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Abstract

Are companies with traded credit default swap (CDS) positions on their debt more likely to default? Using a proportional hazard model of bankruptcy and Merton's contingent claims approach, we estimate the probability of default for U.S. nonfinancial firms. Our analysis does not generally find a persistent link between CDS and default over the entire period 2001-08, but does reveal a higher probability of default for firms with CDS over the last few years of that period. Further, we find that firms trading in the CDS market exhibited a higher Moody's KMV expected default frequency during 2004-08. These findings are consistent with those of Henry Hu and Bernard Black, who argue that agency conflicts between hedged creditors and debtors would increase the likelihood of corporate default. In addition, our paper highlights other explanations for the higher defaults of CDS firms. Consistent with fire-sale spiral theories, we find a positive link between institutional ownership exposure and corporate distress, with CDS firms facing stronger selling pressures during the recent financial turmoil.

Key words: credit derivatives, corporate bankruptcy, Merton's distance to default

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1. INTRODUCTION

The wide-ranging financial reforms recently enacted by Congress have also focused on how to regulate the complex over-the-counter global derivatives market. This proposed legislation has fueled the long-standing debate over the appropriate regulatory framework for the large and complex derivatives market. Title VII of the Dodd-Frank Wall Street and Consumer Protection Act will effectively require that most derivatives be traded on centralized exchanges. While the regulatory reform broadly targets all derivative instruments, the most important derivatives contract under scrutiny after the recent financial meltdown is the credit default swap (CDS).[1]

Since the inception of the credit derivatives market, market participants have underscored its benefits in mitigating concentrations of credit risk, promoting diversification outside the banking system, and enhancing trading liquidity. More recently, however, some policy makers and financial commentators argue that CDS trading actually amplified risks in the recent financial crisis (Stout 2009). One facet of credit derivatives trading that is often under intense scrutiny is the "naked" CDS. Like any other naked trading position, this is a more speculative transaction, because the CDS position is not used to hedge existing exposures to the underlying asset.[2]

Besides these concerns, some argue that even if credit derivatives are used to insure against existing credit risks, these hedges can engender agency problems between creditors and debtholders and raise the likelihood of corporate bankruptcy. This issue has recently attracted significant interest in the press and among finance and legal practitioners.[3] Hu and Black (2008a, 2008b) formalize these agency problems, arguing that creditors who hedge their positions are "empty creditors." In addition to the pecuniary benefits of receiving interest and principal payments, corporate debt owners also have legal rights that allow them to enforce lending terms

[1] Stephen Fidler, Gregory Zuckerman, and Brian Baskin, "Swaps Come Under Fire — U.S. Regulators, European Leaders Seek More Oversight on Trades in Derivatives," *Wall Street Journal*, March 10, 2010.
[2] Wolfgang Münchau, "Time to Outlaw Naked Credit Default Swaps," FT.com, February 28, 2010; Charles Davi, "Naked Credit Default Swaps: Exposed," *Atlantic*, May 2009.
[3] See, for example, "CDS Derivatives Are Blamed for Role in Bankruptcy Filings," *Financial Times*, April 17, 2009; "YRC and the Street's Appetite for Destruction," *Wall Street Journal*, January 5, 2010; Daniel Gross, "Why GM May Go Bankrupt," slate.com, May 12, 2009; Daniel Gross, "The Scary Rise of the Empty Creditor," slate.com, April 21 2009; Caroline Salas and Shannon Harrington, "Darth Wall Street Thwarting Debtors with Credit Swaps," Bloomberg, March 5, 2009; Andrew Ross Sorkin, "Is the Empty Creditor Theory Itself Empty?" NYTimes.com, December 21, 2009.

and take part in restructuring and bankruptcy proceedings. When debtholders hedge their position with a CDS, they are able to "decouple" their economic and legal rights. Because they are hedged, these creditors may not particularly care, or sometimes may even prefer, that the company files for bankruptcy protection. Bankruptcy costs are generally very onerous; therefore, any interference from an empty creditor can lead to an inefficient economic outcome for other creditors, shareholders, and the firm, especially in cases where bankruptcy alternatives, such as restructuring, are more efficient.

While the issue of empty-creditor conflicts between debtholders with CDS protection and the debtor firm (henceforth referred to as the CDS firm) has attracted a lot of interest in the financial press, other interpretations for any unusual rise in default risk among larger CDS firms are possible. A higher default profile among CDS firms may not necessarily be triggered by empty-creditor agency problems but may simply be caused by a rift in investor behavior and a shift in credit sentiment in times of financial instability. In the aftermath of the recent financial crisis, recent studies highlight a number of potential transmission mechanisms of distress across markets that could indiscriminately drag down large and small companies alike. Shleifer and Vishny (2011) and Hau, Lai, and Chua (2011) investigate the upsurge in fire sales of financial assets as a catalyst for financial turmoil. Brunnermeier and Pedersen (2009) focus on the role of margin financing in amplifying liquidity and funding problems and promulgating destabilizing liquidity spirals. It is not difficult to envision under any one of these premises a scenario in which default risks of CDS and non-CDS companies become displaced.

We formally investigate the relationship between credit derivatives and firm bankruptcies using two distinct but related reduced-form methodologies to calibrate a firm's default risk. The first approach is a proportional hazard model that assesses a firm's likelihood of filing for reorganization over its entire public life cycle. The second approach measures corporate default risks using Merton's contingent claims model (Merton 1974). Merton's distance-to-default methodology provides a time-consistent indicator of corporate distress. The first phase of our analysis relies on our own model-derived measures of implied distance-to-default scores to assess the link between credit derivatives and firm default. In our second phase, we reestimate this relationship using Moody's KMV proprietary expected default frequency (EDF) measures, which are also based on Merton's approach to assessing corporate distress.

Initially, we evaluate the impact of credit derivatives by using a binary indicator that identifies firms with nontrivial CDS trading on their debt. We also decompose the effect of the CDS indicator across years to better understand the effect of CDS over time. Our empirical analysis reveals no significant link between CDS and the probability of bankruptcy over the entire panel of U.S. nonfinancial public firms during 2001–08. However, when the effect is decomposed by year, CDS firms exhibit a greater likelihood of default in 2008. In particular, the odds ratio of the probability that a CDS firm will file for bankruptcy divided by the probability that a similar non-CDS firm goes bankrupt surges to 2.57 in 2008.

The estimates of the bankruptcy hazard regressions are driven primarily by the relative distribution of the bankruptcies among CDS and non-CDS firms and the fact that most of the bankruptcy filings of CDS firms are clustered over the past few years. To avoid the lumpiness of corporate bankruptcy events, we use Merton's model to measure the relationship between corporate distress and CDS. The relationship between implied default and the binary of indicator CDS remains insignificant over the entire panel of U.S. nonfinancial firms. The distance-to-default model estimates reveal again a significant increase in default among CDS firms over the past few years, reinforcing some of the findings of the bankruptcy hazard regressions. Although we observe Moody's KMV corporate EDFs starting in 2004, by this metric of corporate distress the regression results are more statistically significant in indicating a higher default risk among CDS firms.

One possible limitation of the empirical analysis is that the observed positive correlation between CDS and bankruptcy may be a case of reverse causality. In anticipation of problems, creditors of the firm may buy protection in the period before bankruptcy and thus create this spurious correlation. We use a two-stage approach to estimate an orthogonal instrument of excess CDS exposure constructed to eliminate these reverse-causality problems. With this more sophisticated approach, we continue to find a strong positive association between the firm-specific index of excess CDS exposure and implied default.

The final phase of our empirical analysis investigates whether the apparent rise in default risk experienced by CDS firms more recently is circumstantial, stemming from the unusual fragility of the financial system. Existing theories describing deleveraging spirals and distressed selling provide various mechanisms by which investors may be forced to sell their holdings when stock prices plunge. In highlighting the importance of financial asset fire sales, Shleifer and

Vishny (2011) note that institutions relying on short-term funding, such as the commercial paper market, are more vulnerable during a financial crisis. Cella, Ellul, and Giannetti (2010) focus on the intensity of institutional ownership to measure stock price selling pressures that could increase volatility and amplify default risks.

