results are similar to Martin and Roychowdhury (2015).

<Insert Table 3.3 Here>

Table 3 presents descriptive statistics of variables used in the subsequent empirical analysis. We present both the CDS sample and matched non-CDS sample across pre-CDS trading period and post-CDS trading period. Please note that, most of these variables are not used to predict the onset of CDS trading in Equation 1, and they are control variables in the analysis of analyst forecast properties. Most variables are similar in economic magnitude between CDS firms and non-CDS firms. But a few variables show a large difference between these two samples. For example, as Panel A shows, the CDS firms has mean market value of 25.06 billion in the pre-CDS trading period, but non-CDS firms (radius 0.5% matching) has mean market value of 5.29 billion. On average, 2.67 more analysts follow CDS firms in every quarter, and CDS firms has 2.74 more segment than non-CDS firms in the pre-CDS trading period. But the stock turnover ratio of non-CDS firms is faster than CDS firms by 4.32, probably due to the smaller size of non-CDS firms. The analyst forecast accuracy for CDS firms is 30% higher than that for non-CDS firms, but the analyst forecast optimism does not exhibit significant difference across CDS firms and non-CDS firms in the pre-trading period. Panel B presents the comparative summary statistics in the post-CDS trading period. The analyst forecast accuracy decreases for both CDS firms and non-CDS firms. But the difference between CDS firms and non-CDS firms becomes larger, 50%. Interestingly, the analyst optimism for CDS firms becomes weaker after CDS trading, but it becomes stronger for non-CDS firms. This trend makes the difference of optimism between CDS firms and non-CDS firms becomes significant after CDS trading. Other variables presents similar pattern as in Panel A. Therefore, the similar magnitude of difference in firm characteristics between CDS and non-CDS firms across Panel A and Panel B implies that the difference of analyst forecast accuracy and optimism between CDS and non-CDS firms across Panel A and Panel B is unlikely driven by these firm characteristics.

<Insert Table 3.4 Here>

In Table 4, we report Pearson and Spearman correlations among variables in Table 3. We only report the correlation table for the radius 0.5% matching method. The other two method produce similar correlation results, which is available upon request. Given large size of 27 variables, we omit some of them for brevity, and the omitted variables generally has a relative smaller correlation coefficients with other variables. As shown in the column of CDSF (indicator variable equal to 1 if a firm has a CDS contract traded over the sample period, and 0 otherwise), it is positively correlation with firm size at 0.42, and positively correlated with number of analyst following at 0.2. These results confirm our findings in Table 1 and Table 3.

4. Empirical analysis

4.1 Measurement of analyst forecast accuracy and optimism

Following Duru and Reeb (2002), we measure an analyst's forecast accuracy for each firm-quarter observation based on the absolute value of the difference between the analyst's forecast value and actual earnings, divided by the stock price at the end of current fiscal quarter[7]:

$$Accuracy_t = (-1) \times \frac{\left| Forecast_t^{t-n} - EARN_t \right|}{Price_t} \times 100$$

where $Accuracy_t$ is the negative of an analyst's absolute forecast error at time t, $Forecast_t^{t-1}$ is the analyst's forecast of period t earnings made at forecast date t-n, $EARN_t$ is the actual earnings per share for period t, and $Price_t$ is the stock price at the end of current fiscal quarter. We multiply the absolute forecast error by (-1) to construct a measure that increases with greater accuracy. Following Gu and Wu (2003), we also adjust the scale by multiplying 100 for the convenience of tabulating the results.

Also following Duru and Reeb (2002) and previous research, we measure optimism (bias) as the signed forecast error, which is the difference between the analyst's forecast value and actual earnings, divided by the stock price at the end of current fiscal quarter:

$$Optimism_t(Bias_t) = \frac{Forecast_t^{t-n} - EARN_t}{Price_t} \times 100$$

Forecast optimism increase as the forecast error becomes greater. It's worth noting that our measurement of analyst forecast accuracy and optimism is at firm-quarter-analyst level. But our results is robust to the alternative measurement at firm-quarter level.

4.2 Research Design

[7] Our results are robust to another accuracy measure: square difference between forecast and actual value.

To address the potential concern that the introduction of CDS trading is simultaneously determined with unobservable variables related to analyst forecast properties, we employ difference-in-difference method in all empirical tests. Specifically, we include two indicator variables in our model: the first indicates whether a firm has CDS trading over the sample period, and the second identifies whether an observation is in the pre-CDS trading 5-year period or post-CDS trading 5-year period. The model is as follows:

$$\begin{aligned} Accuracy_t(Optimism_t) = \beta_0 + \beta_1 POST + \beta_2 CDSF + \beta_3 CDSF \times POST \\ + \sum_{j=1}^{23} \lambda_j Additional\ \ 23\ control\ variables_j \\ + \sum_{i=1}^{K} \gamma_i Industry_i + \sum_{m=1}^{N} \delta_m Year_m + \varepsilon_t \end{aligned}$$

where *CDSF* is equal to one for firms with a CDS traded during the sample period, and 0 for matched control firms. *POST* is an indicator variable equal to 1 (0) if an observation falls in the 5-year period after (before) CDS trade initiation for both the CDS firm and its matched control firms. Our variable of interest in the difference-in-difference analysis is the interaction between *CDSF* and *POST*. Hence, we test whether β_3 is significantly different from zero. Following Saretto and Tookes (2013), industry fixed effect are included to account for time-invariant unobservable differences between industries. Standard errors are clustered at the firm level to account for serial correlation within a firm (Peterson, 2009). Since CDS trade initiation sample spans from 2001 to 2007, the examination of change in analyst forecast accuracy and optimism from five years before to five years after CDS trade initiation implies that the overall period of our empirical analysis extends from 1996 to 2012.

To address the potential issue of omitted variables which could affect analyst forecast through CDS initiation, we control for 23 observable determinants of analyst forecast properties. Our control variables includes three types of determinants. The first type is the firm characteristics, which includes market-to-book ratio, market value size, leverage, return on equity, number of segments, institutional ownership, profit margin, R&D expense, compounded sales growth rate over the last 3 years, stock trading volume in the last year, stock turnover ratio over the last three month, momentum return over the last three month and stock return volatility over the last three month. The second type is the earnings property, which includes earnings skewness over the last 8 quarters, earnings volatility over the last 8 quarter, negative earnings indicator and change in earnings per share from the same quarter of last year. The third type is analyst characteristic, which includes analyst's following experience for a firm, number of analyst following a firm, the analyst's brokerage firm size, analyst forecast horizon and the analyst's coverage breadth in a quarter. All of these control variables is suggested by previous literature (Bhushan, 1989; Barth et al, 2001; Duru and Reeb, 2002; Gu and Wu, 2003; Nagar et al.,2003; Gu and Wang, 2005; Cotter et al, 2006; Frankel et al., 2006; Cowen et al., 2006; Lehavy et al., 2011; Hilary and Hsu, 2013; and Liang and Riedl, 2013). In addition, Kim et al. (2014) find that CDS introduction can discipline management to disclosure more information, so we also include number of management earnings forecasts to account for the potential effect of CDS trading on analyst through management disclosure.

5. Empirical results about Analyst forecast accuracy

5.1 Primary tests

<Insert Table 3.5 Here>

Table 5 presents the regression results on the change of analyst forecast accuracy around the initiation of CDS trading. We report the results for three matching method: column 1 is based on repeated nearest neighbor matching, column 2 is based on 0.5% radius matching, and column 3 is based on 1% radius matching. As shown, the coefficient of *POST* is negative and significant for the all three matching method. This suggests that non-CDS firms experience a decline in analyst forecast accuracy after CDS trading. This is consistent with the descriptive statistics in Table 3. The coefficient on *CDSF* is also negative and significant for the all three matching method. This implies that the analyst forecast accuracy for CDS firms is lower than the non-CDS firms prior to CDS trading initiation, which is not consistent with the summary statistics in Table 3. As shown, the coefficient of *Size* is very significant and positive. Also as shown in Table 4, the correlation between *CDSF* and *Size* is as high as 0.42 and significant. Thus, we conjecture the strong multicollinearity between *CDSF* and *Size* leads to the negative coefficient of *CDSF*. The coefficients of the interaction term between CDSF and POST for three matching methods are positive and significant (t-stat=2.19, 2.66 and 2.86). Economically, compared to non-CDS firms, the forecast accuracy for CDS firms increase 50% (0.286/0.270+0.297) to 77% (0.122/0.069+0.090) after CDS trading, which implies that CDS firms experience an increase in analyst forecast accuracy after CDS trading. These results support our Hypothesis 1: the introduction of a new market for CDS trading can enrich firms' information environment, which can help analysts to increase their earnings forecast accuracy.

For other control variables, we also find generally consistent results with previous literature. For instance, the stock return volatility is significantly negatively related to forecast accuracy, implying that it's hard for analyst to make accurate forecast in a relative volatile information environment. Consistent with Frankel et al. (2006) and Ljungqvist et al. (2007), we find that institutional ownership is strongly positively related with analyst forecast accuracy. Earning skewness and earning volatility are also significantly negatively related to forecast accuracy, which is consistent with Gu and Wu (2003). We also find the loss is negatively related with forecast accuracy, which is consistent with Heflin et al. (2003). In addition, forecast horizon is negatively related to forecast accuracy, which is consistent with Kross, Ro, and Schroeder (1990) and Clement (1999).

