The Effects of Credit Default Swaps Trading on Analyst Forecasts

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Abstract

This paper investigates whether and how the initiation of credit default swaps (CDSs) trading affects analyst forecast accuracy and optimism. Using a difference-in-difference research design, we find significant increases in analyst forecast accuracy after the onset of CDS trading, consistent with the notion that the CDS market facilitates information discovery and dissemination. This effect is more pronounced among firms with greater information asymmetry and higher leverage. In addition, we find that CDS initiation depresses analysts' strategic optimism, suggesting that the CDS market has a discipline effect on financial analysts. The discipline effect is stronger among firms followed by analysts with more experience and affiliated with larger brokerage house. Overall, we show that the CDS trading reveals new information to analysts and discipline analysts to be less optimistic.

Keywords: Credit default swaps; analyst forecast accuracy; analyst forecast optimism

JEL classification: G10, G12, G13, G14, G24

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1. Introduction

This paper investigates the effects of a financial instrument innovation on analysts forecast properties. The financial instrument innovation we focus on is the credit default swap (hereafter CDS), which is widely used by lenders to manage credit risk and speculators to arbitrage mispricing profits. In the last two decades, there has been an explosive growth in the CDS market, with the notional amount increasing from $300 billion in 1998 to $57 trillion at the end of June 2008.[2] Given the large size of the CDS market, it is crucial to identify and quantify the potential effects of this new market on different market participants in the capital market. In this paper, we focus on equity analysts. Our primary goal is to examine whether and how the initiation of CDS trading affects 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. Some bank creditors also serve as dealers in this market, by supplying CDS spread quotes for firms to which they have loan exposure. Due to the possibility of informed trading by these informed lenders, at least some extent of private information could be revealed in this market through CDS pricing (Glantz 2003, and Whitehead 2012).[3] Consistent with this conjecture, 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 relatively larger number of ongoing

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

[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).

banking relationships. Blanco et al. (2005) find that CDS market also leads the bond market. Berndt and Ostrovnaya (2014) find that the CDS market leads equity options market before bad news. Equity analysts gather, acquire, process, and then disseminate information by releasing earnings forecast and other forecasts. Given the information discovery role of the CDS market and financial analysts absorbing information from the CDS market, we conjecture that the analyst forecast accuracy would improve after the initiation of CDS trading.

Next, we investigate the impact of CDS trading on analyst forecast optimism. In particular, we conjecture that the initiation of CDS trading will depress the analysts' strategic forecast optimism. Lim (2001) and Jackson (2005) propose theoretical models to analyze analysts' incentives and constraints. They find that an optimistic (up-biased) forecast is a rational and optimal choice for analysts, after trading off reputation costs, management access and trading commissions. The effects of CDS trading on analysts' strategic optimism lie in two aspects. Firstly, analysts strategically issue optimistic forecasts to gain access to management for private information, which helps analysts to increase forecast accuracy (Lim 2001). However, after the initiation of CDS trading: 1) more private information is revealed in the CDS market; 2) there is more voluntary disclosure by management (Kim et al. 2015). Hence, analysts' reliance on management for private information is decreased after CDS trading. Rationally, analysts will be less intentionally optimistic to please management, which would increase forecast accuracy to build reputation. Secondly, analysts also have concerns about their reputation when issuing optimistic forecasts. The introduction of CDS market makes the information environment more transparent, which increases analyst reputation concerns when issuing optimistic forecasts. If the CDS market already reveals certain bad news about future earnings, 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 to issue less optimistic forecasts in a more transparent information environment.

Our CDS transactions data is from Markit. Markit includes CDS composite and contributor level data for 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 from 2001 to 2008. After eliminating 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 prior 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 effects 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 behaviors, we also employ three different methods of propensity score matching to do the difference-in-difference analysis (Subrahmanyam et al. 2014; Martin and Roychowdhury 2015; Kim et al. 2015). Our sample period is from 1996 to 2012.

