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HOW CREDIT DEFAULT SWAPS AFFECT RISK-SHIFTING*

DOJOON PARK [a], CHANATIP KITWIWATTANACHAI [b] AND JIYOON LEE [a]

[a] *Yonsei University, South Korea*
[b] *Bank of Thailand, Thailand*

We study the effects of credit default swaps (CDSs) on a firm's risk-shifting behavior. Because CDSs provide debtholders (or banks) with protection against credit events, CDS-protected debtholders may not be as vigilant in monitoring borrowers once their credit risks are hedged. In addition, CDSs strengthen debtholders' negotiating power and potentially increase default rates, which strengthens borrowers' incentives for risk-shifting. Therefore, managers of CDS-referenced firms are encouraged to expropriate debtholder wealth by shifting to riskier investments. We find significant empirical evidence that the initiation of CDS trading increases risk-shifting behavior. Moreover, the effects of CDSs on risk-shifting are more pronounced for financially distressed firms. Our results are robust to a falsification test, a reverse causality test, and a test of selection bias.

Keywords: Credit Default Swaps, Risk-shifting, Institutional Monitoring, Empty Creditors
JEL Classification: G32, G34

1. INTRODUCTION

A credit default swap (CDS) is a fixed-income derivative instrument which has been considered one of the most important innovations in financial markets of the past three decades.[1] Since the first CDS was traded in 1994, CDSs have been actively traded after

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[1] A CDS is a bilateral contract between a protection buyer and a protection seller. The protection buyer purchases insurance against credit events on an underlying reference entity or firm. In exchange for the insurance, the protection buyer pays a CDS premium to the protection seller. The protection buyer receives a payment from the protection seller if a credit event occurs on a reference credit instrument within a predetermined time period. Credit events include the reference entity's failure to meet its payment obligations

becoming popular and enjoying exponential growth in the early 2000s. The CDS market reached a peak of $62 trillion in notional value at the end of 2007 (Chang et al., 2019). Public debate over the role of CDSs was ignited by the 2007–2009 financial crisis, which raised considerable concern among regulators. Regulators soon began introducing new rules for the CDS market. For example, the Dodd-Frank Act was enacted in 2009 to regulate the CDS market. In 2012 the European Union banned trading in sovereign CDSs unless investors also hold the underlying bonds, and in 2014 the US and Europe completed the implementation of a central clearing system for CDS transactions.

CDSs provide debtholders (or banks) with an option to hedge. If a CDS is traded on a borrowing firm's debt, the debtholders can buy the CDS to hedge the associated credit risk while retaining ownership of the investment. In a frictionless world, a CDS is a redundant security with no valuation consequences for the referenced firm. The instrument does, however, affect the traditional relationship between borrowers and debtholders and has implications for corporate financial management. On the one hand, CDSs affect debtholders' incentives. Hu and Black (2008) characterize CDS-protected debtholders as empty creditors who have all the same legal rights as creditors but are not exposed to risk associated with the referenced firms' credit events. The financial interests of empty creditors are not aligned with those of creditors without such protection, especially when the referenced firms are experiencing financial distress. The empty creditor issue is modeled by Bolton and Oehmke (2011). In their model, empty creditors are tougher during debt renegotiations. Hence, CDSs introduce gains by allowing debtholders to commit not to renegotiate debt unless the renegotiation terms are attractive enough for the debtholders. Empty creditors are often willing to push a firm into bankruptcy, even when renegotiation via an out-of-court restructuring would be socially efficient. An empirical study by Subrahmanyam et al. (2014) shows that CDSs lead to higher default rates for CDS-referenced firms. On the other hand, CDSs can lead to another unintended externality for borrowers. According to the Morrison (2005) model, the existence of CDSs hinders optimal monitoring. Parlour and Winton (2013) also point out that debtholders may not be as vigilant in monitoring borrowers once their credit risks are hedged. Consequently, reduced monitoring by creditors may provide borrowing firms with more opportunities to increase risk-taking investments. Campello and Matta (2012) show theoretically that CDSs can increase both the probability that default occurs and risk-shifting incentives. From a theoretical standpoint, CDSs affect incentives for both borrowers and debtholders and induce suboptimal decisions regarding bankruptcy or risky investments.

The main purpose of our study is to investigate the effects of CDSs on risk-shifting. Risk-shifting occurs when equityholders invest in risky negative-NPV projects because they benefit from the upside while debtholders suffer from the downside. In general, corporate investment is negatively associated with expected volatility (Pindyck and

on a financial instrument, the reference entity's bankruptcy, and restructuring of bonds issued by the reference firm.

Solimano, 1993; Episcopos, 1995). Eisdorfer (2008), however, finds a positive relationship between expected volatility and investment in financially distressed firms during high-volatility periods, which is empirical evidence of risk-shifting behavior reflected in investment decisions. CDS-protected debtholders are likely to put less effort into monitoring a manager's behavior, which provides stronger incentives for risk-shifting. We propose a simple theoretical framework based on the Merton (1974) model. Inasmuch as the introduction of CDSs has increased the risk of default, the model shows that equityholders of CDS-referenced firms prefer to increase those firms' asset volatility, which raises their share prices. Next, we empirically test whether CDSs increase risk-shifting behavior by examining the effects of CDSs on a referenced firm's investment behavior during high-volatility periods. This paper is, to the best of our knowledge, the first to empirically investigate risk-shifting caused by the initiation of CDS trading. Furthermore, we examine the role that financial distress plays in the relationship between CDSs and risk-shifting. Equityholders have an incentive to expropriate debtholder wealth by shifting to riskier investments, especially those with stakes in distressed firms where risk-shifting behavior has been empirically confirmed (Eisdorfer, 2008). For this purpose, we follow the empirical framework proposed by Eisdorfer (2008) to examine risk-shifting behavior and use Altman's (1968) Z-scores as a measure of a firm's financial distress and default risk.