5.2 Cross-sectional tests

To test H1a, we test whether the change of analyst forecast accuracy around CDS trading introduction varies with some determinants related to information asymmetry. We expect that CDS market, acting as a new information transfer channel, should produce larger marginal impact on analyst forecast accuracy when the firms' information asymmetry is greater. For the already very transparent firms, it's difficult for CDS market to reveal too much shocks. In addition, cross-sectional analysis can also address endogeneity issue of self-selection to some extent. Because this method splits the whole sample into two subsamples within the CDS firms. One subsample can be treated as the comparative subject for another one to control for the unobservable changes embedded in the time-trend.

<Insert Table 3.6 Here>

Following prior literature, we use firm size, stock and earnings volatility to proxy for the information asymmetry (Aboody and Lev, 2000; Zhang, 2006; and Bhattacharya et al. 2013). In Panel A of Table 6, we find that CDS market can significantly increase analyst forecast accuracy for small firms, firms with high stock volatility, and firms with high earnings volatility[8]. Our benchmark to split the whole sample is the sample median. And the effects of CDS trading on forecast accuracy for the three subsamples are also economically significant, ranging from 48.9% (0.45/0.41+0.52) to 67.6% (0.54/0.41+0.39). But we don't find significant results for large firms, and firms with low stock volatility and firms with low earnings volatility. In Panel B, we conduct more tests to validate our conjecture. The frequency of management earnings forecast reflects another dimension of firm's information environment. Our results shows that CDS market only has significant effect on analyst forecast accuracy for firms with fewer management earnings forecasts. In addition, from analysts' angle, their following experience also reflects the information asymmetry between themselves and firms: the information asymmetry is stronger when the analyst's following experience is less. Again, we find that CDS trading only increase forecast accuracy for analysts with less following experience for a firm. Taken together, these results suggests that CDS market exerts much larger positive effect on analyst forecast accuracy for firms with greater information asymmetry.

Next, we conduct the subsample analysis based on firms' leverage. The results is presented in the last two columns of Panel B in Table 6. As shown, the CDS trading only increases analysts' forecast accuracy for firms with relative high leverage, which support our Hypothesis 1b. Because CDS contract is a debt-based derivative instrument written on firm's bond and loan, it can reflect more information about firm's liability compared to

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[8] We only report results for the radius 0.5% matching method for brevity. The nearest neighbor and radius 1% matching method produce qualitatively similar result, which is available upon request.

firm's equity. When the liability side becomes larger in firm's total asset, the information about firm's debt occupies more weight, then CDS trading can reveal more information about the whole firm.

6. Empirical results about Analyst forecast optimism

6.1 Primary tests

<Insert Table 3.7 Here>

Table 7 presents the regression results for the change of analyst forecast optimism around the initiation of CDS trading. We report the results for all three matching methods. The coefficients of POST are not significant and positive, implying that non-CDS firms do not experience an significant change in analyst forecast optimism after CDS trading. In two of three regressions, the coefficients of *CDSF* are marginally significant, weakly suggesting that the analyst forecast optimism is higher for CDS firms than for non-CDS firms in the five-year period preceding CDS initiation. This is weakly consistent with the descriptive statistics in Table 3, which shows an insignificant difference in optimism between CDS and non-CDS firms in the pre-CDS trading period. The coefficients of the interaction between *CDSF* and *POST*, is negatively significant for all three matching methods (t-stat=1.83, 2.08 and 2.14). This indicates that, compared to matched non-CDS firms, CDS firms experience an decline in analyst forecast optimism after CDS trading. These results are consistent with our Hypothesis 2: The initiation of CDS trading can depress analysts' strategic forecast optimism. On the one hand, after the introduction of CDS trading: 1). More private information is revealed in the CDS market. 2). According to Kim et al. (2015), management is also forced by CDS market to do more voluntary information disclosure. Either way, analysts’ demand for management access is decreased after CDS trading. Rationally. They will be less intentional optimistic to try to please management, which can also increase forecast accuracy to build reputation. On the other hand, those analysts with intentional optimistic forecasts (strategic optimism) may also lower their blatant forecasts due to the increased reputation cost in a more transparent information environment after CDS trading (Das et al., 1998; Lim, 2001). We can imagine that, if some of the important stakeholders, such as institutional investors, already feel the potential bad news from CDS market, they could treat strategic analysts' optimistic forecasts as obviously misleading signals. This is a huge cost to analysts' reputation, especially when the voting rights of "All Star" analysts and even the future job offers from buy-side are controlled by these stakeholders.

Similar to the results for accuracy in Section 5.1, we also find that the results for control variables are generally consistent with previous literature. For instance, stock return volatility is positively related with forecast optimism. This implies that analysts are more likely to issue optimistic forecast in less transparent information environment, when the reputation cost is lower (Das et al., 1998; Lim, 2001). We also find loss indicator variable is positively related with forecast optimism, which is driven mostly by firms reporting loss because managers may have difference incentive to manage loss from profits (Hwang et al,. 1996; Brown, 1997,1998; Gu and Xue, 2008). We also find limited evidence that earnings skewness is positively related with forecast optimism (Gu and Wu, 2003). Interestingly, we also find that R&D expense is negatively related forecast optimism, implying that analyst make more conservative estimate for firms with more intangible assets. In addition, we find that the 3-month momentum return preceding earnings announcement is negatively related with forecast optimism. Higher optimism comes with lower momentum return, suggesting that analysts underreact to the bad news reflected in the stock price (Easterwood and Nutt, 199).

6.2 Cross-sectional tests

Prior literature find that there exists popular strategic optimism among analysts (Easterwood and Nutt, 1999; Lim, 2001; Hong and Kubik, 2003; Jackson, 2005). However, the level of strategic optimism is an inner subjective behavior, which is difficult to observe, define and measure. Thus, in order to test H2a, we follow the prior literature and select three different proxies to measure it from different angles. Only if we get consistent results across three measurements, our conjecture could be convincing.

The first proxy for analysts' strategic optimism is analyst following experience. Cowen et al. (2006) find that analyst following experience is positively associated with analysts' strategic optimism. Because analysts who follow a company for long periods develop a close relationship with management, making it difficult to challenge or question management’s performance. This reduced objectivity is likely to be reflected in relatively more optimistic forecasts and recommendations (Francis and Philbrick, 1993; Das et al., 1998; Lim, 2001). We define following experience as the log of the number of quarters that have elapsed between the analyst’s first forecast for the test firm and the current forecast observation.

The second proxy is the log of the sum of stock trading volume in the last 12 months. One of brokerage firms’ primary source of income is commissions from client trade execution. To encourage analysts to produce research that has impact and generates trading volume, firms typically link analyst compensation to commission and soft dollar revenues in the stocks they cover. This is likely to encourage analysts to provide optimistic research that encourages investors to purchase shares. Because optimistic reports are more effective in generating trading volume; any investor can act on a buy recommendation at relatively low cost by buying the stock, whereas negative reports can only be acted on by investors that already own the stock or who are willing to incur the additional costs of short selling (Cowen et al., 2006). Thus, we also choose higher stock trading volume as an proxy for analysts' strategic optimism (Hayes, 1998; Gu and Wu,2003; Irvine, 2004; Jackson, 2005, Agrawal and Chen, 2012).

The third proxy is the analysts' brokerage firm size, which is defined as the log of the number of analysts affiliated to the brokerage firm. Ljungqvist et al. (2007) find that brokerage firms size is positively related to analyst optimism. Because analysts bear the pressure from their employers to stimulate trading volume by issuing optimistic forecasts. And this “brokerage pressure” should be greater when they are affiliated to larger brokerage firms.

<Insert Table 3.8 Here>

The results are presented in Table 8. Consistent with expectation, compared to matched non-CDS firms, CDS initiation significantly depress analysts' strategic optimism after CDS trading in the subsamples of more experienced analysts, more liquid stocks, and larger brokerage houses. In contrast, we do not find significant effect of CDS trading on analyst optimism in the subsamples of less experienced analysts and less liquid stock, and only find marginally significant effect in the subsample of smaller brokerage firms. These results confirms our Hypothesis H2a: The depressing effect of CDS trading on analysts' strategic optimism is stronger for subsamples with higher optimism level.

One concern about our results is whether the negative effect of CDS initiation on analyst optimism is driven by the positive effect of CDS introduction on forecast accuracy. Because Hong and Kubik (2003) find a negative correlation between forecast accuracy and optimism. One way to address this concern is to test whether the effect of CDS initiation on analyst forecast accuracy shows the same pattern: CDS initiation only produce significantly positive effect on accuracy for the subsamples of more experienced analysts, more liquid stocks, and larger brokerage houses, but shows insignificant effect in the opposite subsamples. However, as shown in Panel B of Table 6, CDS trading help less experienced analyst to increase more accuracy, because they suffer greater information asymmetry before CDS introduction. In contrast, we only find significant depressing effect of CDS initiation on more experienced analysts' optimism in Table 10, because of the discipline effect of CDS introduction on these management's "old friends". In the untabulated results, we don't find the effects of CDS initiation on forecast accuracy significantly different from each other for the subsamples of less liquid stocks and more liquid stocks, and for the subsamples of smaller brokerage houses and larger brokerage houses, which are not consistent with our results for analyst optimism. These results suggest that the effects of CDS trading on forecast accuracy and optimism are not substitutes for each other. Accuracy and optimism measures two different dimensions of analyst forecast property. Accuracy is more closely related with information asymmetry, but optimism is more closely related with analysts' strategic behavior. This also corresponds to the different effects of CDS introduction on accuracy and optimism.