Consistent with our expectation, we find significant increases in analyst forecast accuracy after the initiation of CDS trading. In addition, we conduct a series of cross-sectional analysis to investigate when the impact of CDS initiation is more pronounced. First, we expect that the 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 effects in terms of information revelation, thus affecting analysts to a larger extent. The empirical evidence confirms 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 less experienced analysts. Second, we expect that the effect of CDS trading on forecast accuracy is stronger when the underlying firm is more leveraged. CDS is a derivative instrument written on the firm's liability. If a firm's debt has a larger weight in its capital structure, CDS trading would convey more information about this firm. Indeed, we find that the increase in analyst forecast accuracy is only significant for firms with higher leverage.

We document that the introduction of CDS trading depresses analysts' strategic optimism. Moreover, we find the effect to be stronger when the *ex ante* optimism level is higher before CDS introduction. Following prior literature, we use three different proxies to measure *ex ante* optimism. The first proxy is the analyst following experience. Analysts who follow a company for a long period develop a close relationship with the 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. Brokerage firms' primary source of income is commissions from client trade execution, so these firms typically link analyst compensation to commissions from trading volume. This is likely to encourage analysts to provide optimistic research to encourage investors to trade 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 firm size is positively related to analyst optimism because analysts bear greater pressure from their employers to stimulate trading volume when they are in larger brokerage firms. In particular, we find that the depressing effect of CDS trading is only significant in the subsamples with more experienced analysts, more liquid stocks, and larger brokerage houses.

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 with more experienced analysts, more liquid stocks, and larger brokerage houses. However, empirical results show that the impact of CDS trading on analyst forecast accuracy is more pronounced for firms with less experienced analysts, less liquid stocks and smaller brokerage houses. 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 properties. Accuracy is more closely related to information asymmetry while optimism is more closely related to analysts' strategic behaviors.

We also split the full sample based on whether bad news is announced on the earnings announcement date. Previous literature suggests that informed trading, especially those related to bad news, exists in the CDS market (Acharya and Johnson 2007; Qiu and Yu 2012). If the forthcoming bad news is preemptively revealed in CDS market, we expect the depressing effect of CDS trading on analyst forecast optimism to be more pronounced. Indeed, we find that the depressing effect of CDS trading on analyst optimism is stronger when earnings turn out to be negative, when EPS changes 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 effects of CDS trading on analyst forecast properties. In particular, the information dissemination function of CDS market help analysts to increase accuracy. The timely 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 et al. 2014; Kim et al. 2014; Martin and Roychowdhury 2015). This also improves our understanding of this huge but relative opaque derivatives market. Although prior literature criticizes 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 incentives (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 develop 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 enriches firms' information environment, which helps 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 disclosures, future investment projects, 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 officers and CDS trading desks 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). Consistently, some previous researches find that CDS market leads other markets in terms of reflecting private information sometimes (see, e.g. Acharya and Johnson (2007); Blanco et al.(2005); Qiu and Yu (2012); and Berndt and Ostrovnaya (2014)). In the meanwhile, equity analysts also gather, acquire and process information from the CDS market, which could help them to make more accurate forecasts.

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 that the CDS introduction can increase forecast accuracy more for analysts following higher-leveraged firms. 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 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 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) build theoretical models and they find similar conclusion: analysts issue optimistic forecasts because it is a rational and optimal choice after balancing reputation cost, management access and trading commissions. However, the introduction of CDS trading changes the original setting: 1). More private information is revealed in the CDS market due to the participation of informed traders. 2). Kim et al. (2015) find that, management is forced by CDS market to do more voluntary information disclosures. Either way, analysts’ demand for private information from personal management access is decreased. More importantly, this personal management access is usually built on their flattering optimism. So after CDS trading, they will rationally reduce optimism and increases accuracy to earn reputation. On the other hand, the introduction of CDS market decreases the information asymmetry between insiders and investors, which increases analysts' reputation cost when issuing optimistic forecasts in a more transparent environment. Hence, we expect that analysts will become less optimistic after the onset of CDS trading. Similar to H1a, we also expect that this effect is more pronounced when firms' original optimism level is higher due to the larger marginal effect.