To determine the effects of CDSs on risk-shifting, we analyze investment for a sample of US firms following the initiation of CDS trading in 2001 through 2012, when CDS transactions were initiated on the largest number of new firms (Subrahmanyam et al., 2017). We focus on this period because it not only represents unprecedented growth in and subsequent contraction of the CDS market caused by the global financial crisis but also because the Bloomberg database provides CDS quotes contributed by dealers starting in 2001.[2] We introduce a CDS-trading dummy variable, CDSD, to the regression analysis and find significant effects of CDSs on risk-shifting. Specifically, after the introduction of CDS trading, firms increase investment during high-volatility periods. Risk-shifting behavior rises among distressed firms upon the initiation of CDS trading. Overall corporate investment drops, however, after CDS trading begins, which is consistent with previous findings reported by Hong and Wang (2021).

We also conduct several robustness tests. First, we conduct falsification tests to address concerns related to the main variable. Because the dummy variable, CDSD, captures the occurrence of any change that potentially affects a firm's investment decisions in the early 2000s, we perform falsification tests, the results of which increased our confidence in the notion that risk-shifting behavior is triggered by the

[2] Previous literature has investigated the impact of CDS trading initiation on corporate financial management. Most of these studies examine firms that began trading in CDSs in the early 2000s, when the market was growing rapidly. In addition, their sample periods precede the implementation of CDS-related regulations. Hong and Wang's (2021) sample cover the period running from 2002 through 2015, while that of Colonnello et al. (2019) covers the period running from 2001 through 2014.

initiation of CDS trading rather than by random factors. Second, considering that the causal relationship between investment and the initiation of CDS trading could be bidirectional, we address the reverse causality concern by excluding observations of CDS trading that might be triggered by risk-shifting. If debtholders either anticipate or predict financial distress and subsequent risk-shifting, they can trade CDSs to hedge their risk. Hence, we drop observations for a firm that becomes distressed within two years of first trading CDSs. The regression results remain the same, supporting the direction of causality from CDSs to risk-shifting. Third, as firms selected for CDS trading are not randomly assigned, we conduct a matched-sample analysis to address this possibility of selection bias and alleviate concerns regarding endogeneity. Using propensity-score matching, we construct a sample of CDS-referenced firms and matched non-CDS-referenced firms and find that the results obtained with the matched sample are largely the same.

Our paper is closely related to CDS studies by Eisdorfer (2008) and Hong and Wang (2021). Eisdorfer (2008) examines risk-shifting in financially distressed firms based on a real options approach. Investment decisions involve a tradeoff between realizing early cash flows by investing in a project immediately and gaining more information about the value of the project by delaying investment. If a project's cash flow is uncertain, the value of delaying investment increases. Hence, investment is expected to decline with a rise in market volatility (McDonald and Siegel, 1986; Pindyck, 1988). When a firm is experiencing financial distress, however, risk-shifting incentives also play a role in the investment–volatility relationship. Eisdorfer (2008) finds a positive relationship between investment and volatility in distressed firms during high-volatility periods, which represents empirical evidence of risk-shifting in distressed firms. Hong and Wang (2021) examine the effects of CDSs on investment. They insist that both reduced monitoring and an empty creditor problem may increase the cost of capital and discourage investment after CDS trading begins. This paper fills a gap left by these studies by conducting an analysis to determine whether CDS trading affects risk-shifting. While Hong and Wang (2021) examined the direct effects of CDSs on the investment, our paper, adopting empirical procedures from Eisdorfer (2008), focuses on the role of CDSs in encouraging risk-shifting.

A conflict of interest between equityholders and debtholders, known as risk-shifting, was first documented by Galai and Masulis (1976) and Jensen and Meckling (1976). Previous studies have examined factors that can affect risk-shifting behavior, such as secured debt (Smith and Warner, 1979), convertible debt (Green, 1984), debt maturity (Barnea et al., 1980), growth options (Barclay and Smith, 1995), and managerial compensation contracts (Brander and Poitevin, 1992). We add valuable findings to the literature by investigating the role that CDSs play in investment decisions by CDS-referenced firms and showing that CDSs significantly increase equityholders' incentives to engage in risk-shifting.

Our paper contributes to the literature that studies the impacts of CDS trading. Numerous studies investigating the benefits and costs of CDSs for referenced firms have been conducted but have failed to confirm that CDS trading actually reduces the cost of capital. Kim (2016) and Batta et al. (2016) show that CDSs can help reduce the cost of debt, but Narayanan and Uzmanoglu (2018) find that corporate value declines following increases in the cost of capital. Ashcraft and Santos (2009), moreover, find no evidence that CDSs reduce the cost of debt. Our paper adds a new dimension to this literature by examining the effects of CDS trading on corporate risk-taking with a particular focus on financially distressed firms, offering an explanation of higher capital costs following CDS initiation, as documented in prior studies.

Another stream of research has studied CDS-referenced firms to test the effects of CDS trading on such firms through leverage, debt maturity, and the credit supply (Saretto and Tookes, 2013), credit risk and ratings (Subrahmanyam et al., 2014), the restructuring of distressed firms (Danis, 2017), cash holdings and liquidity management (Subrahmanyam et al., 2017), investment (Hong and Wang, 2021), innovation (Chang et al., 2019), managerial compensation (Chen et al., 2019), and moral hazard (Bolton and Oehmke, 2011; Colonnello et al., 2019). This paper also fits in a strand of the literature that investigates the effects of derivatives on underlying assets, in this case the impact of CDSs on investment and risk-shifting behavior.

The rest of the paper proceeds as follows. Section 2 provides the theoretical framework for our analysis of risk-shifting within which we develop our hypotheses. In Section 3 we explain our data and present our regression models. Section 4 presents the empirical results and Section 5 presents various robustness tests. Section 6 concludes.

2. THEORETICAL FRAMEWORK AND TESTABLE PREDICTIONS

In this section, based on Merton's (1974) bond-pricing model, we present the theoretical background for our empirical analysis of risk-shifting caused by the initiation of CDS trading. An equilibrium approach that leads to a similar conclusion can be found in Campello and Matta (2012).