6.3 The effect of CDS initiation on analysts' *ex ante* optimism when bad news indeed happen

Previous research imply that CDS market is very sensitive to bad news and can reveal it preceding other channels such as stock market and option market in some cases (Acharya and Johnson, 2007; Qiu and Yu, 2012; Berndt and Ostrovnaya, 2012). If it's true, then we should find that CDS can strongly depress analysts' *ex ante* optimism when bad news really pop out in the earnings announcement date (H2b). We select two measurements of *ex post* realized bad news according to prior literature. The first one is loss or negative earnings (Hwang et al,. 1996; Brown, 1997,1998, 2001; Gu and Xue, 2008). The second one is the negative EPS change from the same quarter of last year (Lang and Lundholm, 1996). These two measurement are revealed in the earnings announcement, which is not known to analyst when they issue forecasts. We also select another contemporary measurement of bad news: the negative 3-month momentum return before earnings announcement. Analysts can observe this signal, at least partially, before their forecasts.

<Insert Table 3.9 Here>

The results is presented in Table 9. As we can see, compared to non-CDS firms, CDS initiation strongly depress analysts optimism for CDS firms in the subsample of negative earnings, negative EPS change from the same quarter of last year, and negative 3-month momentum return. In contrast, CDS introduction increase analyst optimism for CDS firms in the subsample of positive earnings. And it does not exert significant effect on analyst optimism when EPS change and 3-month momentum is positive. Taken together, these results validate our base argument: CDS reveal bad news timely, which also supports our H2b: CDS initiation can depress *ex ante* analyst optimism more strongly when bad news realized *ex post*.

7. Conclusion

Our paper provides evidence that the initiation of CDS trading can increase analysts' forecast accuracy. Our finding are consistent with notion that the introduction of a new financial market improve the information environment for firms, which helps analysts to make more accurate forecast. In the cross-sectional analysis, we find that the positive effect on forecast accuracy is more pronounced for firms with greater information asymmetry and higher leverage. On the other hand, CDS market can depress analysts' strategic forecast optimism because CDS market reduce analysts' demand for management access and increase their reputation concern in a more transparent information environment. By using several proxies for analysts' strategic optimism level, we find that CDS trading depress analysts' strategic optimism more for subsample with higher optimism level. In addition, the depressing effect is stronger when bad news is realized *ex post*, which are consistent with notion that bad news based informed trading indeed happened in the CDS market.

This study reveals a real effect of CDS market on a group of important capital market participants: equity analysts. This also improves our understanding of this huge but relative opaque derivative market. Although prior literature criticize its existence for exacerbating the recent financial crisis (e.g. Bank of England, 2008; Stanton and Wallance, 2009), for increasing bankruptcy risk (Subrahmanyam et al., 2014) and for decreasing lenders' monitoring incentive (Ashcraft and Santos, 2009; Martin and Roychowdhury, 2015), we do find its positive externalities in term of information discovery function and discipline effect on strategically optimistic analysts. As a comparative research, future work can examine the interaction between CDS market and debt analysts.

Table 3.1: Logistic Regression results on probability of CDS trade initiation

This table reports coefficient estimates from estimating a logistic model to predict the introduction of credit default swaps (CDS) trading. The sample period is from 1997 to 2008 and the regression is based on the data at firm-quarter level. The dependent variable, *CDS*, is equal to 1 if a CDS contract is being traded on a firm, and 0 otherwise. Independent variable include *CAPX/Total Asset*, the ratio of capital expenditure to total assets; *WCAP/Total Asset*, the ratio of working capital to total assets; RE/Total Asset, the ratio of retained earnings to total assets; *PPENT/Total Asset*, the ratio of property, plant, and equipment to total assets; *EBIT/Total Asset*, the ratio of earnings before interest and tax to total assets; *ROA*; the firm's return on asset; *Sales/Total Asset*; the ratio of sales to total assets; *Ln(Assets)*; the natural logarithm of the firm's total asset value; Return Volatility, standard deviation of daily stock return within the last 3 month; *Rating*, an indicator variable equal to 1 if a firm has a S&P credit rating, and 0 otherwise; *Leverage*, total debt scaled by total asset; *MB*, the ratio of market value to book value of equity; *Size*, natural logarithm of market value; *Profit Margin* is the net income scaled by sales; *Investment Grade*, an indicator variable equal to 1 if a firm has a S&P credit rating above BB+, and 0 otherwise; The sample period is 1996-2008;based on quarterly observations. (*** significance at 1% level, ** significant at 5% level; and * significant at the 10% level)

Dependent Variable=Prob(CDS=1)			
Variable	Coeff. Est		p-Value
Intercept	-4.923***		<.0001
CAPX/Total Asset	-0.940**		0.046
WCAP/Total Asset	-0.250**		0.037
RE/Total Asset	-0.0275**		0.033
PPENT/Total Asset	-0.111		0.234
EBIT/Total Asset	0.544**		0.025
ROA	-0.030		0.918
Sales/Total Asset	-0.033		0.704
Ln(Asset)	0.104***		0.005
Return Volatility	0.193***		0.004
Rating	0.621***		<.0001
Leverage	0.967***		<.0001
MB	0.070		0.440
Size	0.098***		0.004
Profit Margin	0.001***		0.001
Investment grade	0.446***		<.0001
Time fixed effect		yes	
Industry fixed effect		yes	
Clustered Standard error		yes	
Pseudo R-Square		0.25	
Wald Test	1104.101		<.0001
Model Score	2391.744		<.0001
Likelihood ratio	1672.509		<.0001
Percent concordant		89.90%	
Percent discordant		6.30%	
Number of firm-quarters		142,167	
Number of CDS=1		518	

Table 3.2: Sample distribution

This table reports sample distribution by the CDS onset year in Panel A and by industry in Panel B, for both CDS firms and their matched firms (non-CDS firms). For the matched firms, the CDS onset year is assumed from their matched CDS firms. We use 3 different methods to do the propensity score matching based on the model in Table 1. The first method is the repeated "nearest neighbor one" matching (NN matching), only select the matching non-CDS firm with the nearest propensity score within the same year. This method produced 273 non-CDS matching firms for 503 CDS firms. The second method is the 0.5% radius matching (R 0.5% matching), select the matching non-CDS firms whose propensity scores is neither greater than 1.005 times of the propensity score of a CDS firm nor smaller than 0.995 times of propensity score of that firm. This method produced 638 non-CDS matching firms. The third method is the 1% radius matching(R 1% matching). This method produces 869 non-CDS matching firms.

Panel A:Sample distribution by CDS onset year for both CDS and non-CDS firms

	CDS Firms		non-CDS (NN matching)		non-CDS (R 0.5% matching)		non-CDS (R 1% matching)	
Year	N	%	N	%	N	%	N	%
2001	172	34.19%	93	34.07%	77	12.07%	86	9.90%
2002	85	16.90%	37	13.55%	46	7.21%	62	7.13%
2003	88	17.50%	48	17.58%	150	23.51%	203	23.36%
2004	80	15.90%	51	18.68%	152	23.82%	211	24.28%
2005	31	6.16%	20	7.33%	112	17.55%	150	17.26%
2006	25	4.97%	10	3.66%	55	8.62%	76	8.75%
2007	22	4.37%	14	5.13%	46	7.21%	81	9.32%
Total	503	100.00%	273	100%	638	100%	869	100%

Panel B:Sample distribution by industry for both CDS and non-CDS firms

	CDS		(NN matching)		(R 0.5% matching)		(R 1% matching)	
Industry (1-digit SIC code)	N	%	N	%	N	%	N	%
Agriculture etc	0	0%	0	0%	2	0.31%	2	0.23%
Mining and construction	40	7.95%	23	8.42%	49	7.70%	69	7.94%
Food, apparel etc	131	26.04%	62	22.71%	112	17.55%	137	15.77%
Rubber etc	128	25.45%	64	23.44%	165	25.86%	233	26.81%
Transportation et.	86	17.10%	62	22.71%	114	17.87%	144	16.57%
Retail and wholesale	56	11.13%	31	11.36%	75	11.76%	107	12.31%
Business service	48	9.54%	22	8.06%	84	13.17%	125	14.38%
Public service	14	2.78%	9	3.30%	37	5.80%	52	5.98%
Total	503	100.00%	273	100%	638	100%	869	100%