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

Qiu and Yu (2012) and Berndt and Ostrovnaya (2014) find that CDS market is especially efficient when certain negative information will be released shortly. If the informed trading based on bad news indeed exists in the CDS market and if bad news is indeed confirmed in the earnings announcement date, we expect the depressing effect of CDS trading on analysts' *ex ante* optimism will be more pronounced than general cases. Because other investors can also observe these signals in the CDS market before announcement, the best choice for analysts is to speak honestly, otherwise they will suffer larger reputation loss by issuing 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.

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

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 a firm's 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 the 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:

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

Where *CDS* is an indicator variable equal to 1 for firms with CDS trading during 2001 to 2007, and zero otherwise; *Investment Grade* 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 the 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 the 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 are chosen based on their roles 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 1 Here>

Table 1 reports the regression results 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 the findings in Martin and Roychowdhury (2015). Based on adverse selection explanation, given that CDS buyers, 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 derivatives. In addition, we find that the ratio of working capital, the ratio of retained earnings and the ratio of capital expenditure are negatively related to the CDS introduction.

Next, we employ propensity score matching method to select the non-CDS control firms. 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 produces 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 are 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 produces 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]. We allow a non-CDS firm to enter the sample more than once every year, if it can serve as a match for more than one treatment (i.e., CDS) firm.

3.3 Descriptive Statistics

<Insert Table 2 Here>

[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).

Table 2 Panel A presents the sample distribution based on the CDS-trade-initiation year for the CDS firms sample and matched non-CDS firms sample. In our final sample, most of CDS contracts is introduced in 2001, which is 172. There is a decreasing trend of CDS initiation as time goes on. This may also reflect the forthcoming of financial crisis. Risk becomes larger and larger, and CDS contract provider becomes 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 the 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 the industry of Rubber, stone, computer, transportation equipment(25.45%), and the third is the transportation, communication, electric, gas and sanitary services(17.10%). The results are similar to Martin and Roychowdhury (2015).

<Insert Table 3 Here>

Table 3 presents descriptive statistics of variables used in the subsequent empirical analysis. We present both the CDS firms sample and matched non-CDS firms sample across the pre-CDS trading period and the post-CDS trading period. Please notice that, most of these variables are not used to predict the onset of CDS trading in Equation 1, but 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 large differences between CDS and non-CDS firms samples. For example, as Panel A shows, the CDS firms have mean market value of 25.06 billion in the pre-CDS trading period, but non-CDS firms (radius 0.5% matching) have 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 segments than non-CDS firms in the pre-CDS trading period. But the stock turnover ratio of non-CDS firms is higher 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 after CDS initiation. But the difference between CDS firms and non-CDS firms increases to 50%. Interestingly, the analyst optimism becomes lower for CDS firms after CDS trading, but it becomes higher for non-CDS firms. This trend makes the difference of optimism between CDS firms and non-CDS firms become significant after CDS trading. Other variables present similar patterns as in Panel A. Therefore, the similar magnitude of differences in firm characteristics between CDS and non-CDS firms across Panel A and Panel B implies that the differences of analyst forecast accuracy and optimism between CDS and non-CDS firms across Panel A and Panel B are unlikely driven by these firm characteristics.