We find a weak link between commercial paper funding and default, with firms relying on this short-term financing exhibiting a slightly higher implied default. To be sure, we expect these funding pressures to be more pertinent among asset-liability managed financial firms that rely more heavily on these short-term sources to finance their activities. According to our regression results, nonfinancial firms that are overly exposed to institutional ownership experience higher default. Despite controlling for these alternative theories, however, we continue to observe a strong positive link between excess CDS exposure and firm distress. The findings are therefore consistent with all those alternative explanations that focus on the importance of agency problems between creditors and debtors as well as the ferocity of the recent financial crisis.

The remainder of this paper proceeds as follows. Section 2 briefly summarizes the empty-creditor hypothesis, outlining the potential agency conflicts between debtholders with CDS protection and debtors, as well as providing alternative explanations for the amplification of corporate default risks. In section 3, we discuss the proportional hazard model of bankruptcy and contrast it to Merton's methodology. Section 4 describes the data sources and presents summary statistics for the regression variables. Section 5 briefly documents the explosive growth of the credit derivatives market. Sections 6 and 7 review our empirical evidence and analyze the importance of CDS on corporate distress. In section 8, we develop an orthogonal instrument of excess CDS exposure designed to eliminate reverse-causality problems. In section 9, we examine more closely a number of competing explanations for the amplified default risks of CDS firms. Section 10 summarizes our findings and presents concluding remarks.

2. MOTIVATION

2.1 *Credit Derivatives and Agency Problems*

The underlying economic intuition behind the empty-creditor concept is grounded on the traditional principal-agent conflict theories formalized in the financial literature (Jensen and Meckling 1976; Fama and Jensen 1983; Myers and Majluf 1984). In their earlier work highlighting the distortionary influence of credit derivatives, Hu and Black (2006, 2007) focused mainly on equity ownership by developing the concept of the "empty voter." Shareholders, in effect, have economic ownership but also voting rights. Under normal conditions, firm shareholders are expected to exercise their voting rights to optimize the value of their equity holdings. Hu and Black point out that a credit derivatives position can weaken the incentives to use voting rights to safeguard economic ownership.

The empty-creditor concept is a similar agency problem because debtholders with CDS have a direct mechanism for influencing a firm's decision through noneconomic rights, such as voting on the restructuring or bankruptcy-related decisions and the exercise of covenants. Credit derivatives and other financial innovations, such as collateralized debt obligation securities, allow debtholders to cushion or entirely eliminate the economic exposure of losing principal and interest while maintaining valuable noneconomic rights. Moreover, debtholders can benefit from a negative economic ownership that arises if their hedge is higher than their principal debt exposure.

The empty-creditor premise has been met with a lot of skepticism from participants in the credit derivatives and fixed-income markets. A recent research paper of the International Swaps and Derivatives Association (ISDA) questions the validity of the empty-creditor hypothesis on logistical grounds (Mengle 2009). This paper argues that CDS hedging strategies cannot be exploited systematically because the market would anticipate and incorporate much of the credit risk and thus make such positions prohibitively expensive to protection buyers.

More recently, Bolton and Oehmke (2009) take a careful look at this issue by developing a theoretical limited-commitment model. The authors show that, at least initially, CDS enhance value by strengthening incentives for borrowers to engage in positive net-present-value projects, raising the likelihood that they can repay their obligations. In a limited-commitment setup, where the borrower is not always bound to pay its debt, the presence of CDS forces debtors to increase investment and lowers strategic default. However, with creditors opting to increase their credit protection using CDS to insure their exposures more effectively, these amplified positions generate empty-creditor conflicts.

Ashcraft and Santos (2009) investigate whether credit derivatives have lowered the cost of debt financing for corporations. The authors identify two channels through which CDS trading could reduce such costs. A CDS can ultimately help lenders hedge their underlying exposure to borrowers. Moreover, the CDS market could also lower the cost of debt by increasing information on traded firms and enhancing price discovery. More important, this study also highlights a downside to credit derivatives trading, pointing out that it may allow lenders to hedge their credit exposures after the loan has been granted in a way that is unobservable to the firm and outside investors. A consequence of CDS hedging is that banks insured against a direct exposure to borrowers would have reduced incentives to monitor these firms ex post.

This reduction-in-monitoring hypothesis is closely associated with the empty-creditor hypothesis in many ways. The agency problems are more threatening in the latter hypothesis, however, because hedged creditors are not only uninterested in monitoring but also stand to benefit if the firm files for bankruptcy. Ashcraft and Santos (2009) find no evidence that CDS firms experience lower credit spreads when issuing in the bond market or syndicated loan market. Instead, their findings suggest that the onset of CDS trading has adversely affected the financing costs of riskier firms as well as those that are more informationally opaque.

Most of the empirical support for the empty-creditor hypothesis is anecdotal in nature, based on reported cases of corporate distress in which a firm with existing CDS contracts was arguably forced into bankruptcy. A recent *Economist* article highlights several bankruptcies blamed on bondholders that had unusual economic exposures (cases included Six Flags, AbitibiBowater, General Growth Properties, and General Motors).[4] Morgan (2009) reports the more recent struggles of Gannet Co. to navigate through a difficult financial period, while apparently facing intense pressure from hedged CDS debtholders. Bolton and Oehmke (2009) provide a table summarizing several potential incidences of the empty-creditor problem over the past few years.

From all the examples cited above, the bankruptcy of AbitibiBowater is one of the most interesting cases because it highlights all facets of the agency-problems gamesmanship between creditors and the debtor. Bowater merged with Abitibi in a leveraged buyout in 2008; burdened by excessive debt, the company wanted to exchange its 9 percent bonds to improve cash flow to ward off bankruptcy. To complete this exchange, the company needed 97 percent acceptance from bondholders. In the end, the company was able to get a 54 percent approval. The failure to

[4] “No Empty Threat: Credit-Default Swaps Are Pitting Firms against Their Own Creditors,” *Economist*, June 18, 2009, page 79.

restructure its debt was largely attributed to bondholders with large CDS positions, who stood to benefit from the company's bankruptcy.

The struggle between hedged bondholders and AbitibiBowater was actually more action packed. On March 20 2009, with their expiration getting closer to maturity, CDS holders lobbied to have AbitibiBowater default on its obligations. To avoid these pressures, AbitibiBowater obtained a court order enabling it to suspend bond payments while working through its restructuring. Running out of time, CDS holders stood to lose close to $500 million. An ISDA ruling on March 28, however, gave CDS holders the right to backdate their claim through a cash-auction system, essentially validating their default claims.

2.2 *Alternative Hypotheses for Rising Default Risks among CDS Firms*

While these agency problems between insured debtholders and debtors outlined above offer an interesting interpretation, other explanations could also account for an increase in default among CDS firms. A higher default profile among larger CDS firms may not be associated with misaligned incentives between insured creditors and debtors but could be simply circumstantial, caused by a fundamental change in credit sentiment in an economic crisis. Shleifer and Vishny (2011) assert that fire sales of financial assets during a crisis could be a possible transmission mechanism of distress across both large and small firms. Under this mechanism, forced sales by distressed financial firms or investors could trigger a cascade of fire sales that spread to other institutions and affect not only the creditworthiness of smaller and more vulnerable non-CDS companies but also bigger CDS corporations.

Several studies in the financial literature argue that investors with shorter trading horizons, such as hedge fund investors and certain institutional investors, might be more predisposed to sell during a financial panic, driving stocks below their fundamental value (De Long, Shleifer, Summers, and Waldman 1990). Brunnermeier and Pedersen (2009) argue that the perils of margin financing can be amplified by market and funding liquidity problems and lead to destabilizing liquidity spirals. Cella, Elul, and Giannetti (2010) find that short-term investors sold more stocks than long-term investors after the collapse of Lehman Brothers. Arguably, one might expect long-term investors to hold a relatively higher fraction of larger CDS firms in their portfolios. In this case, a fire sale by short-term investors should be more detrimental to smaller companies and in theory lead to a widening default premium between CDS and non-CDS firms.

3. MODELING FIRM DEFAULT

The primary focus of our empirical analysis is to investigate the relationship between CDS and the likelihood of debtor default. We use two approaches to measure corporate distress. The more direct method is a reduced-form hazard regression model of bankruptcy. Terminal events such as bankruptcy are not uncommon in the life of a corporation. Over the entire sample period 2001–08, there were more than 520 corporate bankruptcies for publicly traded U.S. nonfinancial corporations included in Compustat. This fairly large sample shrinks substantially when we focus on CDS firms, which experienced only 43 bankruptcies. This smaller number of bankruptcies could be more challenging because much of the proportional hazard analysis is predicated on the relative frequency of these events across CDS and non-CDS firms. To improve statistical power, we investigate an alternative measure of firm distress derived from Merton's model. In contrast to the bankruptcy approach, these implied measures of default are fully observable over the entire life cycle of the firm.