Table 3.3:Summary Statistics

This table reports sample mean and median for main variables in the empirical analysis for both CDS firms and their matching firms (non-CDS firms) for both pre-CDS onset period and post-CDS onset period. The pre-CDS onset period covers five years prior to the onset of CDS and the post-CDS onset period covers five years after the onset of CDS. For non-CDS firms, the onset year is assumed from their matching firms. The sample period spans 1996-2012. *F_Acc* is Analysts' earnings forecast accuracy, defined as the negative absolute value of difference between forecast value and actual value, scaled by the stock price of fiscal quarter end. *F_optm* is Analysts' earnings forecast optimism. *N_analyst*, number of analyst following this firm; *Size*, the firm's market cap at the end of this fiscal quarter (in billion); *MB*, the ratio of market value to book value of equity; *Leverage*, total debt scaled by total asset; *ROE*, the firm's return on equity; *Ins_own*, the ratio of Institutional ownership; *Mom*, the momentum return of previous 3 months; *R_Vol*, standard deviation of daily stock return within the last 3 month; *Turnover*, the stock turnover ratio in the last 3 months; *E_Vol*, earnings volatility in the previous 8 quarters; *Coverage*; the number of firms that analyst is following in the same quarter; *F_Exp*, analyst's following experience, measured as the number of previous quarters this analyst follows this firm; *F_Hor*, the time duration between analyst forecast and earnings announcement; *Bro_size*, the size of analyst brokarage frim, measured as the number of analyst affiliated to this brokerage firm; *E_skew*, earnings skewness, measured as the difference between mean and median in the previous 8 quarters, scaled by the stock price of fiscal quarter end (Gu and Wu, 2003); *N_Seg*, number of segment in this firm; *EPS_Dif*, earnings change from the same quarter of last year; *Sgrate*, compounded sales growth rate in the last three year; *Svolume*, natural logarithm of dollar trading volume of last 4 quarters; *PM* is the net income scaled by sales; *RD*, the R&D expense ratio; *N_MEF;* number of management earnings forecast in this year.

Panel A: Pre-CDS trading period

	CDS Firms			Non-CDS Firms (0.5% radius matching)			
Variable	N	Mean	Median	N	Mean	Median	Mean Diff
F_Acc	52029	-0.23	-0.07	89186	-0.33	-0.1	-0.1***
F_Optm	52029	-0.0003	-0.0003	89186	-0.0001	-0.0004	0.0002
N_analyst	52029	13.71	12	89186	11.04	10	-2.67***
Size	52029	25.06	6.32	89186	5.29	2.14	-19.76***
MB	52029	5.17	2.75	89186	3.77	2.33	-1.40***
Leverage	52029	0.29	0.28	89186	0.26	0.26	-0.03***
ROE	52029	0.04	0.04	89186	0.01	0.03	-0.03***
Ins_own	52029	0.68	0.68	89186	0.71	0.73	0.03***
Mom	52029	0.01	0.01	89186	0.02	0.01	0.01***
R_Vol	52029	0.027	0.02	89186	0.032	0.03	0.004***
Turnover	52029	7.68	5.15	89186	11.99	8.25	4.32***
E_Vol	52029	0.02	0.01	89186	0.06	0.01	0.04***
Coverage	52029	1.33	1.00	89186	1.34	1.00	0.01***
F_Exp	52029	3.63	2.00	89186	3.65	2.00	0.02
F_Hor	52029	3.65	3.83	89186	3.72	3.97	0.07***
Bro_size	52029	0.77	0.69	89186	0.70	0.59	-0.07***
E_Skew	52029	-0.002	0.00	89186	-0.006	0.00	-0.004***
N_seg	52029	16.39	15.00	89186	13.65	12.00	-2.74***
EPS_Dif	52029	-0.02	0.00	89186	0.05	0.02	0.07***
Sgrate	52029	0.12	0.08	89186	0.17	0.10	0.05***
Svolume	52029	19.42	19.28	89186	18.90	18.81	-0.52***
PM	52029	0.05	0.06	89186	-1.02	0.05	-1.07***
RD	52029	0.05	0.00	89186	0.08	0.00	0.03***
N_MEF	52029	0.62	0.00	89186	1.98	0.00	1.36***

Panel A (continued)

	Non-CDS Firms (1% radius matching)				Non-CDS Firms (Nearest Neighbor matching)			
Variable	N	Mean	Median	Mean Diff	N	Mean	Median	Mean Diff
F_Acc	105508	-0.32	-0.1	-0.09***	29291	-0.31	-0.09	-0.08***
F_Optm	105508	-0.0001	-0.0004	0.0002	29291	-0.0004	-0.0004	0.0002
N_analyst	105508	10.98	10	-2.73***	29291	10.85	10	-2.86***
Size	105508	5.12	1.89	-19.93***	29291	10.3	3.14	-14.75***
MB	105508	3.71	2.34	-1.46***	29291	2.83	2.12	-2.34***
Leverage	105508	0.25	0.25	-0.04***	29291	0.29	0.28	-0.001***
ROE	105508	0.01	0.03	-0.03***	29291	0.02	0.03	-0.02***
Ins_own	105508	0.71	0.73	0.03***	29291	0.65	0.68	-0.03***
Mom	105508	0.02	0.01	0.01***	29291	0.01	0.01	0.001***
R_Vol	105508	0.03	0.03	0.004***	29291	0.03	0.03	0.003***
Turnover	105508	12.26	8.57	4.59***	29291	9.14	5.71	1.47***
E_Vol	105508	0.07	0.01	0.05***	29291	0.02	0.01	0.006***
Coverage	105508	1.35	1.00	-0.03***	29291	1.29	1.00	-0.04***
F_Exp	105508	3.66	2.00	0.03	29291	3.65	2.00	0.02
F_Hor	105508	3.73	3.99	0.08***	29291	3.67	3.87	0.02***
Bro_size	105508	0.70	0.58	-0.07***	29291	0.75	0.68	-0.02***
E_Skew	105508	-0.003	0.00	-0.001***	29291	-0.003	0.00	-0.001***
N_seg	105508	13.75	12.00	-2.64***	29291	13.42	12.00	-2.97***
EPS_Dif	105508	0.04	0.02	0.06***	29291	-0.03	0.02	-0.01***
Sgrate	105508	0.17	0.10	0.05***	29291	0.16	0.08	0.04***
Svolume	105508	18.87	18.79	-0.55***	29291	18.88	18.77	0.54***
PM	105508	-0.88	0.05	-0.93***	29291	0.01	0.04	-0.04***
RD	105508	0.08	0.00	0.03***	29291	0.04	0.00	-0.01***
N_MEF	105508	1.91	0.00	1.29***	29291	1.01	0.00	0.38***

Panel B: Post-CDS trading period

	CDS Firms			Non-CDS Firms (0.5% radius matching)			
Variable	N	Mean	Median	N	Mean	Median	Mean Diff
F_Acc	78067	-0.29	-0.1	109690	-0.59	-0.13	-0.30***
F_Optm	78067	-0.0005	-0.0005	109690	0.0011	-0.0005	0.0017***
N_analyst	78067	15.44	14	109690	12.1	10	-3.34***
Size	78067	25.84	9.38	109690	6.67	2.65	-19.16***
MB	78067	2.96	2.29	109690	2.34	2.22	-0.62***
Leverage	78067	0.27	0.26	109690	0.27	0.23	-0.004***
ROE	78067	0.04	0.04	109690	-0.02	0.03	-0.06***
Ins_own	78067	0.76	0.77	109690	0.81	0.85	0.05***
Mom	78067	0.02	0.02	109690	0.03	0.02	0.004***
R_Vol	78067	0.02	0.02	109690	0.03	0.02	0.01***
Turnover	78067	9.96	7.65	109690	13.61	11.17	3.65***
E_Vol	78067	0.02	0.01	109690	0.05	0.01	0.03***
Coverage	78067	1.32	1.00	109690	1.37	1.00	0.05***

F_Exp	78067	6.27	4.00	109690	5.55	4.00	-0.72***
F_Hor	78067	3.57	3.76	109690	3.72	4.08	0.15***
Bro_size	78067	0.72	0.66	109690	0.62	0.54	-0.1***
E_Skew	78067	-0.01	0.00	109690	-0.02	0.00	-0.01***
N_seg	78067	20.20	19.00	109690	15.57	14.00	-4.62***
EPS_Dif	78067	0.01	0.05	109690	-0.03	0.02	-0.04***
Sgrate	78067	0.09	0.07	109690	0.13	0.08	0.04***
Svolume	78067	20.14	20.00	109690	19.45	19.39	-0.69***
PM	78067	0.06	0.07	109690	-0.24	0.06	-0.30***
RD	78067	0.05	0.00	109690	0.07	0.00	0.02***
N_MEF	78067	4.68	2.00	109690	5.77	4.00	1.08***

Panel B (continued)