<Insert Table 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 methods produce similar results, which is available upon request. Given the 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 by 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[6]:

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

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 researches, we measure optimism (bias) as the signed forecast error, which is the difference between an analyst's forecast value and actual earnings, divided by the stock price at the end of current fiscal quarter:

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

4.2 Research Design

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

To address the potential endogeneity issue, we employ the difference-in-difference method in all the 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:

$$\begin{aligned} Accuracy_t(Optimism_t) = {} & \beta_0 + \beta_1 POST + \beta_2 CDSF + \beta_3 CDSF \times POST \\ & + \sum_{j=1}^{23} \lambda_j Additional\ 23\ control\ variables_j \\ & + \sum_{i=1}^{K} \gamma_i Industry_i + \sum_{m=1}^{N} \delta_m Year_m + \varepsilon_t \end{aligned} \tag{2}$$

where *CDSF* is equal to one for firms with a CDS traded during the whole 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 is from five years before to five years after CDS trade initiation. This 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 include 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 properties, which include 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 characteristics, which include analysts' following experience for a firm, the number of analyst following a firm, the analysts' brokerage firm size, analysts forecasts horizon and the analysts' coverage breadth in a quarter. All of these control variables are 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. (2015) find that CDS introduction can discipline management to disclosure more information, so we also include the number of management earnings forecasts to account for the potential effect of CDS trading on analysts forecasts through management disclosure.

5. Empirical results about Analyst forecast accuracy

5.1 Primary tests

<Insert Table 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 the repeated nearest neighbor matching, column 2 is based on 0.5% the radius matching, and column 3 is based on the 1% radius matching. As shown, the coefficients of *POST* are negative and significant for all the three matching methods. 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 coefficients on *CDSF* are also negative and significant for all the three matching methods. 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 coefficients of *Size* are 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 that 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 from 50% (0.286/0.270+0.297) to 77% (0.122/0.069+0.090) after CDS trading. These results support our Hypothesis 1: the introduction of a new market for CDS trading enriches firms' information environment and 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 analysts to make accurate forecasts in a relative uncertain 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 volatility are also significantly negatively related to forecast accuracy, which is consistent with Gu and Wu (2003). Similar to Heflin et al. (2003), we also find the loss indicator is negatively related with forecast accuracy. In addition, forecast horizon is negatively related to forecast accuracy, 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 a firm's information environment is more opaque. For an already very transparent firms, it's difficult for CDS market to reveal too much new information. In addition, cross-sectional analysis 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 the other to control for the unobservable changes embedded in the time-trend.

<Insert Table 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 initiation significantly increases analyst forecast accuracy for smaller firms, firms with higher stock volatility, and firms with higher earnings volatility[7]. Our benchmark to split the whole sample is the sample median. And the effects 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 larger firms, and firms with lower stock volatility and firms with lower 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 trading 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

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

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 suggest that CDS initiation exerts much larger positive effects on analyst forecast accuracy for firms with greater information asymmetry.

Next, we conduct a subsample analysis based on firms' leverage. The results are presented in the last two columns of Panel B in Table 6. As shown, the CDS trading only increases analyst forecast accuracy for firms with relative higher leverage, which supports 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 firm's equity. When the liability side becomes larger in a firm's total asset, the information about the 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 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 the 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*, are negatively significant for all the 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 depresses analysts' strategic forecast optimism.

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 that loss indicator variable is positively related with forecast optimism, which is driven mostly by firms reporting loss because managers may have different incentives 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 expenses are negatively related forecast optimism, implying that analysts 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 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 the 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 a long period could develop a close relationship with the firms' management, making it difficult to challenge or question the 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 an 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 the commissions from client trade execution. To encourage analysts to produce researches that have impact and generate trading volume, brokerage firms typically link analyst compensation to commissions 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 investors can act on a buy recommendation at relatively lower 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 8 Here>

The results are presented in Table 8. Consistent with expectation, compared to matched non-CDS firms, CDS initiation significantly depresses analysts' strategic optimism after CDS trading in the three subsamples of more experienced analysts, more liquid stocks, and larger brokerage houses. In contrast, we do not find significant effects of CDS trading on analyst optimism in the subsamples of less experienced analysts and less liquid stocks, and only find marginally significant effect in the subsample of smaller brokerage firms. These results confirms our Hypothesis H2a: The depressing effects of CDS trading on analysts' strategic optimism are 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 produces significantly positive effects 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 effects 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 this is true, 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 date, which are not known to analysts 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 9 Here>

The results is presented in Table 9. As we can see, compared to non-CDS firms, CDS initiation strongly depresses 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 increases 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 increase analyst 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 effects on forecast accuracy are 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 the real effects 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.