Equityholders prefer high-volatility projects because of their limited liability. They enjoy the rewards when a project succeeds, while debtholders suffer the penalties if the project fails. The Merton (1974) model summarizes this asymmetry in payoffs by viewing equity as a call option on a firm's asset value because, when a firm's debt matures, the debtholders receive compensation for their debts while the equityholders receive the remaining amount. Hence, equity value (E), as a call option (C), will depend on the volatility of the underlying asset and the strike price,[3] as in

$$E = C(V, \sigma, K), \tag{1}$$

[3] The option value also depends on other factors such as time to maturity, dividends, and interest rates, but we do not consider these factors in this paper.

where V is a firm's asset value, σ is asset volatility, and K is the default barrier (or the value of the firm's debt at maturity). Because the call option value increases with rising volatility ($\frac{\partial C}{\partial \sigma} > 0$), equityholders have incentives to increase asset volatility to raise equity value, which is aligned with the incentive for risk-shifting.

Both Bolton and Oehmke (2011) and Campello and Matta (2012) provide theoretical frameworks within which to analyze the effects of CDSs on default risk. In addition, Subrahmanyam et al. (2014) show empirically that CDS trading leads to higher default rates. In the context of the Merton (1974) model, with CDSs on a borrowing firm's debt, its default barrier (K) has risen, which can be written as

$$K_{CDS} > K, \tag{2}$$

where K_{CDS} is the default barrier for the CDS-referenced firm.

Referenced firms of CDSs become more distressed because the default barrier has risen. As a result, equityholders have stronger incentives to increase asset volatility by shifting to riskier investments in the presence of CDSs. Using the Black-Scholes formula for option pricing,

$$\frac{\partial\left(\frac{\partial C}{\partial K}\right)}{\partial \sigma} = \frac{\partial^2 C}{\partial \sigma \partial K} = \frac{\partial\left(\frac{\partial C}{\partial \sigma}\right)}{\partial K} = \frac{\partial Vega}{\partial K} = e^{-rT} N(d_2)\sqrt{T} > 0, \tag{3}$$

where $Vega$ ($\frac{\partial C}{\partial \sigma}$) is the measure of a call option price's sensitivity to volatility, r is the risk-free interest rate, $N(\cdot)$ is the standard normal probability density function, T is the time to maturity (usually assumed to be the time to debt maturity), and $d_2 = \frac{ln(V/K)+(r-\sigma^2/2)T}{\sigma\sqrt{T}}$, we test our hypotheses regarding the relationship between CDS trading and risk-shifting. The first line represents the change in equity value after a CDS on a referenced firm ($\frac{\partial C}{\partial K}$) is introduced as well as the subsequent change in its equity value with respect to greater asset volatility. The last line shows a positive value, indicating that, after introducing CDS trading, the sensitivity of a firm's equity value to its asset volatility increases. Hence, CDSs strengthen equityholders' incentives for shifting to riskier investments to increase asset volatility.

We test two hypotheses to determine the effects of CDSs on risk-shifting. CDSs increase the probability that default occurs and weaken debtholders' incentives to monitor, permitting a borrowing firm to undertake riskier projects. Equityholders' risk-shifting incentives can result in a positive relationship between expected volatility and investment during high-volatility periods. Our first hypothesis (*H1*) tests the impact of the introduction of CDS trading on risk-shifting. We expect to observe an Increase in risk-shifting associated with the initiation of CDS trading on the debt of individual firms and propose our first hypothesis on that basis:

Hypothesis 1: *Risk-shifting behavior, such as investment during high-volatility periods, increases after the introduction of CDSs that reference a firm's debt.*

Firms are more likely to engage in risk-shifting when they experience financial distress, as shown by Eisdorfer (2008). Hence, the impact of CDSs on investment during volatile periods is expected to be more pronounced for financially distressed firms. We propose our second hypothesis (*H2*) to test whether this is indeed the case:

Hypothesis 2: *The effects of CDSs on risk-shifting are more pronounced for financially distressed firms.*

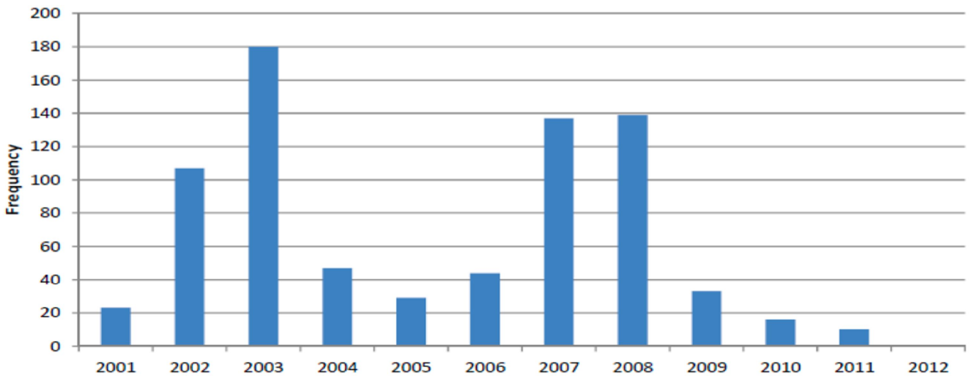
3. DATA AND REGRESSION MODELS

3.1. Data

The data used in this paper comprise CDS bid and offer prices, expected market volatility, and firm-level variables. Our main variable, CDSD, is a CDS-trading dummy variable that equals one for a firm after the inception of CDS trading on its debt and zero prior to that time. It is important to note that obtaining accurate CDS transaction data is difficult because CDS trading does not occur on centralized exchanges. As we focus on the initiation of CDS trading and its effects on investment, we carefully collect data from the first year of each firm's CDS bid or offer prices on Bloomberg. We treat the first year as the initial CDS trading year and assume that CDSs are traded continuously thereafter.[4] CDS trading for the 765 firms began between 2001 and 2012. Figure 1 displays the distribution of initial CDS trading by year. The CDS dummy indicates that CDSs on a firm's debt are being traded in over-the-counter markets.