	Non-CDS (1% radius matching)				Non-CDS (Nearest Neighbor matching)			
Variable	N	Mean	Median	Mean Diff	N	Mean	Median	Mean Diff
F_Acc	131792	-0.57	-0.14	-0.29***	31880	-0.37	-0.11	-0.08***
F_Optm	131792	0.0009	-0.0006	0.0014***	31880	-0.0001	-0.0005	0.0005***
N_analyst	131792	12.11	10	-3.33***	31880	12.16	11	-3.28***
Size	131792	6.46	2.48	-19.38***	31880	15.41	4.04	-10.42***
MB	131792	2.71	2.2	-0.24***	31880	1.58	2.16	-1.38***
Leverage	131792	0.26	0.23	-0.01***	31880	0.24	0.22	0.01***
ROE	131792	0.01	0.03	-0.03***	31880	0.01	0.03	-0.03***
Ins_own	131792	0.81	0.85	0.05***	31880	0.73	0.77	-0.02***
Mom	131792	0.02	0.02	0.002***	31880	0.03	0.02	0.008***
R_Vol	131792	0.03	0.02	0.01***	31880	0.02	0.02	0.001***
Turnover	131792	13.83	11.47	3.86***	31880	10.4	8.4	0.44***
E_Vol	131792	0.05	0.01	0.02***	31880	0.02	0.01	-0.001
Coverage	131792	1.38	1.00	0.02***	31880	1.26	1.00	-0.06***
F_Exp	131792	5.52	4.00	-0.75***	31880	5.81	4.00	-0.46***
F_Hor	131792	3.72	4.08	0.15***	31880	3.66	3.95	0.09***
Bro_size	131792	0.61	0.53	-0.11***	31880	0.68	0.60	-0.04***
E_Skew	131792	-0.01	0.00	-0.01***	31880	-0.004	0.00	-0.001***
N_seg	131792	15.61	14.00	-4.59***	31880	17.67	15.00	-2.53***
EPS_Dif	131792	-0.03	0.02	-0.05***	31880	-0.01	0.03	-0.03***
Sgrate	131792	0.13	0.08	0.04***	31880	0.08	0.07	-0.01***
Svolume	131792	19.43	19.35	-0.71***	31880	19.54	19.46	-0.60***
PM	131792	-0.19	0.06	-0.25***	31880	0.00	0.07	-0.06***
RD	131792	0.08	0.00	0.03***	31880	0.06	0.00	0.01***
N_MEF	131792	5.62	3.00	0.93***	31880	5.77	4.00	1.08***

Table 3.4: Correlation table

This table reports Pearson (below diagonal) and Spearman (above diagonal) correlation among some variables used in the empirical analysis. We omit some other variables because the full table is too large to tabulate, and the omitted variables generally has a relative smaller correlation coefficient with other variables. The complete table is available upon request. The sample period spans 1996-2012. *F_Acc* is Analysts' earnings forecast accuracy, defined as the negative absolute value of difference between forecast value and actual value, scaled by the stock price of fiscal quarter end. *F_optm* is Analysts' earnings forecast optimism. *POST* is an indicator variable equal to 1 if a firm falls into the five-year period after CDS-trade-initiation year, and zero otherwise. The matching control firms take on the same value of *POST* as the matched CDS firms. *CDSF* is an indicator variable equal to 1 if a firm has a CDS contract traded over the sample period, and 0 otherwise. *N_analyst*, number of analyst following this firm; *Size*, the firm's market cap at the end of this fiscal quarter (in billion); *MB*, the ratio of market value to book value of equity; *Leverage*, total debt scaled by total asset; *Mom*, the momentum return of previous 3 months; *N_MEF;* number of management earnings forecast in this year. We only report the correlation table for the radius 0.5% matching method. The other two method produce similar correlation results, which is available upon request.

	F_Acc	*F_optm*	*POST*	*CDSF*	*Mom*	*MB*	*Size*	*Leverage*	*N_MEF*
F_acc	1	0.34*	-0.11*	0.09*	0.04*	0.38*	0.31*	-0.19*	0.09*
F_optm	-0.85	1	-0.03*	0.03*	-0.06*	0.05*	0.04*	0.02*	-0.05*
POST	-0.02	0.01*	1	0.05*	0.02*	-0.08*	0.11*	-0.03*	0.40*
CDSF	0.03*	-0.01*	0.05*	1	0.01*	0.06*	0.42*	0.07*	-0.08*
Mom	0.03*	-0.03*	0.01*	-0.01*	1	0.14*	0.08*	-0.03*	0.05*
MB	0.00	0.00	-0.02*	0.01*	0.00	1	0.48*	-0.30*	0.08*
Size	0.11*	-0.04*	0.11*	0.42*	0.03*	0.04*	1	-0.36*	0.06*
Leverage	-0.10*	0.06*	-0.01*	0.03*	0.00	-0.02*	-0.35*	1	-0.19*
N_MEF	0.03*	-0.01*	0.32*	-0.08*	0.00	0.00	0.08*	-0.18*	1

Table 3.5: Multivariate regression results on the relation between CDS introduction and analyst forecast accuracy: full sample

This table presents the multivariate regression result of the impact of CDS introduction on analyst earnings forecast accuracy. The dependent variable is *F_Acc*, Analysts' earnings forecast accuracy: defined as the negative absolute value of difference between forecast value and actual value, scaled by the stock price of fiscal quarter end. *POST* is an indicator variable equal to 1 if a firm falls into the five-year period after CDS-trade-initiation year, and zero otherwise. The matching control firms take on the same value of *POST* as the matched CDS firms. *CDSF* is an indicator variable equal to 1 if a firm has a CDS contract traded over the sample period, and 0 otherwise. *N_analyst*, number of analyst following this firm; *Size*, the firm's market cap at the end of this fiscal quarter (in billion); *MB*, the ratio of market value to book value of equity; Leverage, total debt scaled by total asset; *ROE*, the firm's return on equity; *Ins_own*, the ratio of Institutional ownership; *Mom*, the momentum return of previous 3 months; *R_Vol*, standard deviation of daily stock return within the last 3 month; *Turnover*, the stock turnover ratio in the last 3 months; *E_Vol*, earnings volatility in the previous 8 quarters; *Coverage*; the number of firms that analyst is following in the same quarter; *F_Exp*, analyst's following experience, measured as the number of previous quarters this analyst follows this firm; *F_Hor*, the time duration between analyst forecast and earnings announcement; *Bro_size*, the size of analyst brokarage frim, measured as the number of analyst affiliated to this brokerage firm; *E_skew*, earnings skewness, measured as the difference between mean and median in the previous 8 quarters, scaled by the stock price of fiscal quarter end (Gu and Wu, 2003); *N_Seg*, number of segment in this firm; *EPS_Dif*, earnings change from the same quarter of last year; Loss, indicator variable equal to 1 if this quarter has a negative earnings, and 0 otherwise. *Sgrate*, compounded sales growth rate in the last three year; *Svolume*, natural logarithm of dollar trading volume of last 4 quarters; *PM* is the net income scaled by sales; *RD*, the R&D expense ratio; *N_MEF;* number of management earnings forecast in this year. The sample period spans from 1996 to 2012, based on firm-quarter-analyst observation. The regression results based 3 matching method are presented: nearest neighbor matching, 0.5% radius matching, 1% radius matching. Year and industry fixed effects are included, and standard error are clustered at firm level. (*** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.)

Table 3.5 (continued)

Dependent Variable=Analyst Forecast Accuracy							
	Nearest Neighbor Matching	Radius Matching PS Dif.<0.5%	Radius Matching PS Dif.<1%		Nearest Neighbor Matching	Radius Matching PS Dif.<0.5%	Radius Matching PS Dif.<1%
POST	-0.069*	-0.258**	-0.270**	*Mom*	0.012	0.190**	0.205**
	(-1.68)	(-2.25)	(-2.44)		(0.33)	(2.07)	(2.38)
CDSF	-0.090*	-0.273***	-0.297***	*EPS_Dif*	0.023	0.144***	0.054*
	(-1.80)	(-3.75)	(-4.22)		(1.09)	(3.09)	(1.72)
CDSF*POST	**0.122****	**0.292*****	**0.286*****	*Loss*	-0.146***	-0.125*	-0.196***
	(2.19)	**(2.66)**	**(2.86)**		(-3.82)	(-1.76)	(-3.12)
Coverage	-0.024**	0.004	0.000	*Sgrate*	-0.139	0.009	0.034
	(-2.34)	(0.20)	(0.02)		(-0.49)	(0.15)	(0.52)
F_Exp	-0.001	0.001	-0.001	*Svolume*	-0.044*	-0.114***	-0.093**
	(-0.98)	(0.21)	(-0.38)		(-1.77)	(-2.70)	(-2.07)
F_Hor	-0.030***	-0.036***	-0.040***	*ROE*	-0.022	0.062	0.067
	(-4.61)	(-2.76)	(-3.54)		(-0.78)	(0.91)	(1.03)
Bro_size	0.022**	-0.005	-0.011	*MB*	0.000	-0.000	-0.000
	(2.20)	(-0.30)	(-0.65)		(0.15)	(-0.70)	(-0.47)
R_Vol	-14.281***	-50.129***	-46.691***	*Size*	0.100***	0.218***	0.200***
	(-2.89)	(-3.92)	(-4.23)		(4.11)	(4.19)	(3.96)
Turnover	0.008	0.029***	0.022***	*Leverage*	-0.109	-1.115	-1.025
	(1.53)	(3.14)	(2.71)		(-0.84)	(-1.09)	(-1.09)
N_analyst	0.001	0.000	0.000	*PM*	-0.002	0.000	-0.000
	(0.70)	(0.03)	(0.09)		(-0.10)	(0.23)	(-0.13)
E_Skew	-11.815***	-0.589***	-0.157	*RD*	0.077	0.154	0.155
	(-4.52)	(-3.06)	(-1.01)		(0.61)	(0.89)	(1.16)
E_Vol	-9.165***	-0.375***	-0.134	constant	0.191	2.375***	2.026***
	(-6.60)	(-3.03)	(-1.64)		(0.52)	(3.01)	(2.75)
Ins_own	0.200***	0.658**	0.659**	Year Fixed Effect	yes	yes	yes
	(2.75)	(2.10)	(2.28)	Industry Fixed Effect	yes	yes	yes
N_MEF	0.004**	-0.002	-0.001	Clustered Standard Error	yes	yes	yes
	(-2.12)	(-0.41)	(-0.22)	No. of Obs.	191267	328972	367394
N_seg	-0.001	0.001	-0.000	R-Squared	0.18	0.05	0.05
	(-0.08)	(0.37)	(-0.06)				