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Table 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 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 Firms (NN matching)		non-CDS Firms (R 0.5% matching)		non-CDS Firms (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		non-CDS (NN matching)		non-CDS (R 0.5% matching)		non-CDS (R 1% matching)	
Industry (1-digit SIC code)	N	%	N	%	N	%	N	%
Agriculture, forestry and fishing	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, petroleum refining, and paper and printing	131	26.04%	62	22.71%	112	17.55%	137	15.77%
Rubber, stone, computer, transportation equipment	128	25.45%	64	23.44%	165	25.86%	233	26.81%
Transportation, communication, electric, gas and sanitary services	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: 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	52,029	-0.23	-0.07	89,186	-0.33	-0.10	-0.1***
F_Optm	52,029	-0.0003	-0.0003	89,186	-0.0001	-0.0004	0.0002
N_analyst	52,029	13.71	12.00	89,186	11.04	10.00	-2.67***
Size	52,029	25.06	6.32	89,186	5.29	2.14	-19.76***
MB	52,029	5.17	2.75	89,186	3.77	2.33	-1.40***
Leverage	52,029	0.29	0.28	89,186	0.26	0.26	-0.03***
ROE	52,029	0.04	0.04	89,186	0.01	0.03	-0.03***
Ins_own	52,029	0.68	0.68	89,186	0.71	0.73	0.03***
Mom	52,029	0.01	0.01	89,186	0.02	0.01	0.01***
R_Vol	52,029	0.027	0.02	89,186	0.032	0.03	0.004***
Turnover	52,029	7.68	5.15	89,186	11.99	8.25	4.32***
E_Vol	52,029	0.02	0.01	89,186	0.06	0.01	0.04***
Coverage	52,029	1.33	1.00	89,186	1.34	1.00	0.01***
F_Exp	52,029	3.63	2.00	89,186	3.65	2.00	0.02
F_Hor	52,029	3.65	3.83	89,186	3.72	3.97	0.07***
Bro_size	52,029	0.77	0.69	89,186	0.70	0.59	-0.07***
E_Skew	52,029	-0.002	0.00	89,186	-0.006	0.00	-0.004***
N_seg	52,029	16.39	15.00	89,186	13.65	12.00	-2.74***
EPS_Dif	52,029	-0.02	0.00	89,186	0.05	0.02	0.07***
Sgrate	52,029	0.12	0.08	89,186	0.17	0.10	0.05***
Svolume	52,029	19.42	19.28	89,186	18.90	18.81	-0.52***
PM	52,029	0.05	0.06	89,186	-1.02	0.05	-1.07***
RD	52,029	0.05	0.00	89,186	0.08	0.00	0.03***
N_MEF	52,029	0.62	0.00	89,186	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	105,508	-0.32	-0.10	-0.09***	29,291	-0.31	-0.09	-0.08***
F_Optm	105,508	-0.0001	-0.0004	0.0002	29,291	-0.0004	-0.0004	0.0002
N_analyst	105,508	10.98	10.00	-2.73***	29,291	10.85	10.00	-2.86***
Size	105,508	5.12	1.89	-19.93***	29,291	10.3	3.14	-14.75***
MB	105,508	3.71	2.34	-1.46***	29,291	2.83	2.12	-2.34***
Leverage	105,508	0.25	0.25	-0.04***	29,291	0.29	0.28	-0.001***
ROE	105,508	0.01	0.03	-0.03***	29,291	0.02	0.03	-0.02***
Ins_own	105,508	0.71	0.73	0.03***	29,291	0.65	0.68	-0.03***
Mom	105,508	0.02	0.01	0.01***	29,291	0.01	0.01	0.001***
R_Vol	105,508	0.03	0.03	0.004***	29,291	0.03	0.03	0.003***
Turnover	105,508	12.26	8.57	4.59***	29,291	9.14	5.71	1.47***
E_Vol	105,508	0.07	0.01	0.05***	29,291	0.02	0.01	0.006***
Coverage	105,508	1.35	1.00	-0.03***	29,291	1.29	1.00	-0.04***
F_Exp	105,508	3.66	2.00	0.03	29,291	3.65	2.00	0.02
F_Hor	105,508	3.73	3.99	0.08***	29,291	3.67	3.87	0.02***
Bro_size	105,508	0.70	0.58	-0.07***	29,291	0.75	0.68	-0.02***
E_Skew	105,508	-0.003	0.00	-0.001***	29,291	-0.003	0.00	-0.001***
N_seg	105,508	13.75	12.00	-2.64***	29,291	13.42	12.00	-2.97***
EPS_Dif	105,508	0.04	0.02	0.06***	29,291	-0.03	0.02	-0.01***
Sgrate	105,508	0.17	0.10	0.05***	29,291	0.16	0.08	0.04***
Svolume	105,508	18.87	18.79	-0.55***	29,291	18.88	18.77	0.54***
PM	105,508	-0.88	0.05	-0.93***	29,291	0.01	0.04	-0.04***
RD	105,508	0.08	0.00	0.03***	29,291	0.04	0.00	-0.01***
N_MEF	105,508	1.91	0.00	1.29***	29,291	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	78,067	-0.29	-0.1	109,690	-0.59	-0.13	-0.30***
F_Optm	78,067	-0.0005	-0.0005	109,690	0.0011	-0.0005	0.0017***
N_analyst	78,067	15.44	14.00	109,690	12.1	10.00	-3.34***
Size	78,067	25.84	9.38	109,690	6.67	2.65	-19.16***
MB	78,067	2.96	2.29	109,690	2.34	2.22	-0.62***
Leverage	78,067	0.27	0.26	109,690	0.27	0.23	-0.004***
ROE	78,067	0.04	0.04	109,690	-0.02	0.03	-0.06***
Ins_own	78,067	0.76	0.77	109,690	0.81	0.85	0.05***
Mom	78,067	0.02	0.02	109,690	0.03	0.02	0.004***
R_Vol	78,067	0.02	0.02	109,690	0.03	0.02	0.01***
Turnover	78,067	9.96	7.65	109,690	13.61	11.17	3.65***