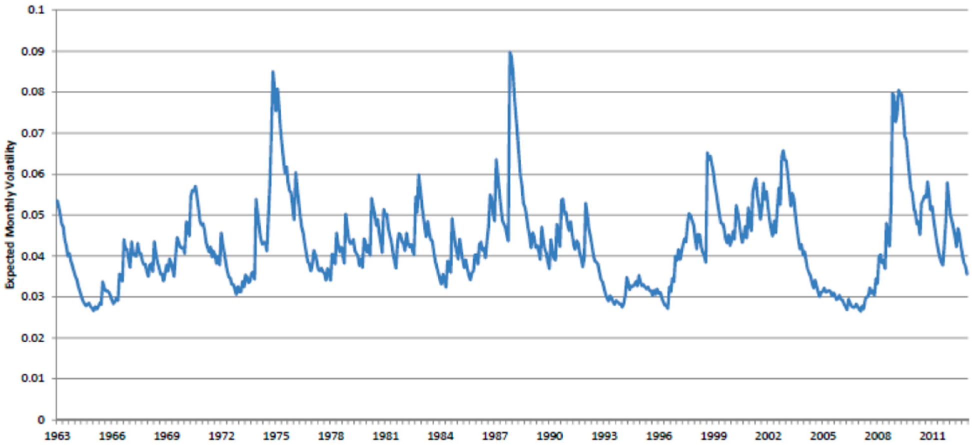
To measure expected market volatility, we use a generalized autoregressive conditional heteroskedasticity (GARCH) model as specified by Bollerslev (1986). GARCH(1,1) models have found widespread use in economics and finance to describe randomly varying volatility (Bollerslev et al., 1992; Hansen and Lunde, 2005; Eisdorfer, 2008). We estimate our GARCH(1,1) model using monthly S&P 500 Index returns from 1927 through 2012. For each calendar year, the expected volatility is measured by 12-month-ahead forecasted volatility conditional on the availability of information from the final month of the previous year. Figure 2 displays the monthly expected market volatility for the last 50 years, from 1963 through 2012, as calculated using the GARCH(1,1) model.

[4] When a firm's debt securities are popular, CDSs are accessible to debtholders and quoted by dealers. The availability of CDS quotes on Bloomberg indicate that over-the-counter trading of CDSs on a firm's debts is sufficiently robust to influence corporate investment.



Notes: The graph shows the number of firms for which CDS trading was initiated during the year.

Figure 1. The Distribution of Initial CDS Trading by Year



Notes: The expected market volatility is estimated by applying a GARCH(1,1) model to monthly returns on the S&P 500 index from 1963 through 2012.

Figure 2. Expected Volatility Derived from a GARCH(1,1) Model

To measure our firm-level variables, we acquire annual accounting data from Compustat for the period running from 2001 through 2012. Following Fazzari et al. (1988), Almeida and Campello (2007), and Eisdorfer (2008), we calculate investment intensity as the ratio of capital expenditures for a given year to property, plant, and equipment (PP&E) at the beginning of the year. To measure a firm's financial distress and default probability, we use Z-scores as specified by Altman (1968). A Z-score is a linear combination of five financial ratios. A high (low) Z-score value indicates low (high) default probability. If a Z-score value is less than 1.81, a firm is classified as being in the distress zone, which means the Altman (1968) model predicts that the company's financial position is in distress. We include four determinants of investment as control variables. Firm size (Size) is the natural logarithm of firm value (the market value of equity plus the book value of liabilities). The market-to-book ratio (Market-to-book) is the market value of equity divided by the book value of equity. Leverage ratio (LEV) is the book value of total liabilities divided by total assets. Cash flow (CF) is a firm's operating cash flow divided by PP&E at the beginning of a given year. After eliminating sample firms for which variables are missing variables, the final sample yields 105,747 firm-year observations involving 12,710 firms. Table 1 presents an overview and summary statistics for the firm-level variables used in the empirical analysis. In addition to the means and standard deviations for our sample observations, the 25th, 50th, and 75th percentiles are also shown. Investment intensity, our dependent variable, has a mean and standard deviation of 0.20 and 0.28, respectively, similar to comparable figures documented in the literature, such as in Almeida and Campello (2007). The mean Z-score value is 4.27 and the 25th percentile value is 1.99, indicating that most firms in the sample are financially healthy and not in the distress zone.

Table 1. Definition of Variables and Summary statistics

Panel A: Definition of Variables

Investment intensity	The ratio of capital expenditures to property, plant, and equipment (PP&E) at the beginning of a given year.
Z-score	Z-score is based on Altman's (1968) model for predicting bankruptcy
Size	The natural logarithm of firm value (the market value of equity plus the book value of liabilities)
Market-to-Book	The market value of equity divided by the book value of equity
LEV	The book value of total liabilities divided by total assets
CF	The operating cash flow divided by PP&E at the beginning of the year

Panel B: Summary statistics

	Mean	Std	P25	P50	P75
Investment intensity	0.20	0.28	0.07	0.12	0.22
Z-score	4.27	4.76	1.99	3.27	5.03
Size	5.64	2.13	3.95	5.50	7.14
Market-to-Book	2.33	2.87	0.90	1.49	2.60
LEV	0.57	0.30	0.38	0.56	0.72
CF	0.15	0.83	0.02	0.12	0.29

Note: The results are based on 105,747 firm-year observations over the 2001–2012 period.

3.2. Regression Model

In this section of the paper, we develop our empirical framework. First, we test whether firms' decisions to increase or decrease investment are affected by expected volatility, using the following regression model,

$$INV_{i,t} = \alpha + \beta E[Vol]_t + \gamma_1 X_{i,t} + \gamma_2 M_t + \varepsilon_{i,t}, \tag{4}$$

where the dependent variable ($INV_{i,t}$) is firm-specific investment intensity, which is calculated as the ratio of capital expenditures for a given year to PP&E at the beginning of the year. Independent variables include expected market volatility ($E[Vol]_t$) at the beginning of the year as derived from the GARCH(1,1) model. Control variables are selected based on prior literature (Eisdorfer, 2008), where certain firm-level characteristics have been found to influence a firm's investment strategy. Firm-level control variables ($X_{i,t}$) are firm size (Size), the market-to-book ratio (*Market-to-book*), the leverage ratio (*LEV*), and cash flow in the previous year (*Lagged CF*). To control for macroeconomic effects on investment, we include a set of macroeconomic control variables (M_t) at the beginning of a given year. The first macroeconomic variable is an NBER recession dummy (*Recession*). The default spread (*Default spread*) is the yield difference between BAA- and AAA-rated bonds and the interest rate (*Interest rate*) is nominal returns on 1-month Treasury bills. We use data obtained from the website of the Federal Reserve Bank of St. Louis. The estimate of β in Equation (4) exhibits the marginal impacts of expected volatility on investment intensity and tells us whether expected volatility affects investment. If the expected volatility generally has negative effects on investment, we expect β to be statistically significant and negative.