3.1 *A Proportional Hazard Model of Bankruptcy*

Several academic papers have proposed various reduced-form approaches to modeling corporate bankruptcy. Early studies relied primarily on accounting variables to predict the probability of bankruptcy (Altman 1968; Ohlson 1980). Altman's original study uses discriminant analysis to develop firm Z-scores that are widely used in the academic literature and by practitioners to evaluate corporate distress. Recent studies propose a dynamic cross-sectional time-series logit model to estimate the conditional probability of bankruptcy (Shumway 2001; Campbell, Hilscher, and Szilagyi 2008). Our empirical analysis investigates firm distress using a hazard model to compare the bankruptcy rate of CDS and non-CDS firms. This methodology, which offers a convenient framework for analyzing credit risk over the entire life cycle of public firms, has been extensively applied in the financial literature. Chava and Jarrow (2004) provide a broad comparison of the forecasting efficiency of these various bankruptcy models.

The actual termination event in the hazard regression model is firm bankruptcy. We use a proportional hazard framework to analyze the default rate of corporate debt securities. Assume that τ_i denotes a random variable representing the time to bankruptcy for company (i). The hazard rate is defined as the probability that the firm files for bankruptcy in the next period, given that it has not done so up to now. More formally, the bankruptcy rate can be defined as

$$\lambda_i(t) = \lim_{\Delta t \to 0} \frac{P(t \le \tau_i \le t + \Delta t \mid \tau_i \ge t)}{\Delta t}. \quad (1)$$

The basic proportional hazard framework asserts that

$$\lambda_i(\tau) = h(\tau)\exp(z_{it\bullet}\beta). \quad (2)$$

The vector $z_{it\bullet}$ represents the vector of exogenous variables affecting firm bankruptcy. The function $h(\tau)$ is commonly referred to as the baseline hazard function. Essentially, the proportional hazard specification is a semiparametric method of estimation that conditions out the baseline hazard and focuses on the proportionality factor $\exp(z_{ti\bullet}\beta)$ to estimate the influence of the explanatory variables.

We can rewrite equation (2) to formalize our general hypothesis of testing the influence of CDS on the bankruptcy. In particular, the model can be specified as

$$\lambda_i(\tau) = h(\tau)\exp(\alpha_0 + \alpha_1 I_t + \alpha_2 I_{SIC} + \beta x_{t-1,i\bullet} + \gamma CDS_{ti}). \quad (3)$$

The explanatory variable I_t is a dummy variable controlling for time variation, while I_{SIC} measures industry effects at the one-digit SIC level. The lagged explanatory vector $x_{t-1,i\bullet}$ controls for variation observed across the panel of firms. Finally, the variable CDS_{ti} represents a binary indicator of firms with outstanding CDS on their debt. This specification allows us to test the following general hypothesis.

Hypothesis 1: A positive and statistically significant coefficient on γ would be consistent with empty-creditor agency problems between creditors and the debtor firm, indicating that CDS increase the bankruptcy rate.

Hypothesis 1 is a broad test of the empty-creditor premise, which asserts that CDS firms exhibit a higher default over the entire sample period. In reality, the CDS dummy variable is just a simple proxy for potential empty-creditor problems and does not fully capture the underlying composition of the protection buyers and the intensity of the empty-creditor problem. In theory, agency problems will be greater if the protection buyers are existing bondholders —potential empty creditors—as opposed to other nonvoting investors and dealers taking a short position on the company's credit. Ideally, we would want to control for the intensity of the CDS (for instance, the volume of existing CDS relative to outstanding debt) and the distribution of protection buyers, particularly whether they are creditors or not. Unfortunately, this information is not historically available at the company level.

Another possible limitation of the specification defined by equation (3) is that it assumes that agency problems between creditors and borrower would manifest over the entire 2001–08 period. To be sure, these conflicts were evident even in the earlier part of our sample period. The first such case reported in the financial press was Marconi Corporation's effort to restructure in 2001. This struggling U.K. telecommunication company faced unyielding members of the bank syndicate that refused to agree to any restructuring unless it was formally classified as a credit event under ISDA rules. The potential for empty-creditor conflicts was formally discussed in a 2006 report published by an association of solvency professionals, which detailed the impact of credit derivatives on restructuring and bankruptcy.[5]

It is plausible that empty-creditor hedging strategies might have surfaced more gradually as participants in the CDS market became more sophisticated and developed more complex strategies. Bolton and Oehmke (2010) demonstrate that the intensity of the agency conflicts are likely to be much higher when creditors take larger bets and overinsure against the debtor. Their theoretical findings suggest that debtor-creditor conflicts would be prevalent in a market with widespread use of the credit derivatives products. Moreover, these conflicts would be magnified in financial downturns, because the higher incidence of corporate distress would increase the value of the CDS contract.

To capture this possible incremental effect of credit derivatives on the likelihood of corporate distress, we modify the regression specification defined by equation (4) to include the interaction of yearly dummy variables I_t with the CDS binary indicator. In particular,

$$\lambda_i(\tau) = h(\tau)\exp(\alpha_0 + \alpha_1 I_t + \alpha_2 I_{SIC} + \beta x_{t-1,i\bullet} + \sum_{t=2001}^{2008} \gamma_t CDS_{ti} \times I_t). \tag{4}$$

This specification leads to the following hypothesis.

Hypothesis 2: A positive and statistically significant coefficient on γ_t $(t = 2001, \ldots, 2008)$ is consistent with the presence of empty-creditor agency problems between creditors and debtor firms in that particular year t.

[5] See "Credit Derivatives in Restructurings: A Guidance Booklet," INSOL International, 2006. http://www.insol.org/page/60/credit-derivatives-in-restructuring.

3.3 *Merton's Contingent Claims Approach*

In his seminal paper, Merton (1974) models a firm's equity as a call option on the value of assets. The strike price of the option is determined by the firm's contractual liabilities. Crosbie and Bohn (2001) outline a calibration method that constructs a distance-to-default (DD) measure from the underlying Black-Scholes option-theoretic model proposed by Merton. Several studies use Merton's model to estimate the probability of default for nonfinancial firms (Vassalou and Xing 2004; Bharath and Shumway 2008; Campbell, Hilscher, and Szilagyi 2008). Park and Peristiani (2007) apply this same methodology to determine the probability of the failure of publicly traded banks. In a nutshell, the Merton model can be represented by a two-equation system:

$$V_{Eti} = V_{Ati}\ N(d_{1ti}) - e^{-rT} L_{ti}\ N(d_{2ti}), \tag{5}$$

and

$$\sigma_{Eti} = \frac{V_{Ati}}{V_{Eti}}\ N(d_{1ti})\ \sigma_{Ati}. \tag{6}$$

The variable V_{Eti} denotes the i-th firm's market value of equity at period (t), V_{Ati} represents the market value of assets, and L_{ti} is total debt, which corresponds to the exercise price. Consistent with the Black-Scholes framework, V_{Ai} is assumed to follow a geometric Brownian process with drift μ and volatility σ_{Ati}. Similarly, the variable σ_{Eti} denotes the volatility of firm equity, r_t is the risk-free interest rate, and T is time to expiration. The Black-Scholes distance terms are defined by $d_{1ti} = [\ln(V_{Ati} / L_{ti}) + T(r_t + 0.5\sigma^2_{Ati})] / \sigma_{Ati}\sqrt{T}$ and $d_{2ti} = d_{1ti} - \sigma_{Ati}\sqrt{T}$.

As described by Crosbie and Bohn (2001), this nonlinear two-equation system can be solved to derive estimates of $\tilde{V}_A$ and $\tilde{\sigma}_A$ using known values for V_E, σ_E, and debt.[6] Based on these estimates, the distance to default at period t is given by

$$DD_{ti} = \frac{\ln(\tilde{V}_{Ati} / L_{ti}) + T(\mu - 0.5\tilde{\sigma}^2_{Ati})}{\tilde{\sigma}_{Ati}\sqrt{T}}. \tag{7}$$

[6] To solve the nonlinear system of two unknowns and two equations, we used the SAS PROC MODEL procedure. Estimates for the firm's asset value $(\tilde{V}_{Ait})$ and volatility $(\tilde{\sigma}_{Ait})$ were solved using Newton's nonlinear approximation technique.