E_Vol	78,067	0.02	0.01	109,690	0.05	0.01	0.03***
Coverage	78,067	1.32	1.00	109,690	1.37	1.00	0.05***
F_Exp	78,067	6.27	4.00	109,690	5.55	4.00	-0.72***
F_Hor	78,067	3.57	3.76	109,690	3.72	4.08	0.15***
Bro_size	78,067	0.72	0.66	109,690	0.62	0.54	-0.1***
E_Skew	78,067	-0.01	0.00	109,690	-0.02	0.00	-0.01***
N_seg	78,067	20.20	19.00	109,690	15.57	14.00	-4.62***
EPS_Dif	78,067	0.01	0.05	109,690	-0.03	0.02	-0.04***
Sgrate	78,067	0.09	0.07	109,690	0.13	0.08	0.04***
Svolume	78,067	20.14	20.00	109,690	19.45	19.39	-0.69***
PM	78,067	0.06	0.07	109,690	-0.24	0.06	-0.30***
RD	78,067	0.05	0.00	109,690	0.07	0.00	0.02***
N_MEF	78,067	4.68	2.00	109,690	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	131,792	-0.57	-0.14	-0.29***	31,880	-0.37	-0.11	-0.08***
F_Optm	131,792	0.0009	-0.0006	0.0014***	31,880	-0.0001	-0.0005	0.0005***
N_analyst	131,792	12.11	10.00	-3.33***	31,880	12.16	11.00	-3.28***
Size	131,792	6.46	2.48	-19.38***	31,880	15.41	4.04	-10.42***
MB	131,792	2.71	2.20	-0.24***	31,880	1.58	2.16	-1.38***
Leverage	131,792	0.26	0.23	-0.01***	31,880	0.24	0.22	0.01***
ROE	131,792	0.01	0.03	-0.03***	31,880	0.01	0.03	-0.03***
Ins_own	131,792	0.81	0.85	0.05***	31,880	0.73	0.77	-0.02***
Mom	131,792	0.02	0.02	0.002***	31,880	0.03	0.02	0.008***
R_Vol	131,792	0.03	0.02	0.01***	31,880	0.02	0.02	0.001***
Turnover	131,792	13.83	11.47	3.86***	31,880	10.4	8.40	0.44***
E_Vol	131,792	0.05	0.01	0.02***	31,880	0.02	0.01	-0.001
Coverage	131,792	1.38	1.00	0.02***	31,880	1.26	1.00	-0.06***
F_Exp	131,792	5.52	4.00	-0.75***	31,880	5.81	4.00	-0.46***
F_Hor	131,792	3.72	4.08	0.15***	31,880	3.66	3.95	0.09***
Bro_size	131,792	0.61	0.53	-0.11***	31,880	0.68	0.60	-0.04***
E_Skew	131,792	-0.01	0.00	-0.01***	31,880	-0.004	0.00	-0.001***
N_seg	131,792	15.61	14.00	-4.59***	31,880	17.67	15.00	-2.53***
EPS_Dif	131,792	-0.03	0.02	-0.05***	31,880	-0.01	0.03	-0.03***
Sgrate	131,792	0.13	0.08	0.04***	31,880	0.08	0.07	-0.01***
Svolume	131,792	19.43	19.35	-0.71***	31,880	19.54	19.46	-0.60***
PM	131,792	-0.19	0.06	-0.25***	31,880	0.00	0.07	-0.06***
RD	131,792	0.08	0.00	0.03***	31,880	0.06	0.00	0.01***
N_MEF	131,792	5.62	3.00	0.93***	31,880	5.77	4.00	1.08***