Next, we examine the effects of expected volatility on investment using a CDS-trading dummy variable ($CDS^D_{i,t}$) to test our first hypothesis. The extended regression model is given by

$$INV_{i,t} = \alpha + \beta_1 E[Vol]_t + \beta_2 CDS^D_{i,t} + \beta_3 E[Vol]_t \times CDS^D_{i,t} + \gamma_1 X_{i,t} + \gamma_2 M_t + \varepsilon_{i,t}. \tag{5}$$

The question is whether the initiation of CDS trading significantly increases investment during high-volatility periods. The main coefficient of interest is β_3 (the coefficient for $E[Vol]_t \times CDS^D_{i,t}$) in Equation (5). In addition, the estimate of β_2 (the coefficient for $CDS^D_{i,t}$) exhibits direct effects of CDSs on investment.

To further investigate the impact of CDSs on risk-shifting, we test whether the impact of CDSs on investment during volatile periods is more pronounced for financially distressed firms. We use Altman (1968) Z-scores to measure a firm's level of financial distress. The regression model, including interaction terms between expected volatility and Z-scores, is

$$\begin{aligned} Inv_{i,t} = {} & \alpha + \beta_1 E[Vol]_t + \beta_2 Z\text{-}Score_{i,t} + \beta_3 CDS^D_{i,t} + \beta_4 E[Vol]_t \times Z\text{-}Score_{i,t} \\ & + \beta_5 E[Vol]_t \times CDS^D_{i,t} + \beta_6 E[Vol]_t \times Z\text{-}Score_{i,t} \times CDS^D_{i,t} \\ & + \gamma_1 X_{i,t} + \gamma_2 M_t + \varepsilon_{i,t}. \end{aligned} \tag{6}$$

All the other variables are the same as those included in Equation (4) and Equation (5). The main coefficient of interest is β_6 (the coefficient for $\beta_6 E[Vol]_t \times Z\text{-}Score_{i,t} \times CDS_{i,t}^D$).

4. EMPIRICAL RESULTS

This section presents our empirical findings pertaining to the effects of CDS trading on a firm's risk-shifting, such as investment during high-volatility periods. We first conduct an analysis of the effects of the introduction of CDS trading on risk-shifting. We then test whether the effects are more pronounced for distressed firms.

4.1. Primary Results

Table 2 displays the regression results for *H1* with all the control variables using Equation (4) and Equation (5). t-statistics (reported in parentheses) are calculated using standard errors clustered by firms. As shown in column (1) of Table 2, the estimate of the coefficient on *E[Vol]* in Equation (4) is negative and statistically significant at the 5% level. Consistent with previous findings (Pindyck and Solimano, 1993; Episcopos, 1995), expected volatility has a negative impact on investment in general. All other estimates of the coefficients on control variables are significant at the 1% level.

Column (2) of Table 2 shows the results obtained in testing the effects of CDS trading on risk-shifting. As we explain above, risk-shifting behavior of CDS-referenced firms should increase investment during periods of high volatility, so our framework predicts that the coefficient on $E[Vol]_t \times CDS_{i,t}^D$ in Equation (5) will be positive. The estimate of the coefficient is positive and statistically significant at the 1% level, indicating that a firm increases investment during volatile periods after the inception of CDS on its debt. Hence, the results provide evidence that risk-shifting behavior does exist for CDS-referenced firms, supporting *H1*. The sign for the CDS-trading variable is negative, indicating that firms reduce investment after introducing CDS trading, which is consistent with the results reported by Hong and Wang (2021).

4.2. Distressed Firms

To further investigate the impact of CDSs on risk-shifting, we use Z-scores as a measure of financial distress. Table 3 displays the regression results obtained using Equation (6) to test *H2*. As shown, the estimate of the coefficient on $E[Vol]_t \times Z\text{-}Score_{i,t} \times CDS_{i,t}^D$ is negative and statistically significant at the 1% level. As a higher Z-score value indicates a lower probability that default occurs, a negative coefficient on the interaction variable exhibits the reduced risk-shifting behavior for financially healthy firms. The results also confirm the presence of stronger effects of CDSs on risk-shifting for more highly distressed firms, supporting *H2*. The results also confirm the occurrence

Table 2. Regression of Investment on Expected Volatility and CDS Trading

Explanatory Variables	(1)	(2)
Intercept	0.259***	0.259***
	(40.47)	(40.04)
E[Vol]	−0.223**	−0.267***
	(-2.27)	(-2.71)
CDS^D		−0.106***
		(-13.74)
$E[Vol] \times CDS^D$		1.528***
		(13.76)
Size	−0.004***	−0.003***
	(-6.83)	(-5.61)
Market-to-book	0.015***	0.015***
	(29.17)	(29.18)
LEV	−0.155***	−0.154***
	(-28.99)	(-28.90)
Lagged CF	0.005***	0.005**
	(2.46)	(2.38)
Recession	−0.017***	−0.015***
	(-6.36)	(-5.75)
Default spread	−3.054***	−3.084***
	(-14.52)	(-14.64)
Interest rate	0.960***	0.937***
	(22.10)	(21.38)
N	105,747	105,747
R^2	0.066	0.066