In line with most studies in the literature, we assume a yearly framework ($T = 1$), and L_{it} is measured by debt obligations with one-year maturity plus half the longer-term debt (debt maturing after one year). Following Campbell, Hilscher, and Szilagyi (2008), the drift parameter is estimated by $\tilde{\mu} = 0.06 + r$ where the risk-free is measured by the three-month Treasury bill rate and the value 0.06 represents the equity risk premium.[7] For our purpose, there is no need to adjust DD_{ti} because it provides a time-consistent indicator of solvency over the life cycle of the firm. Thus, our structural Merton distance-to-default estimate is appropriate for investigating the hypothesis that CDS amplify agency problems between creditors and debtors.

Merton's method has been applied extensively in the recent financial literature to estimate corporate default and is the foundation for Moody's KMV model (Kealhofer 2003). Instead of relying on our derived measures of default, we choose to use the KMV EDFs as a proxy for corporate distress. Moody's KMV uses a large proprietary database of defaults to calibrate the EDFs to the historical experience.

To tests the implications of a CDS in the Merton method, we need to formally define an econometric model for the determinants of DD_{it}. Admittedly, this "reverse engineering" approach is an unusual exercise because, as described above, the gist of Merton's methodology is to calibrate solvency risks based on a handful of key factors (market value of equity, face value of debt, equity volatility, and risk-free rate). If the Merton approach were not available, a simple alternative would have been to gauge corporate distress by the firm's stock volatility (effectively the key input in Merton's model). However, if we can model the underlying factors that influence firm volatility, it follows by the same logic that we can also use a regression specification to understand the determinants of the implied measure of default (in addition to the known inputs used in Merton's calibration).

Our analysis investigates the most straightforward relationship between Merton's DD_{ti} measure of debtor default and the presence of CDS. A company's distance to default is assumed to vary over time and across industry and generally be determined by firm-specific factors, including, of course, equity volatility and the debt ratio. More precisely, the model is defined as

[7] Studies in the literature have proposed different ways to estimate the drift. For instance, Vassalou and Xing (2004) estimate μ based on the firm's equity return. This approach is more difficult in a panel with a shorter time dimension as it is more likely to yield noisier and less efficient estimates of the drift.

$$DD_{ti} = \alpha_0 + \alpha_i + \alpha_1 I_t + \alpha_2 I_{SIC} + \beta x_{t-1,i\bullet} + \gamma CDS_{ti} + \varepsilon_{ti}. \tag{8}$$

This model is very similar to the parametric component of the hazard regression, with the exception that now the specification includes a fixed-effects regressor to absorb all the unobserved heterogeneity among firms. This specification tests again the general premise defined by hypothesis (1). In the current framework, a negative and statistically significant coefficient on γ would suggest the presence of empty-creditor agency problems between creditors and the debtor firm, in the sense that the CDS decreases the distance to default and brings the firm closer to default.

We also examine a weaker form of this hypothesis estimated by the model

$$DD_{ti} = \alpha_0 + \alpha_i + \alpha_1 I_t + \alpha_2 I_{SIC} + \beta x_{t-1,i\bullet} + \sum_{t=2000}^{2008} \gamma_t CDS_{ti} \times I_t + \varepsilon_{ti}. \tag{9}$$

This more flexible specification asserts that these agency conflicts manifest under certain economic conditions. A negative and statistically significant coefficient on γ_t $(t = 2000,\dots,2008)$ would indicate the presence of empty-creditor agency problems between creditors and debtor firms in year t.

4. DATA

This study uses several sources of information to identify firms with existing CDS trades and investigate the bankruptcy rate and distress risks of publicly traded companies. The primary source for firm-specific information is the Compustat database. To measure stock market performance, we use information from the Center for Research in Security Prices (CRSP) daily stock file. These two primary data sources were complemented with additional firm-specific information from Capital IQ.

We relied on several sources to formally identify firms that filed for bankruptcy protection (Chapter 11 and 7). Most of our information on bankruptcies during the period 2001–08 is derived from SDC Platinum and Capital IQ. Together, SDC Platinum and Capital IQ provide an extensive list of bankruptcies going back to the 1980s. To fill some occasional gaps in these two databases, we also used information from the Moody’s Default Database and the CRSP delisting header file. In the case of the latter, we identified as bankruptcies only those firms with a delisting code of 574. In the Moody's Default Database, we considered only defaults that had an explicit bankruptcy type code.

It is important to emphasize that the terminal default events are limited to bankruptcies but exclude restructurings.[8] In the U.S. CDS market, restructuring was not typically considered a trigger event for speculative-grade single-name reference entities. However, restructuring was often included in the list of possible credit events for investment-grade contracts. In spite of these conventions, Altman and Karlin (2009) point out that there was a recurring ambiguity in deciding whether debt-exchange restructurings could trigger a payout. Even though a restructuring was often included in the menu of credit events, the general practice was not to consider it a trigger for default. The difficulty with enforcing restructuring as a credit event was that ISDA documentation specified that this event be binding on all parties; in practice, restructuring is typically binding only on investors that accept its terms. In 2009, ISDA formally resolved this ambiguity by ruling that these restructuring events do not constitute a default event trigger.

Although technically foreign companies can file for bankruptcy in U.S. courts, we limited the sample of public companies to U.S. domiciled firms. Because our information traces primarily U.S. bankruptcies, we cannot fully account for the possibility that a foreign company may have filed for bankruptcy in its home country or in some other overseas jurisdiction. In addition to dropping foreign firms, we also eliminated any firm with missing values for assets, all financial firms (that is, firms with SIC codes in the range 6000–6999), and utility companies (SIC codes in the range 4900–4999). The final sample traces the financial performance of a panel of U.S. nonfinancial firms during the period 2001–08.[9]

We identified CDS firms in the sample by using the Markit CDS Pricing Database. Markit was founded in 2003 after the company entered into agreements with nearly all large market participants to establish a reference entity database to enhance liquidity, transparency, and standardization in the credit derivatives market. Currently, Markit provides CDS spread

[8] As shown by Altman and Karlin (2009), the majority of firm restructurings eventually drift into bankruptcy. Thus, even though these restructurings are not initially considered as defaults, they subsequently appear in our bankruptcy sample a few years later.

[9] A major complication with financial firms is that often the resolution process is taken over by the regulator. These potential empty-creditor problems are therefore obfuscated by the presence of the regulatory agency. For instance, the insolvent insurance company Ambac Assurance was recently forced to undergo an intricate reorganization that included a partial takeover by its regulatory authority. Even so, ISDA classified Ambac's failure as a bankruptcy instead of a restructuring event, triggering a payment to CDS protection buyers of Ambac's bonds.

information on most corporations with nontrivial CDS trading (around 3,000 firms and sovereigns). Markit's coverage of the earlier period is also quite broad, covering most companies with CDS trades (in 2002, the coverage included roughly 1,400 companies and sovereigns).

Despite the long historical coverage, the Markit database does not include every company with CDS trading. Markit acknowledges that a small fraction of traded reference entities might not be reported because information on market participants is not adequate for construction of an accurate composite measure of CDS spread. The undisclosed information on these CDS firms raises concerns about sample bias, as many of them will be included in the non-CDS sample. However, the misclassification of CDS firms as non-CDS firms would actually work against the null hypothesis that credit derivatives contribute to higher default.

Markit provides exact information on the existence of an outstanding CDS contract on the firm's dollar-denominated senior unsecured debt. Markit uses its unique tickers to identify companies that do not always correspond to the official company equity ticker. To compensate for these discrepancies in tickers, we manually matched each U.S. firms' CDS ticker in Markit to its actual exchange ticker using Capital IQ. Finally, to ensure the accuracy and completeness of the Markit CDS population, we compared this information to a smaller list of companies with CDS trading available from Bloomberg and the Depository Trust and Clearing Corporation (DTCC**)**. [10]

Last, a key variable in our analysis examining the public life cycle of a company is firm age. To determine the age of the public firms in our sample, we use information from the New Issues Database from SDC Platinum. That database contains information on most initial public offerings (IPOs) in United States starting in the mid-1980s. For the more mature firms that were in existence before the 1980s, the missing IPO date was filled with origination date from the CRSP header file.