Table 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; *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; *PM* is the net income scaled by sales; *RD*, the R&D expense ratio; *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*	*R_Vol*	*Turnover*	*N_analyst*	*E_Vol*	*Ins_own*	*Mom*	*MB*	*Size*	*Leverage*	*PM*	*N_MEF*
F_acc	1	0.34*	-0.11*	0.09*	-0.16*	-0.12*	0.11*	-0.41*	-0.02*	0.04*	0.38*	0.31*	-0.19*	0.21*	0.09*
F_optm	-0.85	1	-0.03*	0.03*	-0.02*	-0.07*	0.00	-0.08*	-0.05*	-0.06*	0.05*	0.04*	0.02*	-0.09*	-0.05*
POST	-0.02	0.01*	1	0.05*	-0.25*	0.19*	0.09*	-0.03*	0.23*	0.02*	-0.08*	0.11*	-0.03*	0.07*	0.40*
CDSF	0.03*	-0.01*	0.05*	1	-0.17*	-0.23*	0.20*	-0.06*	-0.14*	0.01*	0.06*	0.42*	0.07*	0.08*	-0.08*
R_Vol	-0.16*	0.09*	-0.19*	-0.16*	1	0.43*	0.05*	0.30*	-0.03*	-0.17*	-0.08*	-0.26*	0.00	-0.25*	-0.32*
Turnover	-0.02*	-0.01*	0.08*	-0.18*	0.43*	1	0.30*	0.05*	0.44*	-0.03*	0.09*	-0.05*	-0.24*	-0.02*	0.14*
N_analyst	0.04*	-0.01*	0.09*	0.20*	0.03*	0.25*	1	-0.14*	0.04*	-0.03*	0.21*	0.52*	-0.32*	0.17*	0.04*
E_Vol	-0.02*	0.01*	0.00	-0.01*	0.03*	-0.005*	-0.02*	1	-0.06*	-0.11*	-0.48*	-0.40*	0.28*	-0.41*	-0.20*
Ins_wn	0.04*	-0.02*	0.19*	-0.09*	-0.06*	0.29*	0.03*	-0.02*	1	0.05*	0.01*	-0.16*	-0.07*	0.005*	0.25*
Mom	0.03*	-0.03*	0.01*	-0.01*	-0.08*	0.01*	-0.03*	-0.01*	0.00	1	0.14*	0.08*	-0.03*	0.09*	0.05*
MB	0.00	0.00	-0.02*	0.01*	0.01*	0.02*	0.03*	0.00	0.00	0.00	1	0.48*	-0.30*	0.34*	0.08*
Size	0.11*	-0.04*	0.11*	0.42*	-0.26*	-0.04*	0.51*	-0.05*	-0.12*	0.03*	0.04*	1	-0.36*	0.38*	0.06*
Leverage	-0.10*	0.06*	-0.01*	0.03*	0.07*	-0.12*	-0.28*	0.03*	-0.06*	0.00	-0.02*	-0.35*	1	-0.23*	-0.19*
PM	0.00	0.00	0.01*	0.01*	0.00	0.00	0.01*	0.00	0.01*	0.00	0.00	0.01*	-0.02*	1	0.11*
N_MEF	0.03*	-0.01*	0.32*	-0.08*	-0.22*	0.01*	0.06*	-0.01*	0.19*	0.00	0.00	0.08*	-0.18*	0.01*	1