Table 3.6: Cross-sectional analysis of CDS introduction and analyst forecast accuracy

This table compares the subsample relations between CDS introduction and analyst forecast accuracy. The subsample is split based on the median of six control variables. Panel A presents the subsample analysis based on firm size, stock volatility and earnings volatility; Panel B presents the subsample analysis based on leverage, the number of management earnings forecast and Loss. The dependent variable is *F_Acc*, Analysts' earnings forecast accuracy: defined as the negative absolute value of difference between forecast value and actual value, scaled by the stock price of fiscal quarter end. *POST* is an indicator variable equal to 1 if a firm falls into the five-year period after CDS-trade-initiation year, and zero otherwise. The matching control firms take on the same value of *POST* as the matched CDS firms. *CDSF* is an indicator variable equal to 1 if a firm has a CDS contract traded over the sample period, and 0 otherwise. *N_analyst*, number of analyst following this firm; *Size*, the firm's market cap at the end of this fiscal quarter (in billion); *MB*, the ratio of market value to book value of equity; Leverage, total debt scaled by total asset; *ROE*, the firm's return on equity; *Ins_own*, the ratio of Institutional ownership; *Mom*, the momentum return of previous 3 months; *R_Vol*, standard deviation of daily stock return within the last 3 month; *Turnover*, the stock turnover ratio in the last 3 months; *E_Vol*, earnings volatility in the previous 8 quarters; *Coverage*; the number of firms that analyst is following in the same quarter; *F_Exp*, analyst's following experience, measured as the number of previous quarters this analyst follows this firm; *F_Hor*, the time duration between analyst forecast and earnings announcement; *Bro_size*, the size of analyst brokarage frim, measured as the number of analyst affiliated to this brokerage firm; *E_skew*, earnings skewness, measured as the difference between mean and median in the previous 8 quarters, scaled by the stock price of fiscal quarter end (Gu and Wu, 2003); *N_Seg*, number of segment in this firm; *EPS_Dif*, earnings change from the same quarter of last year; Loss, indicator variable equal to 1 if this quarter has a negative earnings, and 0 otherwise. *Sgrate,* compounded sales growth rate in the last three year; *Svolume*, natural logarithm of dollar trading volume of last 4 quarters; *PM* is the net income scaled by sales; *RD*, the R&D expense ratio; *N_MEF;* number of management earnings forecast in this year. The sample period spans from 1996 to 2012, based on firm-quarter-analyst observation. We only present the regression results based on the 0.5% radius matching method. Nearest neighbor matching and 1% radius matching produce qualitatively similar results. The result is available upon request. Year and industry fixed effects are included, and standard error are clustered at firm level. We omit the coefficient of 15 of 22 control variables for tabulation. The result is available upon request. (*** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.)

Table 3.6 (continued)

Panel A						
	Dependent Variable=Analyst Forecast Accuracy					
	Small	Large	Low Svol	High Svol	Low Evol	High Evol
POST	-0.411*	-0.030**	-0.009	-0.398**	-0.003	-0.492**
	(-1.92)	(-2.30)	(-1.09)	(-1.98)	(-0.53)	(-2.25)
CDSF	-0.522***	-0.036*	-0.003	-0.410***	-0.006	-0.416***
	(-3.59)	(-1.82)	(-0.23)	(-3.50)	(-0.75)	(-3.31)
CDSF*POST	**0.456****	**0.023**	**-0.019**	**0.546*****	**0.001**	**0.483****
	(2.56)	**(1.14)**	**(-1.33)**	**(2.73)**	**(0.09)**	**-2.47**
Coverage	-0.002	-0.003	-0.002	0.006	-0.001	-0.009
	(-0.08)	(-0.89)	(-0.75)	(0.18)	(-0.42)	(-0.30)
F_Exp	0.004	0.001	0.001	0.003	0.003	0.003
	(0.92)	(0.19)	(0.06)	(0.63)	(1.07)	-0.84
F_Hor	-0.057**	-0.008***	-0.008***	-0.056**	-0.005***	-0.047*
	(-2.47)	(-2.76)	(-3.14)	(-2.44)	(-2.75)	(-1.78)
Bro_size	-0.031	0.001	-0.003	0.006	-0.007	-0.001
	(-0.92)	(0.44)	(-0.47)	(0.24)	(-1.49)	(-0.03)
R_Vol	-62.872***	-3.743***	-2.117	-57.766***	-0.650**	-63.874***
	(-3.59)	(-2.81)	(-1.61)	(-3.86)	(-2.05)	(-3.81)
E_Skew	-0.790***	-4.061**	1.069	-0.795***	0.131	-0.616***
	(-2.80)	(-2.41)	(1.19)	(-2.89)	(0.04)	(-3.03)
Size	0.551***	0.054***	0.076***	0.356***	0.038***	0.303***
	(4.54)	(4.39)	(7.52)	(4.44)	(5.98)	(2.83)
constant	0.695	0.294	0.129	3.530***	-0.018	2.508***
	(0.73)	(1.41)	(0.96)	(3.38)	(-0.00)	(2.58)
Other 15 Control Variables	yes	yes	yes	yes	yes	yes
Year Fixed Effect	yes	yes	yes	yes	yes	yes
Industry Fixed Effect	yes	yes	yes	yes	yes	yes
Clustered Standard Error	yes	yes	yes	yes	yes	yes
No. of Obs.	171298	157674	137503	191469	160403	168569
R-Squared	0.07	0.14	0.06	0.06	0.05	0.07

Panel B						
	Dependent Variable=Analyst Forecast Accuracy					
	L_MEF	M_MEF	Less Exp	More Exp	Low Lev	High Lev
POST	-0.405**	-0.035	-0.299**	-0.209**	-0.021	-0.453**
	(-2.08)	(-1.22)	(-2.06)	(-2.53)	(-1.38)	(-2.18)
CDSF	-0.384***	0.136	-0.303***	-0.214***	-0.059**	-0.470***
	(-3.90)	(0.63)	(-3.48)	(-3.61)	(-2.44)	(-3.39)
CDSF*POST	**0.442****	**-0.039**	**0.337****	**0.208*****	**0.041**	**0.427****
	(2.38)	**(-0.34)**	-2.27	-2.76	**(1.49)**	**(2.55)**
Coverage	0.003	0.004	0.017	-0.021	-0.009**	0.01
	(0.13)	(0.19)	-0.46	(-1.15)	(-2.14)	(0.28)
F_Exp	0.002	-0.001	0.016	-0.001	-0.001	0.006
	(0.47)	(-0.50)	-1.47	(-0.62)	(-1.50)	(1.21)
F_Hor	-0.033*	-0.035*	-0.034*	-0.040***	-0.016***	-0.04
	(-1.75)	(-1.92)	(-1.88)	(-3.42)	(-3.57)	(-1.35)
Bro_size	-0.002	0.033	-0.04	0.034	-0.001	0.004
	(-0.12)	(1.34)	(-0.85)	-0.79	(-0.21)	(0.14)
R_Vol	-51.991***	-34.037**	-52.986***	-47.337***	-6.393***	-72.538***
	(-3.32)	(-2.12)	(-3.55)	(-4.44)	(-3.46)	(-3.70)
E_Skew	-0.579***	-2.611	-0.615***	-3.03	4.404	-0.909***
	(-2.68)	(-1.04)	(-2.77)	(-1.52)	(1.57)	(-2.96)
Size	0.249***	0.023	0.213***	0.243***	0.064***	0.370***
	(3.47)	(0.28)	-3.26	-4.99	(3.96)	(4.37)
constant	2.624**	0.734	2.476***	1.808	0.226	4.231***
	2.52	0.01	-2.6	0	(0.92)	(3.32)
Other 15 Control Variables	yes	yes	yes	yes	yes	yes
Year Fixed Effect	yes	yes	yes	yes	yes	yes
Industry Fixed Effect	yes	yes	yes	yes	yes	yes
Clustered Standard Error	yes	yes	yes	yes	yes	yes
No. of Obs.	203868	125104	197520	131452	166372	162600
R-Squared	0.05	0.15	0.2	0.07	0.2	0.07

Table 3.7: Multivariate regression results on the relation between CDS introduction and analyst forecast optimism: full sample