[10] Markit as well as Bloomberg uses dealer quotes to construct its composites. It is quite plausible therefore that a reported CDS spread may not necessarily reflect a trade. Our analysis presumes that, when dealers are making market on a firm, some trades have been executed at some point in the past. Using DTCC information, we were able to identify about 250 nonfinancial U.S. firms with existing gross notional CDS positions in 2009. Of the largest 100 companies in our sample, most of those identified as CDS firms have a reported outstanding gross notional volume. Nearly all of these top 100 firms not in the DTCC list are large technology firms (Microsoft, Google, Apple, etc.) that have very little debt and therefore should not have made the cutoff. Consistent with these findings, we find that all large non-CDS on the largest 100 list were not included on the DTCC list. This quick comparison suggests that firms reported in the Markit database have existing traded CDS positions on their debt.

4.1 *Description of Explanatory Variables*

The specifications examining the determinants of the distance to default and bankruptcy rate are closely related. Both models control for time effects, industry effects, and stock exchange listings. For the most part, the explanatory vector $x_{t-1,i\bullet}$ controls for firm characteristics, is also very similar in both default models. These specifications also allow for the possibility that the default or bankruptcy rate will likely vary over the life cycle of the firm, rising as the firm matures but then declining after the firm reaches some optimal scale. One advantage of the proportional hazard model is that it intrinsically captures this nonlinearity in bankruptcy rates. In the distance-to-default specification, the concavity of the default probability is captured by including the age of the firm (AGE) and AGE squared as explanatory variables.[11]

A key determinant of corporate distress is firm size (SIZE), measured by the logarithm of total market capitalization. We considered various accounting variables in our regression analysis. The regression models include several financial ratios used in the earlier bankruptcy literature. The ratio of working capital to total assets (WORKING_CAP) gauges a firm's capital adequacy. The specifications take account of the firm's ability to generate sales and profits by controlling for the EBITDA-to-assets ratio (EBITDA_ASSETS), the total sales-to-assets ratio (SALES_ASSETS), and the ratio of cash assets (CASH_ASSETS).

Shumway (2001) demonstrates that market-based measures of firm performance are useful predictors of bankruptcy. A key indicator of firm riskiness in both the default and the bankruptcy models is stock volatility (STOCK_VOLATILITY). In addition, a firm's abnormal stock return is a good proxy for idiosyncratic risk (STOCK_RETURN). We computed annual measures of stock volatility for each firm (measured by the standard deviation of daily returns). Similarly, we estimated STOCK_RETURN as the average yearly abnormal stock return (firm stock return minus the value-weighted total market CRSP return). In addition to market-derived variables, the models include firm valuation, which is defined as the market value divided by the book value of assets (MARKET_BOOK). This variable is a simplified version of the q ratio that could reflect a firm's franchise value and capture its potential growth prospects.

Leverage is also an important trigger of default. To assess the effect of corporate debt structure, the models control for the debt-to-assets ratio (DEBT_ASSETS). Gilson, John, and

[11] The variable AGE is measured from the time of IPO. For firms with missing IPO dates, the baseline for age is its first public listing reported in the CRSP header files.

Lang (1990) point out that firms with complex debt structures—that is, a wide variety and classes of debt—are less likely to resolve through a restructuring. To investigate the role of debt complexity, the preliminary specifications also examined the effect of the loan-to-debt ratio and a Hirschman-Herfindahl concentration measure of debt structure. Overall, these corporate debt structure variables were not statistically significant and therefore were omitted from the final specification.[12]

To reduce the influence of outliers, we winsorized all firm-specific explanatory variables at the 1st and 99th percentile values computed over the entire sample period of 2001–08. Table 1 summarizes the sample means for all the continuous explanatory variables for CDS and non-CDS companies. The table illustrates again the considerable size gap between CDS and non-CDS firms. CDS firms are more mature, with an average life of 25.6 years compared to 12.9 years for the non-CDS firms. While larger CDS companies are generally less risky and exhibit less volatility, they also garner significantly smaller abnormal stock returns. Non-CDS firms maintain higher working capital ratios and cash-to-asset ratios to compensate for their greater risk profile.

5. THE RAPID GROWTH OF THE CREDIT DERIVATIVES

Banks first introduced credit derivatives in the early 1990s to lower exposure to corporate credit risk. Beginning in 2002, credit derivatives attracted greater interest from institutional investors and hedge funds and reached over $62 trillion in notional market outstanding by the end of 2007 (figure 1). Indexed CDS were a key contributor to the high growth in the mid-2000s. In contrast to “single name” CDS, these indexes offer protection against a group of equally represented corporate entities (typically, 125 corporate names). This explosive growth of the credit derivatives market suggests that the intensity of debtor-creditor problems might have risen more incrementally during this period. As shown by figure 1, in 2000 the existing volume of credit derivatives amounted to roughly 9.7 percent of the total outstanding value of international debt securities. By 2007, this ratio surged to over 270 percent.

Table 2 presents the growth of the CDS market by tracing the number of U.S. domiciled nonfinancial public firms with traded positions as of January 2001. Despite the relatively small

[12] Information on the debt breakdown is available from Capital IQ. We decomposed total debt into six categories (term loans, revolving credit, senior bonds, subordinated bonds, commercial paper, and other debt). Based on these categories, we calibrated a firm’s degree of debt complexity by using a simple Herfindahl-Hirschman index formula.

volume of notional volume outstanding in the early 2000s, many of the large public U.S. companies were trading in the credit derivatives market. The table also documents a wide size differential between these two groups of firms. The average CDS firm was more than 20 times larger than the average non-CDS firms during this period. Figure 2 shows that smaller firms are unlikely to attract any significant interest from CDS buyers. Despite the considerable size gap between these two subsets of companies, companies with outstanding credit derivatives show significant heterogeneity. For instance, about half the firms located in the 90th percentile of asset size have existing CDS contracts on their debt. The diversity in CDS coverage among large firms is very useful in assessing the importance of agency problems between creditors and debtors.

6. THE IMPACT OF CDS ON THE BANKRUPTCY RATE

The first stage of our empirical analysis investigates the relationship between corporate bankruptcy and credit derivative contracts. Table 3 presents the evolution of the unconditional bankruptcy rate for CDS and non-CDS over the entire sample period. The number of smaller non-CDS firms declines steadily over the 2001–08 period because of the large wave of consolidations through mergers and acquisitions in the latter half of this period. In contrast, the number of CDS firms rises gradually, with credit derivatives becoming a popular contract among banks and institutional investors.

In total, 43 bankruptcies occurred among CDS firms over the entire sample period, amounting to about 6.4 percent of cumulative bankruptcies. Non-CDS firms experienced 480 bankruptcies, corresponding to close to 14 percent of the cumulative bankruptcy rate. The bulk of bankruptcies for CDS companies occurred primarily over the last few years of the sample. In comparison, bankruptcies of non-CDS firms are clustered in the earlier part of the sample period, following the dot-com collapse and the economic downturn in 2001. It is noteworthy that the bankruptcy rate for large CDS firms in 2008 is 3.42 percent, significantly greater than the 1.23 percent rate experienced by non-CDS firms.

The specifications reported in the first and second columns in each panel of table 4 are defined to test hypothesis 1 and 2, respectively. At the bottom of the table, we report the likelihood ratio χ^2 statistics for the hazard regressions. The strong significant values of the likelihood ratio statistics indicate that all the hazard specifications fit the data very well. We generally observe a strong link between market-based explanatory variables and the conditional probability of bankruptcy. The positive and negative patterns of significant coefficients on the quadratic terms of log(MARKET_CAP) signify a concave relationship between firm size and bankruptcy. This concave relationship is consistent with the Gilson, John, and Lang (1990) paper, which argues that larger companies with more complex debt structures will be more inclined to file for bankruptcy. This pattern of rising likelihood of default, however, eventually dissipates for larger and safer corporations.

Firms with higher values of stock volatility exhibit a significantly greater likelihood of filing for bankruptcy, while better-performing firms with larger excess returns are less likely to file. Consistent with the previous bankruptcy literature, we find that accounting variables that measure profitability and capitalization are also strong determinants of firm survival. The significant negative effect of WORKING_CAP confirms that better capitalized companies are less likely to become insolvent. The estimates also reveal that firms with higher franchise value, measured by MARKET_BOOK, exhibit a lower likelihood of bankruptcy.