Table 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 5 (continued)

	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%
	Dependent Variable=Analyst Forecast Accuracy						
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 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 6 (continued)

Panel A

	Dependent Variable=Analyst Forecast Accuracy					
	Small Firms	Large Firms	Low Svolatility	High Svolatility	Low Evolatility	High Evolatility
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.	171,298	157,674	137,503	191,469	160,403	168,569
R-Squared	0.07	0.14	0.06	0.06	0.05	0.07

Panel B						
	Dependent Variable=Analyst Forecast Accuracy					
	Less MEF	More MEF	Less Experience	More Experience	Low Leverage	High Leverage
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.	203,868	125,104	197,520	131,452	166,372	162,600
R-Squared	0.05	0.15	0.20	0.07	0.20	0.07

Table 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 7 (continued)

	Dependent Variable=Analyst Forecast Optimism						
	Nearest Neighbor Matching	Radius Matching PS Dif.<0.5%	Radius Matching PS Dif.<0.5%		Nearest Neighbor Matching	Radius Matching PS Dif.<0.5%	Radius Matching PS Dif.<0.5%
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.	191,267	328,972	367,394
Mom	-0.088**	-0.212**	-0.223***	R-Squared	0.02	0.02	0.02
	(-2.44)	(-2.38)	(-2.65)				

Table 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.)

	Dependent Variable=Analyst Forecast Optimism					
	Less Experience	More Experience	Low Volume	High Volume	Small Brokerage	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.	197,520	131,452	163,540	165,432	161,961	167,011
R-Squared	0.02	0.03	0.03	0.05	0.03	0.01

Table 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 9 (continued)

	Dependent Variable=Analyst Forecast Optimism					
	Positive Earnings	Negative Earnings	Positive EPSD	Negative EPSD	Positive Mom	Negative 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	-1.03***	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)
15 controls	yes	yes	yes	yes	yes	yes
Year Fixed	yes	yes	yes	yes	yes	yes
Industry Fixed	yes	yes	yes	yes	yes	yes
Clustered SE	yes	yes	yes	yes	yes	yes
No. of Obs.	272,146	56,826	185,920	143,052	175,449	153,523
R-Squared	0.18	0.09	0.01	0.05	0.02	0.03