Notes: This table presents the estimates of the coefficients used in the regression of investment on expected volatility and CDS trading. The dependent variable is firm-specific actual investment intensity. Variables are defined in Table 1. *E[Vol]* denotes the expected volatility. CDS^D denotes a CDS-trading dummy variable. *Recession* denotes an NBER recession dummy variable. *Default spread* is the yield spread between BAA and AAA-rated-rated bonds. *Interest rate* denotes nominal returns on 1-month Treasury bills. The sample period runs from 2001 through 2012 at annual frequency. T-statistics are reported in parentheses with standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3. Regression Analysis for the Distressed Firms

Explanatory Variables	(1)
Intercept	0.108***
	(14.99)
E[Vol]	0.292**
	(2.21)
Z-Score	0.018***
	(13.88)
CDS^D	−0.064***
	(-9.90)
E[Vol] × *Z-Score*	−0.110***
	(-3.73)
E[Vol] × CDS^D	1.045***
	(8.66)
E[Vol] × *Z-Score* × CDS^D	−0.139***
	(-4.18)
Size	−0.003***
	(-6.07)
Market-to-book	0.006***
	(14.34)
LEV	−0.012***
	(-2.84)
Lagged CF	−0.001
	(-0.45)
Recession	−0.015***
	(-6.11)
Default spread	−1.811***
	(-9.26)
Interest rate	0.695***
	(17.02)
N	92,887
R^2	0.126

Note: This table presents the estimates for the coefficients used in the regression analysis of distressed firms. The dependent variable is firm-specific actual investment intensity. Variables are defined in Table 1. *E[Vol]* denotes the expected volatility. *Z-score* is based on Altman (1968). CDS^D denotes a CDS-trading dummy variable. *Recession* denotes an NBER recession dummy variable. *Default spread* is the yield spread between BAA- and AAA-rated bonds. *Interest rate* denotes nominal returns on 1-month Treasury bills. The sample period runs from 2001 through 2012 at annual frequency. T-statistics are reported in parentheses with standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

of risk-shifting behavior found by Eisdorfer (2008), as distressed firms increase investment during high-volatility periods. The estimate of the coefficient on $E[Vol]_t \times Z\text{–}Score_{i,t}$ is negative and statistically significant at the 1% level, which indicates reduced risk-shifting behavior among healthy firms.

5. ROBUSTNESS TEST

This section presents robustness checks for the main empirical results. We perform a falsification test, exclude reverse-causality scenarios, and control for selection bias with propensity-score matching.

5.1. Falsification Test

The dummy variable, CDS^D, takes the values of zero or one to indicate the absence or presence of a factor that can influence a firm's investment decision. This dummy variable could capture the occurrence of any change that potentially affects a firm's investment decisions in the early 2000s, when the CDS market was growing substantially. Given concerns regarding this dummy variable that might arise, this section provides the results of falsification tests.

We introduce another dummy variable, *AFTER*, which equals zero for the pre-2001 period and one for the post-2001 period. We use *AFTER* instead of CDS^D in Equation (5) and test whether this falsified variable can reproduce the results obtained in Table 2. Table 4 shows the results of the falsification tests. Column (1) shows regression results obtained after replacing CDS^D with *AFTER*. Although the estimate of the coefficient on *AFTER* is negative and statistically significant at the 1% level, the estimate of the coefficient on $E[Vol] \times AFTER$ is not statistically significant. The falsification test fails to reproduce the previous results obtained for CDS^D.

Next, we add CDS^D to column (2) of Table 4. The estimate of coefficient for CDS^D is negative and the estimate of the coefficient on $E[Vol] \times CDS^D$ is positive in the presence of the post-2001 period dummy variable. Both estimates are significant at the 1% level. In summary, utilizing *AFTER*, we fail to detect a significant change in the effects of CDSs on risk-shifting. This provides additional assurance regarding the results reported in Table 2 and shows that the results remain the same after the addition of the dummy variable, *AFTER*.

5.2. Reverse Causality

It is plausible that endogeneity results in reverse causality running from risk-shifting to the initiation of CDS trading. A firm's risk-shifting behavior might make it more likely that it initiates CDS trading on its debt. If debtholders either anticipate or predict future deterioration of a firm's credit quality and subsequent risk-shifting, they could initiate CDS trading to hedge their risk. To alleviate this reverse-causality concern, we repeat the analysis while excluding observations for a firm whose CDS trading is possibly triggered by expected risk-shifting. As candidates for such firms, we consider firms that are experiencing financial distress within two years of CDS initiation. Debtholders may predict that a firm will face financial distress within the next few years, but it is less likely that they can foresee such a threat far into the future. Therefore, we drop all observations for firms that experience financial distress within two years after the initiation of CDS trading and run the same regressions as those associated with Table 2 and Table 3.

Table 4. Regression Analysis for Falsification Test

Explanatory Variables	(1)	(2)
Intercept	0.312***	0.310***
	(39.77)	(39.24)
E[Vol]	−0.395***	−0.396***
	(-2.91)	(-2.92)
AFTER	−0.064***	−0.060***
	(-8.55)	(-8.02)
CDS^D		−0.068***
		(-8.49)
E[Vol] × *AFTER*	0.129	0.071
	(0.79)	(0.43)
E[Vol] × CDS^D		0.809***
		(7.04)
Size	−0.003***	−0.002***
	(-4.53)	(-3.58)
Market-to-book	0.015***	0.014***
	(29.09)	(29.09)
LEV	−0.157***	−0.157***
	(-29.13)	(-29.04)
Lagged CF	0.005**	0.005**
	(2.36)	(2.28)
Recession	0.005*	0.005**
	(1.74)	(2.01)
Default spread	−2.367***	−2.334***
	(-10.84)	(-10.70)
Interest rate	0.145***	0.130**
	(2.73)	(2.43)
N	105,747	105,747
R^2	0.071	0.071