This table presents the multivariate regression result of the impact of CDS introduction on analyst earnings forecast optimism. The dependent variable is *F_Optm*, Analysts' earnings forecast optimism: defined as the difference between forecast value and actual value, scaled by the stock price of fiscal quarter end. *POST* is an indicator variable equal to 1 if a firm falls into the five-year period after CDS-trade-initiation year, and zero otherwise. The matching control firms take on the same value of *POST* as the matched CDS firms. *CDSF* is an indicator variable equal to 1 if a firm has a CDS contract traded over the sample period, and 0 otherwise. *N_analyst*, number of analyst following this firm; *Size*, the firm's market cap at the end of this fiscal quarter (in billion); *MB*, the ratio of market value to book value of equity; Leverage, total debt scaled by total asset; *ROE*, the firm's return on equity; *Ins_own*, the ratio of Institutional ownership; *Mom*, the momentum return of previous 3 months; *R_Vol*, standard deviation of daily stock return within the last 3 month; *Turnover*, the stock turnover ratio in the last 3 months; *E_Vol*, earnings volatility in the previous 8 quarters; *Coverage*; the number of firms that analyst is following in the same quarter; *F_Exp*, analyst's following experience, measured as the number of previous quarters this analyst follows this firm; *F_Hor*, the time duration between analyst forecast and earnings announcement; *Bro_size*, the size of analyst brokarage frim, measured as the number of analyst affiliated to this brokerage firm; *E_skew*, earnings skewness, measured as the difference between mean and median in the previous 8 quarters, scaled by the stock price of fiscal quarter end (Gu and Wu, 2003); *N_Seg*, number of segment in this firm; *EPS_Dif*, earnings change from the same quarter of last year; Loss, indicator variable equal to 1 if this quarter has a negative earnings, and 0 otherwise. *Sgrate,* compounded sales growth rate in the last three year; *Svolume,* natural logarithm of dollar trading volume of last 4 quarters; *PM* is the net income scaled by sales; *RD,* the R&D expense ratio; *N_MEF;* number of management earnings forecast in this year. The sample period spans from 1996 to 2012, based on firm-quarter-analyst observation. The regression results based 3 matching method are presented: nearest neighbor matching, 0.5% radius matching, 1% radius matching. Year and industry fixed effects are included, and standard error are clustered at firm level. (*** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.)

Table 3.7 (continued)

	Dependent Variable=Analyst Forecast Optimism						
	NN	R 0.5%	R 1%		NN	R 0.5%	R 1%
POST	0.045	0.17	0.165	*EPS_Dif*	-0.079***	-0.132**	-0.051
	(1.39)	(1.55)	(1.56)		(-3.27)	(-2.43)	(-1.62)
CDSF	0.028	0.083*	0.083*	*Loss*	0.314***	0.337***	0.405***
	(1.00)	(1.80)	(1.85)		(5.88)	(4.58)	(6.36)
CDSF*POST	**-0.072***	**-0.206****	**-0.193****	*Sgrate*	-0.388	-0.107	-0.121
	(-1.83)	**(-2.08)**	**(-2.14)**		(-1.64)	(-1.16)	(-1.32)
Coverage	0.001	-0.009	-0.009	*Svolume*	-0.02	-0.076**	-0.083**
	(0.08)	(-0.44)	(-0.58)		(-0.83)	(-2.12)	(-2.24)
F_Exp	0	-0.001	-0.001	*ROE*	-0.012	0.065	0.052
	(0.09)	(-0.96)	(-0.44)		(-0.35)	(0.79)	(0.67)
F_Hor	0.007	0.019	0.019*	*MB*	0	0	0
	(1.2)	(1.55)	(1.78)		(0.66)	(-0.36)	(-0.42)
Bro_size	-0.028**	-0.026	-0.030*	*Size*	0.012	0.068	0.077*
	(-2.28)	(-1.48)	(-1.78)		(0.42)	(1.48)	(1.73)
R_Vol	6.698***	31.927**	28.372**	*Leverage*	-0.061	0.897	0.841
	(2.82)	(2.49)	(2.58)		(-0.64)	(0.89)	(0.91)
Turnover	-0.002	-0.019**	-0.013**	*PM*	-0.048	0	0
	(-0.76)	(-2.11)	(-1.98)		(-1.06)	(0.82)	(1.11)
N_analyst	0.004**	0.006	0.006*	*RD*	-0.370***	-0.308*	-0.307**
	(2.23)	(1.63)	(1.68)		(-3.26)	(-1.93)	(-2.37)
E_Skew	-3.2	0.575***	0.183	*N_MEF*	-0.003	0.002	0.002
	(-1.27)	(2.62)	(1.43)		(-1.63)	(0.45)	(0.56)
E_Vol	-1.619	0.326**	0.105	constant	-0.086	-0.36	-0.314
	(-1.12)	(2.38)	(1.41)		(-0.25)	(-0.51)	(-0.49)
Ins_own	-0.044	-0.253	-0.244	Year Fixed Effect	Yes	yes	yes
	(-0.69)	(-0.84)	(-0.88)	Industry Fixed Effect	Yes	yes	yes
N_seg	-0.002	-0.004	-0.003	Clustered Standard Error	Yes	yes	yes
	(-1.30)	(-1.27)	(-1.04)	No. of Obs.	191267	328972	367394
Mom	-0.088**	-0.212**	-0.223***	R-Squared	0.02	0.02	0.02
	(-2.44)	(-2.38)	(-2.65)				

Table 3.8: The effect of CDS introduction on analysts' strategic optimism for different optimism level

This table study the effect of CDS introduction on analysts' strategic optimism. We choose 3 variables related with analysts' strategic optimism to evenly split the full sample. These 3 variable are analyst following experience, stock trading volume, and brokerage firm size. The dependent variable is *F_Optm*, Analysts' earnings forecast optimism: defined as the difference between forecast value and actual value, scaled by the stock price of fiscal quarter end. *POST* is an indicator variable equal to 1 if a firm falls into the five-year period after CDS-trade-initiation year, and zero otherwise. The matching control firms take on the same value of *POST* as the matched CDS firms. *CDSF* is an indicator variable equal to 1 if a firm has a CDS contract traded over the sample period, and 0 otherwise. *N_analyst*, number of analyst following this firm; *Size*, the firm's market cap at the end of this fiscal quarter (in billion); *MB*, the ratio of market value to book value of equity; Leverage, total debt scaled by total asset; *ROE*, the firm's return on equity; *Ins_own*, the ratio of Institutional ownership; *Mom*, the momentum return of previous 3 months; *R_Vol*, standard deviation of daily stock return within the last 3 month; *Turnover*, the stock turnover ratio in the last 3 months; *E_Vol*, earnings volatility in the previous 8 quarters; *Coverage*; the number of firms that analyst is following in the same quarter; *F_Exp*, analyst's following experience, measured as the number of previous quarters this analyst follows this firm; *F_Hor*, the time duration between analyst forecast and earnings announcement; *Bro_size*, the size of analyst brokarage frim, measured as the number of analyst affiliated to this brokerage firm; *E_skew*, earnings skewness, measured as the difference between mean and median in the previous 8 quarters, scaled by the stock price of fiscal quarter end (Gu and Wu, 2003); *N_Seg*, number of segment in this firm; *EPS_Dif*, earnings change from the same quarter of last year; Loss, indicator variable equal to 1 if this quarter has a negative earnings, and 0 otherwise. *Sgrate*, compounded sales growth rate in the last three year; *Svolume*, natural logarithm of dollar trading volume of last 4 quarters; *PM* is the net income scaled by sales; *RD*, the R&D expense ratio; *N_MEF;* number of management earnings forecast in this year. The sample period spans from 1996 to 2012, based on firm-quarter-analyst observation. We only present the regression results based on the 0.5% radius matching method. Nearest neighbor matching and 1% radius matching produce qualitatively similar results. The result is available upon request. Year and industry fixed effects are included, and standard error are clustered at firm level. We omit the coefficient of 15 of 22 control variables for tabulation. The result is available upon request. (*** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.)

Table 3.8 (continued)

	Dependent Variable=Analyst Forecast Optimism					
	Less Exp	More Exp	Low Vol	High Vol	Small Bro	Large Brokerage
POST	0.195	0.160**	0.255	0.068	0.214	0.117*
	(1.43)	(1.99)	(1.12)	(1.46)	(1.41)	(1.70)
CDSF	0.088*	0.077	0.176*	0.006	0.106*	0.048
	(1.87)	(1.51)	(1.81)	(0.16)	(1.73)	(1.25)
CDSF*POST	**-0.216**	**-0.175****	**-0.289**	**-0.114****	**-0.227***	**-0.172****
	(-1.63)	**(-2.45)**	**(-1.55)**	**(-2.08)**	**(-1.85)**	**(-2.33)**
Coverage	-0.023	0.02	-0.014	0.005	-0.003	-0.019
	(-0.60)	(1.10)	(-0.48)	(0.29)	(-0.11)	(-0.76)
F_Exp	-0.023**	0.001	-0.004	0	0	-0.003
	(-2.34)	(0.76)	(-1.26)	(-0.20)	(0.13)	(-1.31)
F_Hor	0.016	0.023*	0.019	0.011	0.011	0.030*
	(0.98)	(1.71)	(1.01)	(1.30)	(0.35)	(1.72)
Bro_size	0.019	-0.076*	-0.035	-0.037***	-0.167*	0.089
	(0.39)	(-1.77)	(-1.15)	(-2.69)	(-1.79)	(0.72)
R_Vol	33.731**	33.675***	65.391**	8.743**	41.913**	21.554**
	(2.31)	(2.96)	(2.26)	(2.00)	(2.50)	(2.22)
E_Skew	0.613***	0.179	0.710*	-6.106	0.765***	0.386*
	(2.80)	(0.17)	(1.75)	(-1.27)	(2.73)	(1.93)
Size	0.025	0.056	0.164	0.059	0.071	0.07
	(0.44)	(1.20)	(1.62)	(1.34)	(1.16)	(1.42)
constant	-0.839	-0.631	-1.882	0.56	0.814	-0.16
	(-1.00)	(-0.90)	(-1.03)	(1.20)	(0.74)	(-0.22)
Other 15 Control Variables	yes	yes	yes	yes	yes	yes
Year Fixed Effect	yes	yes	yes	yes	yes	yes
Industry Fixed Effect	yes	yes	yes	yes	yes	yes
Clustered Standard Error	yes	yes	yes	yes	yes	yes
No. of Obs.	197520	131452	163540	165432	161961	167011
R-Squared	0.02	0.03	0.03	0.05	0.03	0.01