More important, the effect of the CDS dummy variable over the entire panel of firms is positive but insignificant (first column of table 4), indicating no close link between credit derivatives and corporate bankruptcy. As noted earlier, it is quite plausible that empty-creditor problems would manifest more gradually over a longer period. Bolton and Oehmke (2009) point out that these hedging positions have to be quite large for empty-creditor problems to surface. These CDS pressures would more likely accumulate over time and become more valuable to buyers, and therefore more intrusive, during economic downturns when corporations are less solvent.

The second column in table 4 reports the time-varying influence by decomposing the CDS effect across years. The results reveal a positive and significant CDS coefficient for 2008, indicating a higher incidence of bankruptcy among CDS firms relative to non-CDS firms for that year. In a way, this outcome is not surprising, since the simple summary statistics in table 3 illustrated a significant surge in bankruptcy filings among CDS companies in 2008. To better understand the economic significance, we present the importance of CDS for the probability of bankruptcy in terms of an odds ratio (table 5). Formally, the odds ratio represents the probability that a CDS firm will file for bankruptcy protection divided by the probability that a non-CDS firm will go bankrupt.[13] If the odds ratio is not significantly different from one, we cannot reject the hypothesis that the presence of CDS does not influence firm bankruptcy. Looking at the pattern of the bankruptcy odds ratios, we do not find any support for empty-creditor arguments in the earlier years. The evidence is much stronger in 2008, when the odds ratio rose significantly higher than 1 to 2.57.

The results of the hazard regression suggest a rise in bankruptcy rates among CDS firms in 2008. Arguably, the CDS dummy variable cannot gauge the true extent of the pressures coming from protection buyers. Yet, despite this shortcoming, we cannot fully discount these results because such a binary measure would generally bias the estimates against finding a link between CDS exposure and the likelihood of bankruptcy.[14] Overall, the evidence from the bankruptcy regressions does not offer any support to the empty-creditor hypothesis; however, the results reveal a stronger likelihood of the presence of these agency problems among CDS firms in 2008.

7. CDS AND DISTANCE-TO-DEFAULT

While the reduced-form hazard model provides a direct framework for testing the empty-creditor agency hypothesis, these results are inherently determined by the incidence of bankruptcy among CDS and non-CDS companies. In effect, much of the statistical inference of the hazard regression model is determined by the comparison of the 43 bankruptcies of CDS companies with those experienced by the non-CDS control (specifically, the 480 reorganization filings over the entire sample of nonfinancial firms). The smaller number of bankruptcy events among CDS companies leaves open the possibility that the results may be circumstantial, stemming from the unusual ferocity of the recent financial crisis.

To avoid the infrequency and lumpiness of bankruptcy events, we use Merton's method to measure the relationship between the implied firm default and credit derivatives. Merton's approach offers a time-consistent measure of firm solvency. The distance-to-default specification

[13] Specifically, the bankruptcy hazard odds ratio is defined as $\frac{P(\text{firm bankruptcy} / CDS = 1)}{P(\text{firm bankruptcy} / CDS = 0)}$.

[14] The CDS indicator cannot distinguish the exact exposure to credit derivatives. Essentially, firms with small or large credit derivatives trading are simply assigned the same weight of 100 percent. Firms with smaller CDS exposures (for example, a company like Exxon) should not face any significant interference from hedged creditors. Yet, these companies are assigned a weight of 100 percent, meaning that the binary CDS indicator would be underestimating the true impact of credit derivatives.

also allows us to correct for unobserved heterogeneity by including firm fixed-effects in the regression model. In theory, it is possible to correct for heterogeneity in a survival model by using a frailty specification that assumes that the hazard function varies from firm to firm. In practice, these frailty models are very computationally challenging to estimate and may not fully capture the extent of heterogeneity among firms.

Not surprising, smaller and riskier non-CDS companies garner lower distance-to-default values than CDS firms (figure 3). CDS firm realized on average a distance-to-default score of around 13.8, while smaller non-CDS firms attained only 9.8. The top panel in figure 3 illustrates that the distance to default is somewhat symmetrically distributed, although skewed to the right by the presence of large firms. In comparison, the implied probability of default, defined by $p_{ti} = N(-DD_{ti})$, is actually asymmetrically distributed with most of the values clustered closer to zero (bottom panel of figure 3). This asymmetric shape demonstrates that the implied-default measure would not be a very effective dependent variable because it violates the normality assumption of regression analysis.

Panel A in figure 4 plots the path of the distance-to-default measures over time, while the bottom graph presents the corresponding implied probabilities of default. It is evident from the lower panel that Merton’s implied-default probabilities are quite uneven, considerably higher than normal during periods of financial distress and quite small in more normal economic times. The large dispersion in implied defaults can be attributed mostly to the equity volatility that often dominates all other inputs in the derivation of the distance to default. One of the key contributions of the Moody’s KMV methodology is that it recalibrates these implied defaults to be consistent with the firm’s history of failure.

This simple graphical analysis also reveals a narrowing of the distance-to-default gap between CDS and non-CDS firms during the more tumultuous dot-com bubble collapse and the more recent severe financial problems caused by the subprime mortgage crisis. The average distance-to-default indicator in 2008 for CDS companies was 6.14, just slightly above the 6.02 average value attained by non-CDS firms. Looking at the bottom panel in figure 4, we observe that the gap in implied-default probability between CDS and non-CDS firms actually widened in 2008.

Estimates of the distance-to-default specifications, formally defined by equations (8) and (9), are presented in table 6. Overall, the findings of the distance-to-default model are consistent with those of the hazard regression. Note that distance to default is inversely related to the probability of bankruptcy (that is, firms with smaller distance to default are riskier). This relationship is captured by the negative and significant effect of STOCK_VOLATILITY. Larger companies are safer, having on average larger distance-to-default measures, while firms with a higher debt-to-assets burden are less solvent.

It is notable that the coefficients of the distance-to-default model are not always consistent with the bankruptcy estimates. In contrast to the bankruptcy model, firms with higher working capital and market-to-book ratios have higher distance to default. Although bankruptcy and implied default are closely linked, they are not tautological. Typically, small companies have higher market-to-book ratios and larger working capital ratios; therefore, equity investors may view these variables more cautiously as indicators of higher growth and a potential warning signal of higher default risk. In comparison, in a corporate reorganization framework, more working capital and higher franchise value are viewed more positively because they reduce the likelihood of bankruptcy.

Over the entire panel of CDS and non-CDS firms, we observe a negative but insignificant relationship between implied default and the simple CDS indicator (first column of table 6). The time-varying impact of CDS on distance to default, however, is concentrated primarily over the last few years. The estimates reveal a significant decline in distance to default among CDS firms in 2008, reinforcing some of the findings of the hazard bankruptcy regressions. The last column in table 6 presents the regression estimates when the sample is restricted to those companies with outstanding senior and subordinated bond issues in this period. Although creditors could hedge their exposure using a loan CDS, firms with outstanding bonds should attract closer scrutiny in the credit derivatives market. Overall, the regression findings are fairly robust to this sample specification.

The distance-to-default model estimates also reveal that CDS firms' implied-default measures were adversely affected in 2002 right after the collapse of the technology firms. This result may appear counterintuitive to some extent, given that CDS pressures are expected to build up over time, but it is consistent with figure 3, which actually reveals a decline in distance-to-default scores for CDS companies in 2002. One possible explanation for this rise in defaults is that CDS contracts are more valuable to hedged creditors and therefore could become more intrusive during periods of financial instability.

7.1 *Measuring Corporate Default Using Moody's KMV Expected Default Frequency*

The underlying structure of Moody's KMV model is Merton's contingent claims model (Crosbie and Bohn 2001; Kealhofer 2003; Bharath and Shumway 2008). The key information provided by KMV is the EDF, representing a forward-looking default probability. This probability of default is again extracted from the market value of firm assets, volatility, and current capital structure. One important difference between our Merton implied-default probabilities discussed in the previous section and the EDF measure is that the latter is recalibrated to fit the empirical distribution of corporate defaults. Based on this historical information, KMV adjusts distance to default to provide a more normative EDF measure that better reflects the corporate default experience and captures real-time developments in the market.