Notes: This table presents the estimates for the coefficients used in the regression analysis for a falsification test. The dependent variable is firm-specific actual investment intensity. Variables are defined in Table 1. *E[Vol]* denotes the expected volatility. *AFTER* is a dummy variable that equals zero for the pre-2001 period and one for the post-2001 period. CDS^D denotes a CDS-trading dummy variable. *Recession* denotes an NBER recession dummy variable. *Default spread* is the yield spread between BAA and AAA-rated bonds. *Interest rate* denotes nominal returns on 1-month Treasury bills. The sample period runs from 2001 through 2012 at annual frequency. T-statistics are reported in parentheses with standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Regression Analysis Excluding Reverse Causality Scenarios

Explanatory Variables	(1)	(2)	(3)	(4)
Intercept	0.255***	0.105***	0.259***	0.108***
	(38.59)	(14.42)	(40.04)	(14.99)
E[Vol]	−0.271***	0.292**	−0.262***	0.297**
	(-2.68)	(2.17)	(-2.65)	(2.25)
Z-Score		0.018***		0.018***
		(13.78)		(13.88)
CDS^D	−0.120***	−0.074***	−0.114***	−0.069***
	(-13.78)	(-9.56)	(-13.93)	(-10.43)
E[Vol] × *Z-Score*		−0.110***		−0.110***
		(-3.71)		(-3.74)
E[Vol] × CDS^D	1.528***	1.096***	1.652***	1.157***
	(11.43)	(5.97)	(13.84)	(8.68)
E[Vol] × *Z-Score* × CDS^D		−0.116***		−0.143***
		(-2.67)		(-4.19)
Size	−0.003***	−0.003***	−0.003***	−0.003***
	(-4.30)	(-4.99)	(-5.61)	(-6.07)
Market-to-book	0.015***	0.006***	0.015***	0.006***
	(28.89)	(14.06)	(29.19)	(14.35)
LEV	−0.154***	−0.012***	−0.154***	−0.012***
	(-28.58)	(-2.67)	(-28.88)	(-2.83)
Lagged CF	0.005**	−0.001	0.005**	−0.001
	(2.21)	(-0.62)	(2.38)	(-0.45)
Recession	−0.016***	−0.016***	−0.015***	−0.015***
	(-5.97)	(-6.27)	(-5.78)	(-6.13)
Default spread	−3.108***	−1.821***	−3.113***	−1.831***
	(-14.32)	(-9.07)	(-14.69)	(-9.32)
Interest rate	0.971***	0.718***	0.935***	0.694***
	(21.64)	(17.20)	(21.32)	(16.98)
N	102,628	90,409	105,476	92,670
R^2	0.064	0.123	0.066	0.125

Note: This table presents the estimates for the coefficients used in the regression analysis to exclude reverse-causality scenarios. The dependent variable is firm-specific actual investment intensity. Variables are defined in Table 1. *E[Vol]* denotes the expected volatility. *Z-score* is based on Altman (1968). CDS^D denotes a CDS-trading dummy variable. *Recession* denotes an NBER recession dummy variable. *Default spread* is the yield spread between BAA- and AAA-rated bonds. *Interest rate* denotes nominal returns on 1-month Treasury bills. The sample period runs from 2001 through 2012 at annual frequency. T-statistics are reported in parentheses with standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

We report the results of the analysis in column (1) and column (2) of Table 5. If reverse causality were driving our results, we would observe lower estimates of the coefficient or lower statistical significance. The estimates of the coefficients on *E[Vol]* × CDS^D and *E[Vol]* × *Z-Score* × CDS^D are statistically significant with no reduction in magnitude. We also re-run the regression after excluding observations of distressed firms within a two-year period instead of excluding all observations. The statistical significance and magnitude of the coefficients reported in column (3) and column (4) are almost identical to those reported in column (1) and column (2). As such, the results remain qualitatively the same when we exclude firms that experience financial distress within two years of initiating CDS trading.

5.3. Selection Bias: Propensity-Score Matching

Another concern regarding our empirical results is selection bias might have affected their validity. Firms selected for CDS trading may have special characteristics that correlate with how they invest during volatile periods. Hence, an increase in investment during high-volatility periods might be caused by certain characteristics of CDS-referenced firms rather than by the initiation of CDS trading. We therefore apply propensity-score matching to alleviate this concern. Propensity-score matching selects firms for the analysis that are similarly likely to initiate CDS trading.[5] For each CDS-referenced firm, we choose three non-CDS-referenced firms based on the nearest propensity scores obtained by estimating a probit model of the likelihood that CDS trading occurs.[6] Next, we investigate risk-shifting behavior in this matched sample.

Following Subrahmanyam et al. (2014), a propensity score is calculated from 14 covariates, including firm size (*Size*) measured as the natural logarithm of firm value (the market value of equity plus the book value of liabilities), the ratio of the book value of total liabilities to total assets (*LEV*), a firm's return on assets (*ROA*), a firm's excess returns over the past year ($R_{i,t-1}$-$R_{m,t-1}$), a firm's annualized equity volatility (*Equity Volatility*), the ratio of property, plant, and equipment to total assets (*PP&E/Total Asset*), the ratio of sales to total assets (*Sales/Total Asset*), the ratio of earnings before interest and taxes to total assets (*EBIT/Total Asset*), the ratio of working capital to total assets (*WCAP/Total Asset*), the ratio of retained earnings to total assets (*RE/Total Asset*), the ratio of cash to total assets (*Cash/Total Asset*), the ratio of capital expenditures to total assets (*CAPX/Total Asset*), an investment-grade dummy variable (*Investment Grade*), and a credit-rating dummy variable (*Rated*).

The results obtained from a probit model are reported in Table 6. The results are largely consistent with those reported in Subrahmanyam et al. (2014). It is important to note that firms selected for CDS trading are not financially distressed. As shown in Table 6, the estimates of the coefficients on *Investment Grade* and *Rated* are positive and statistically significant at the 1% level, indicating that firms that earn high credit ratings are more likely to be involved in CDS transactions. This first informal evidence alleviates the concern that our results are driven solely by selection bias related to distressed firms.

[5] For the details on propensity-score matching, refer to Roberts and Whited (2013).

[6] Using one or two matching non-CDS firms yields similar results.