Table 3.9: The effect of CDS introduction on ex ante analyst forecast optimism in the case of ex post bad news

This table reports the effect of CDS introduction on *ex ante* analyst forecast optimism in the case of *ex post* bad news. We select two ex post measurements of bad news: negative earnings and negative EPS change from the same quarter of last year. Also, we select negative 3-month momentum return before earnings announcement as a contemporary measurement of bad news. The dependent variable is *F_Optm*, Analysts' earnings forecast optimism: defined as the difference between forecast value and actual value, scaled by the stock price of fiscal quarter end. *POST* is an indicator variable equal to 1 if a firm falls into the five-year period after CDS-trade-initiation year, and zero otherwise. The matching control firms take on the same value of *POST* as the matched CDS firms. *CDSF* is an indicator variable equal to 1 if a firm has a CDS contract traded over the sample period, and 0 otherwise. *N_analyst*, number of analyst following this firm; *Size*, the firm's market cap at the end of this fiscal quarter (in billion); *MB*, the ratio of market value to book value of equity; Leverage, total debt scaled by total asset; *ROE*, the firm's return on equity; *Ins_own*, the ratio of Institutional ownership; *Mom*, the momentum return of previous 3 months; *R_Vol*, standard deviation of daily stock return within the last 3 month; *Turnover*, the stock turnover ratio in the last 3 months; *E_Vol*, earnings volatility in the previous 8 quarters; *Coverage*; the number of firms that analyst is following in the same quarter; *F_Exp*, analyst's following experience, measured as the number of previous quarters this analyst follows this firm; *F_Hor*, the time duration between analyst forecast and earnings announcement; *Bro_size*, the size of analyst brokarage frim, measured as the number of analyst affiliated to this brokerage firm; *E_skew*, earnings skewness, measured as the difference between mean and median in the previous 8 quarters, scaled by the stock price of fiscal quarter end (Gu and Wu, 2003); *N_Seg*, number of segment in this firm; *EPS_Dif*, earnings change from the same quarter of last year; Loss, indicator variable equal to 1 if this quarter has a negative earnings, and 0 otherwise. *Sgrate*, compounded sales growth rate in the last three year; *Svolume*, natural logarithm of dollar trading volume of last 4 quarters; *PM* is the net income scaled by sales; *RD*, the R&D expense ratio; *N_MEF;* number of management earnings forecast in this year. The sample period spans from 1996 to 2012, based on firm-quarter-analyst observation. We only present the regression results based on the 0.5% radius matching method. Nearest neighbor matching and 1% radius matching produce qualitatively similar results. The result is available upon request. Year and industry fixed effects are included, and standard error are clustered at firm level. We omit the coefficient of 15 of 22 control variables for tabulation. The result is available upon request. (*** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.)

Table 3.9 (continued)

	Dependent Variable=Analyst Forecast Optimism					
	Pos Ea	Neg Ea	Pos EPSD	Neg EPSD	Pos Mom	Neg Mom
POST	-0.018	0.887	0.004	0.354	0.008	0.358
	(-1.23)	(1.63)	(0.20)	(1.51)	(0.44)	(1.63)
CDSF	-0.062**	0.339	-0.063*	0.14	0.02	0.158*
	(-2.54)	(0.92)	(-1.83)	(1.27)	(1.12)	(1.84)
CDSF*POST	**0.048****	**-0.983****	**0.012**	**-0.458****	**-0.022**	**-0.421***
	(2.29)	**(-2.24)**	**(0.42)**	**(-2.07)**	**(-0.94)**	**(-1.90)**
Coverage	-0.009**	0.001	-0.007	-0.028	0.008	-0.029
	(-2.51)	(0.01)	(-0.82)	(-0.63)	(1.19)	(-0.68)
F_Exp	0	-0.015	0.001	-0.006*	0	-0.001
	(-0.43)	(-1.41)	(0.80)	(-1.77)	(-0.01)	(-0.51)
F_Hor	-0.004	0.036	-0.003	0.050**	0.006	0.004
	(-1.09)	(0.4)	(-0.42)	(2.00)	(0.70)	(0.16)
Bro_size	-0.003	-0.163*	-0.006	-0.073**	-0.002	-0.057*
	(-0.32)	(-1.92)	(-0.47)	(-2.29)	(-0.14)	(-1.89)
R_Vol	-5.120*	72.345***	-1.765	53.621***	6.185*	49.349**
	(-1.92)	(3.14)	(-0.46)	(2.92)	(1.82)	(2.54)
E_Skew	2.727*	0.695	-0.041	10.904	-1.031***	0.948**
	(1.79)	(1.58)	(-0.32)	(1.30)	(-3.91)	-2.47
Size	0.043***	0.118	0.097***	0.097	0.021	0.057
	(3.75)	(0.41)	(4.79)	(0.65)	(1.31)	(0.61)
constant	0.471**	3.612	0.705***	-0.557	0.135	-0.856
	(2.25)	(1.61)	(3.25)	(-0.57)	(0.70)	(-0.80)
Other 15 Control Variables	yes	yes	yes	yes	yes	yes
Year Fixed Effect	yes	yes	yes	yes	yes	yes
Industry Fixed Effect	yes	yes	yes	yes	yes	yes
Clustered Standard Error	yes	yes	yes	yes	yes	yes
No. of Obs.	272146	56826	185920	143052	175449	153523
R-Squared	0.18	0.09	0.01	0.05	0.02	0.03

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APPENDIX

A1. The Variable Definitions in Essay 2

XRET02	Abnormal stock returns over the earnings announcement window [0, +2]. The abnormal stock return is calculated as the buy-and-hold return of a particular stock minus the buy-and-hold return from a portfolio of stocks of similar size (market value of equity, two groups), book-to-market ratio (three groups), and 12-month momentum (three groups), similar to Daniel and Titman (1997).
XRET71	Abnormal stock returns over the Pre-earnings-announcement window [-7, -1].
AXRET02	Absolute value of XRET02.
AXRET71	Absolute value of XRET71.
IV Spread	Each day, implied volatility spread is calculated as the weighted average difference between implied volatilities of call and put options matched on strike price and maturity date, where the weight is the combined open interest of the pair, scaled by the combined open interest of all available pairs.
IV Skew	Each day, volatility skew is calculated as Implied volatility of the out-of-the-money (OTM) put option minus the implied volatility of the at-the-money (ATM) call option. We select all call options that have a delta in the range [+0.4,+0.7], and choose the one closest to 0.5. Its implied volatility is the ATM implied volatility. We then select all put options that have a delta in the range [–0.15,–0.45], and choose the one closest to –0.3. Its implied volatility is the OTM implied volatility.
IV_ATM	The implied volatility of ATM call options. We identify for each day all call options of a firm with time-to-maturity between 10 and 90 days and expire after the earnings announcements or Pseudo events. Among those we select call options that have a delta in the range of [+0.4,+ 0.7], and choose the one closest to 0.5. Its implied volatility is the ATM implied volatility.
O/S Ratio	Ln(O/S) is the natural logarithm of the total daily option trading volume divided by the daily stock trading volume. Total daily option trading volume for each firm is calculated across all options listed on the stock (we account for the fact that each contract is for 100 shares of stock).
_Base	The average of IV Spread, IV Skew, IV_ATM or O/S Ratio over the Base window [-30,-8].
_Pre	The average of IV Spread, IV Skew, IV_ATM or O/S Ratio over the Pre window [-7,-1].
BAspd	The average of relative bid-ask spread of options in the window [-7,-1]. The relative bid-ask spread is the end-of-day ask price minus bid price then divided by the average of the bid and ask price.
OS_BAspd	The average of the ratios of option relative bid-ask spread to the underlying stock relative bid-ask spread in the Pre window [-7,-1]. It is shown in hundreds.
Size	The natural logarithm of market value of equity.
BM	The natural logarithm of book to market ratio.
Momentum	The buy and hold return of during the previous 12 months (t-12 through t-1).
Hvol	Annualized historical stock returns volatility. It is calculated the standard deviation of stock returns in the previous two months. It is then annualized by multiplying by square root of 252.