Figure 6 traces one-year EDFs for CDS and non-CDS firms over the period 2004–08. As illustrated previously by figure 4, Merton's model-derived scores of implied default are generally more volatile. In contrast, by design EDFs are relatively more stable and better track the actual corporate defaults for these two subsets of firms. The EDF and Merton's implied-probability measures generally follow the same path over this period, converging after 2004 but diverging in 2008 after the onset of the financial crisis.

Consistent with the distribution of the implied-default probability, EDFs are also clustered close to zero, with a median value around 0.27 percent and a 75th percentile threshold close to 1.4 percent (top panel of figure 7). Considering the nonnormal shape of the EDF densities, the implied-default measure would not be a very effective dependent variable in a regression model. A simple way to address this nonnormality problem is to use the probit function to transform the EDF measures into normalized distance to defaults (bottom panel of figure 7).[15] We should emphasize that the goal of this probit transformation is not to back out KMV's implied distance-to-default values but simply to normalize the default variable for the regression analysis.

To further examine the robustness of our findings, table 7 summarizes again the distance-to-default specification, but this time the dependent variable is the normalized measure of EDF. Because the probit transformation maps the EDFs into pseudo measures of distance to default,

[15] The probit function represents the inverse cumulative distribution function. In the case of a normal distribution, the probit transformation means that $\Pr\text{obit}(N(z)) = z$ where $N(z)$ simply represents the cumulative normal distribution.

the negative and significant coefficient on the CDS dummy variables indicates again that companies with outstanding credit derivatives on their debt have greater risk of default. In fact, Moody's KMV implied measures generally exhibit a statistically significant positive link between CDS and firm default across the entire sample period. This finding is important because, as noted above, the EDFs are specifically calibrated to the actual likelihood that the firm will default. Translating the influence back into EDFs, the significant coefficient estimate of the CDS coefficient (model 1) indicates that firms with credit derivatives trading experienced roughly a 20 percent higher likelihood of default during 2004–08.

7.2 *The Influence of CDS Conditional on Bankruptcy*

The distance-to-default regression analysis presented so far is an unconditional approach in the sense that the sample includes both firms with and firms without a bankruptcy filing. As will be discussed in greater detail in the next section, this unconditional model is fraught with possible endogeneity problems. In this section, we investigate the default risks of CDS firms, focusing only on those firms that filed for bankruptcy. In a statistical context, these conditional regression models that focus on firms experiencing a bankruptcy offer an interesting perspective for analyzing ex ante default risks. While this approach ignores a large segment of the sample represented by firms that did not file for bankruptcy, its more narrow focus better isolates the dynamic effects of credit derivatives leading into bankruptcy.

To investigate this conditional framework, we reformulate the regression specification to capture the influence of CDS before bankruptcy. Specifically, the model is defined by

$$DD_{ti} = \alpha_0 + \alpha_1 I_t + \alpha_2 I_{SIC} + \beta x_{t-1,i\bullet} + \sum_{j=-K}^{0} \gamma_j CDS_{ti} \times Y_j + \sum_{j=-K}^{0} \delta_j (1 - CDS_{ti}) \times Y_j + \varepsilon_{ti}. \quad (11)$$

The variable Y_j is a binary indicator of the j-th year before bankruptcy. In the current framework, two specification tests are of interest. Under the empty-creditor hypothesis, we want to examine if $\gamma_j \le \delta_j$; that is, do CDS firms suffer a greater decline in distance to default (j) years before bankruptcy? This hypothesis test can be generalized to encompass all (K+1) years before bankruptcy.

The estimates of the conditional regression model defined above are reported in table 8. Looking at panel A, which summarizes the impact on distance to default, we observe that the γ coefficients, which measure the pre-bankruptcy effects for CDS firms, are generally more negative than corresponding δ coefficients for non-CDS firms, although the pairwise comparisons are not statistically significant in the years preceding bankruptcy. The large and statistically significant F-test statistic, reported at the bottom of table 8, indicates that CDS firms experience a greater decrease in implied default before the terminal event of bankruptcy.[16] Turning to panel B, which reports the estimates for Moody's KMV regression model, we observe that CDS firms experience a greater increase in implied default, especially in the years just before the bankruptcy event, although again the difference between CDS and non-CDS companies is not statistically significant.

8. ADDRESSING ENDOGENEITY PROBLEMS

The analysis so far has revealed some evidence of a positive association between CDS and firm default, although that evidence is much stronger in the more recent years of the sample period. This observed link between CDS and default, however, may result from reverse causality, or what is formally referred to in econometrics as an endogeneity problem. Put in simple terms, when a firm's creditors anticipate problems, they may buy protection in the periods before bankruptcy and thus create this spurious correlation. The incentives to hedge existing credit risks may be particularly strong before and during periods marred by deteriorating economic conditions and financial instability.

These endogeneity problems surface because financial analysts and investors are able to anticipate corporations' underlying condition going forward. Creditors rely on public and sometimes private information to decipher a firm's financial condition. Public companies facilitate this process in part because they are required by the SEC to publish information detailing their current financial condition and providing guidance about their future performance. It is critical, though, for investors and creditors to obtain timely information that is not fully priced by the market. Equity and bond markets efficiently reflect company information, but generally it is unclear which one of these two markets is a better source of price discovery. Hotchkiss and Ronen (2002) find that neither market achieves a significant pricing advantage and that they often respond to similar company information. Recent evidence suggests that

[16] One shortcoming of this event-study approach is that the small number of bankruptcies among CDS firms and the fixed-sample period of the panel limit the number of degrees of freedom for estimating the γ and δ coefficients. At the time of bankruptcy (that is, when $J = 0$), there are 43 degrees of freedom for CDS firms. Five years before bankruptcy, the number of degrees of freedom decreases to just over 10.

syndicated loan lenders may also take advantage of more timely information (Altman, Gande, and Saunders 2004; Allen, Gottesman, and Peng 2008).

It is plausible that creditors who sense a weakness in the firm might try to offset their risks by buying CDS protection. This simultaneity between the dependent variable default and the supposedly exogenous variable CDS engenders a correlation between the random error and the explanatory variables. The regression specifications presented earlier attempt to reduce the impact of possible endogeneity problems by using lagged explanatory variables. Typically, lagged explanatory variables are a simple but effective way of lessening a more generic form of endogeneity in which the dependent variable may have some unspecified contemporaneous link with explanatory information. Unfortunately, lagged explanatory variables cannot fully remove reverse-causality effects stemming from specific events such as bankruptcy. To address these potential endogeneity issues more effectively, we use a formal econometric technique to construct a more orthogonal instrument for measuring the impact of CDS that is not influenced by the creditworthiness of the firm.

8.1 *Constructing an Instrument of Excess CDS Exposure*

Researchers often use an instrumental variable approach based on a two-stage estimation method or system of structural equations (such as two-stage least squares or three-stage least squares) to resolve simultaneity problems between the dependent and the independent variables and eliminate the endogeneity bias. This two-step approach has been effectively applied in many situations in which the cause of endogeneity is event specific (see, for example, Mehran and Peristiani 2010). In the current framework, the first stage uses a qualitative model describing why firms attract CDS trading on their debt to construct an orthogonal instrument of CDS exposure. More formally, the model is

$$\begin{aligned} &y^*_{ti} = \lambda w_{ti\bullet} + \upsilon_{ti}, \\ &y_{ti} = 1 \text{ if } y^*_{ti} > 0 \quad \text{(firm has existing CDS);} \\ &y_{ti} = 0 \text{ if } y^*_{ti} \le 0 \quad \text{(othewise).} \end{aligned} \tag{10}$$

The dependent variable y^*_{ti} represents an index that measures a firm's capacity to attract CDS interest. Note that y^*_{ti} is latent; instead, we observe only the dummy variable y_{ti} which indicates whether the firm has traded CDS. The model asserts that firms with positive values of the latent index y^*_{ti} have a greater chance of having CDS protection on their debt. The explanatory vector

$w_{ti\bullet}$ includes the determinants of CDS trading, and υ_{ti} is random error. Depending on the distribution of the error component, equation system (10) can be reshaped into a classic probit or logit model. Both these models can be estimated using maximum likelihood to find the determinants of the probability that a firm has an outstanding CDS position on its debt.