Using the CDS-referenced firms and their matched non-CDS-referenced firms, we run the same regression as that associated with Table 2 and Table 3. The results are reported in Table 7. Column (1) of Table 7 shows the regression results using Equation (5). The estimates of the coefficients on CDS^D and $E[Vol] \times CDS^D$ are statistically significant at the 1% level, with the same sign as in column (2) of Table 2, although the magnitudes are smaller. As such, the results remain similar after controlling for the effects of observable firm-level characteristics.

Table 6. Probability of CDS Trading

Explanatory Variables	(1)
Intercept	−8.402***
	(-41.39)
Size	0.576***
	(33.88)
LEV	1.326***
	(12.05)
ROA	−0.838***
	(-4.19)
$R_{i,t-1}$-$R_{m,t-1}$	0.001
	(1.32)
Equity Volatility	0.021
	(0.24)
PP&E/Total Asset	0.557***
	(5.02)
Sales/Total Asset	0.079***
	(2.93)
EBIT/Total Asset	0.080
	(0.25)
WCAP/Total Asset	0.416**
	(2.50)
RE/Total Asset	0.183***
	(2.82)
Cash/Total Asset	0.217
	(0.81)
CAPX/Total Asset	−2.754***
	(-5.62)
Investment Grade	0.539***
	(11.98)
Rated	0.987***
	(14.51)
Year, Industry	Yes
N	34,427
Pseudo R^2	0.223

Notes: This table presents the estimates of the probability that CDS trading occurs, obtained using a probit model. Variables are defined in Table 1. $R_{i,t-1} - R_{m,t-1}$ is the firm's excess return over the preceding year. *Equity Volatility* is the firm's annualized equity volatility. Financial ratios are calculated on the basis of total assets. *Investment Grade* and *Rated* are dummy variables that equals one if firm's credit rating is investment grade or firm is rated. The sample period runs from 2001 through 2012 at annual frequency. Standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7. Regression Analysis with the Propensity-Score-Matching Sample

Explanatory Variables	(1)	(2)
Intercept	0.318***	0.207***
	(16.99)	(9.30)
E[Vol]	−0.412***	−0.259
	(-2.60)	(-0.96)
Z-score		0.012***
		(4.11)
CDS^D	−0.044***	−0.028***
	(-5.82)	(-3.94)
E[Vol] × *Z-Score*		−0.040
		(-0.58)
E[Vol] × CDS^D	0.613***	0.698***
	(4.91)	(4.90)
E[Vol] × *Z-Score* × CDS^D		−0.142***
		(-3.81)
Size	−0.014***	−0.013***
	(-8.46)	(-7.66)
Market-to-book	0.010***	0.005***
	(9.06)	(4.43)
LEV	−0.147***	−0.033***
	(-10.08)	(-2.61)
Lagged CF	0.039***	0.036***
	(4.45)	(4.13)
Recession	0.003	−0.005
	(0.80)	(-1.20)
Default spread	−0.809***	−0.386
	(-2.70)	(-1.37)
Interest rate	0.443***	0.421***
	(6.02)	(5.89)
N	18,649	18,649
R^2	0.108	0.143

Note: This table presents the estimates of the coefficients with the propensity-score-matching sample. The dependent variable is firm-specific actual investment intensity. Variables are defined in Table 1. *E[Vol]* denotes the expected volatility. CDS^D denotes a CDS-trading dummy variable. *Recession* denotes an NBER recession dummy variable. *Default spread* is the yield spread between BAA- and AAA-rated bonds. *Interest rate* denotes nominal returns on 1-month Treasury bills. The sample period runs from 2001 through 2012 at annual frequency. T-statistics are reported in the parenthesis with standard errors clustered by firms. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

An observation similar to that reported above applies to the second column using Equation (6). The estimate of the coefficient on $E[Vol] \times CDS^D$ remains highly significant. The estimates of the coefficients on the triple interaction term, $E[Vol] \times Z\text{-}Score \times CDS^D$, remains highly significant at almost the same magnitude as reported in Table 3. The statistical significance of the two coefficient estimates confirms our evidence that the initiation of CDS trading encourages risk-shifting behavior and the effects of CDSs on risk-shifting are stronger for more highly distressed firms. Overall, the analysis using propensity-score matching confirms that our results are robust and not driven by selection bias.

6. CONCLUSION

This paper investigates the impact of the introduction of CDS trading on reference firms' risk-shifting. We provide a theoretical background for the analysis and find significant empirical evidence of risk-shifting when CDSs are traded on a firm's debt. Possible explanations include stronger incentives for equityholders to shift risk with a rise in default risk and reduced monitoring efforts by debtholders (or banks) when they are insured against credit risk.

The regression analysis reveals a positive relationship between investment and expected volatility during high-volatility periods after the initiation of CDS trading. This positive relationship is even stronger for firms experiencing financial distress. The empirical results are robust to a falsification test, a reverse-causality test, and a test of selection bias. We also find evidence that firms invest less robustly after CDS trading begins.

CDSs represent an important recent innovation in global financial markets. While public debates over whether CDSs contributed to the financial crisis and how the CDS market should be regulated have drawn attention, few studies have examined the role of CDS trading in a firm's investment decisions, specifically regarding risk-shifting. This paper fills these gaps by revealing unintended consequences of credit derivatives on investment.

Although our findings suggest that CDS-referenced firms take on excessive risk by investing in value-decreasing projects, our results should be generalized with caution, especially with respect to large and financially healthy firms. CDSs have also had positive welfare effects. As shown by Hong and Wang (2021), CDS trading discourages investment, which can mitigate the problems caused by overinvestment in firms that suffer from agency problems. Our findings are important for scholars and regulators who are interested in understanding the net welfare effects of CDSs. The negative welfare effects of CDSs may stem from a divergence of financial and control rights through insurance purchases. Future research could seek to identify the underlying mechanism to prevent these unintended consequences, possibly through risk retention on the part of empty creditors.

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Mailing Address: Jiyoon Lee, Yonsei University, School of Business, 50 Yonsei-ro, Seodaemun-gu, Seoul, 03722, South Korea; Email: jiyoonlee@yonsei.ac.kr.

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