Neither the probit nor logit estimation model, however, can provide an instrument to mitigate these possible endogeneity violations in our framework. Essentially, a proper instrumental variable approach must produce an estimate of the latent index y^*_{ti}. Methods like probit and logit can only estimate $P(y^*_{ti} > 0)$. To derive an estimate for y^*_{ti}, we use a linear probability approach. The linear probability model asserts that $E(y^*_{ti}) = \lambda w_{ti\bullet}$. The simplicity of this approach is that the parameter vector can be estimated using ordinary least squares. The least-squares estimator produces the sought out estimate of y^*_{ti} defined by $\hat{y}^*_{ti} = \hat{\lambda} w_{ti\bullet}$.

Using this linear probability estimate, we can compute a residual measure of excess CDS exposure (CDS_EXPOSURE) defined by $y_{ti} - \hat{y}^*_{ti}$. Specifically, for the subset of CDS firms, CDS_EXPOSURE is defined by $1-\hat{y}^*_{ti}$, while for non-CDS firms it is defined by $-\hat{y}^*_{ti}$. Simply put, CDS_EXPOSURE represents the excess level of CDS protection over and above what we would normally expect the firm to garner in the market. By definition, the excess CDS exposure instrument is orthogonal to the explanatory vector $w_{ti\bullet}$, removing all the inherent endogeneity problems and other biases.

Another point to consider is that the aim of the linear probability approach is not to estimate the probability that the firm will have an existing CDS but simply to derive a proxy for the latent index y^*_{ti}. By definition y^*_{ti} could be positive or negative; therefore, the current application of the linear probability model does not suffer from the usual shortcomings that surface when this procedure is used to estimate event probabilities (see Green 1993, section 21.3). A negative score for y^*_{ti} indicates that the firm should not be attracting much CDS trading. In contrast, firms with $y^*_{ti} > 1$ should be experiencing a significant interest from CDS investors.

The linear probability model includes again the customary year and industry effects that may influence market participants' desire to buy protection against a firm. The vector $w_{ti\bullet}$ incorporates an array of firm characteristics that determine why investors buy protection against firm (i). As evident from table 1, firm size is a crucial determinant of CDS interest. Firms with a higher debt-to-assets ratio (DEBT_ASSETS) are expected to have a relatively greater volume of CDS contracts. Merton's distance to default is an important explanatory variable controlling whether the intensity of CDS protection is driven by the company's riskiness. This control ensures that the eventual instrument will be independent of the default-risk incentives that may prompt creditors to buy protection against the firm. In addition, the set of explanatory variables includes several company financial ratios: the return on assets (ROA) and capital expenditures to assets (CAPX_ASSETS). The model indirectly controls the possible influence of acquisitions by including the goodwill-to-asset ratio (GOODWILL).[17] Goodwill is a good indicator of a firm's acquisitions activities.[18]

The parameter estimates of the linear probability model are briefly summarized in table 9. Firm size is the most important determinant of the CDS index, having by far the largest explanatory power. We also observe that firms with larger CDS exposure are more profitable and more liquid, exhibiting higher ROA, SALES_ASSETS, and CASH_ASSETS ratios.

The linear probability regression uncovers a negative relationship between CDS and distance to default, indicating a greater desire to buy protection on riskier firms. This result confirms the propensity of participants in the CDS market to focus on risky companies, which generates this possible endogeneity biases. Mengle (2009) argues that such CDS hedging strategies would be very difficult to implement because negative firm information can be easily disseminated to the public. Market participants can therefore incorporate and price much of the rising credit risks, making it prohibitively expensive for protection buyers to hedge against riskier companies. Despite facing these additional costs of the risk premium, riskier firms attract greater CDS trading, controlling for other factors, according to our evidence.

[17] A merger could adversely affect creditors and CDS buyers and sellers. These hazards were evident in the recent leveraged buyout (LBO) of Equity Properties Office REIT by Blackstone. Equity Properties Office had a significant debt exposure prior to the LBO with restrictive covenants. These covenants stipulated that bondholders had to be made whole at $1.4. This was an expensive option for retiring existing debt for the acquirer. Blackstone instead was able to tender to buy at a lower price, convincing the majority of debtholders to go along to drop the covenant clause. This was a classic prisoner's dilemma problem. While the majority of bondholders had to settle for less than the covenant claim, they were able to sell at a premium. CDS protection sellers fared much worse because the remaining bonds (now the reference bonds) were relegated to a junk rating.

[18] Firm goodwill often reflects its acquisitions activities, representing the difference between the fair and the actual value of the acquired target; therefore the GOODWILL ratio is a good indicator of acquiring companies.

8.2 *The Accuracy of Excess CDS Exposure*

In the second stage of the instrumental variable approach, we replace the CDS indicator with the excess CDS exposure instrument. The simple binary CDS indicator assumes that the exposure is one for CDS firms and zero for non-CDS companies. [19] The CDS_EXPOSURE instrument offers a more accurate model-based measure of exposure. CDS_EXPOSURE is generally positive between zero and one for CDS firms (panel B in table 10). Therefore, this model-based measure assumes a lower exposure for firms with existing credit derivatives than the simple dummy CDS variable, which uniformly assigns a value of one. CDS firms with negative $\hat{y}^*_{ti}$ values (corresponding to very small companies in the first and second asset quintile groups) realize a CDS_EXPOSURE score greater than one, indicating that these companies are overexposed to credit derivatives. In a handful of cases, some very large CDS companies achieve negative CDS_EXPOSURE values, signifying that these firms have lower-than-anticipated interest given their size.

The interpretation of CDS_EXPOSURE is similar for firms without existing CDS protection (panel A in table 10). In this case, the excess exposure estimate is $-\hat{y}^*_{ti}$; non-CDS firms with positive (negative) $\hat{y}^*_{ti}$ scores experience negative (positive) excess exposure. Non-CDS firms with a positive predicted $\hat{y}^*_{ti}$ score are actually underexposed (remember, the actual exposure-point estimate for these companies is zero). Likewise, very small non-CDS firms will be overexposed because their actual exposure estimate of zero is greater than the negative CDS_EXPOSURE prediction.

Although the CDS_EXPOSURE proxy appears to be intuitive and well behaved, the ultimate decisive factor is whether this proxy is an accurate measure of CDS intensity at the firm level. In particular, is it indicative of the potential agency problems facing a firm with a high volume of CDS positions? This question is difficult to answer within the historical context of our sample period because there is no firm-specific information on total CDS outstanding volumes. However, in 2009, the DTCC began to publish gross notional values of traded CDS for the top thousand reference entities. This list of large reference entities includes information on about 50

[19] In the current framework, the binary y_{ti} scores zero and one serve as point estimates of the latent index y^*_{ti}. These point estimates are quite convenient; however, they can be easily replaced by any other pair of values as long as it conforms to the setup of equation system (10) (for example, $(-\frac{1}{2},\frac{1}{2})$).

percent of our Compustat sample with existing CDS contracts (corresponding to roughly 240 companies).

Although the DTCC information does not overlap with our sample, it is contiguous and thus allows for a formal comparison of the actual measure of firm-specific gross notional CDS exposure with our CDS_EXPOSURE proxy. The goal of this validation exercise is simply to determine the link between the firm's gross notional CDS ratio in 2009 and the CDS_EXPOSURE estimate in 2008. The gross notional CDS ratio is defined by $\log(100 \times (\text{gross notional CDS})/(\text{total assets}))$. In this case, the logarithmic transformation is applied to normalize the ratio whose values tend to be asymmetrically skewed. Using DTCC information, we calculated this gross notional CDS ratio in 2009 for over 240 firms in our sample. We excluded from this initial sample a handful of observations corresponding to small firms with relatively large gross notional ratio values. The results are very robust, even when these outliers are included in the analysis.

The relationship between the 2009 gross notional CDS ratio and the 2008 CDS_EXPOSURE score is depicted by the scatter plot in figure 8. The graphical analysis reveals a strong association between these two measures. The R-square of the simple regression of the gross notional ratio on excess CDS exposure is about 0.29, corresponding to a 0.53 correlation coefficient. Given the cross-sectional nature of the sample, this very strong and statistically significant correlation confirms that the CDS_EXPOSURE instrument is a very accurate proxy of the intensity of CDS protection.

8.3 *Excess CDS Exposure and Firm Default*

Table 11 presents the reestimated distance-to-default models using the derived instrument of excess CDS exposure. This distance-to-default specification continues to be consistent with equation (8), except that now we decompose the effect of CDS_EXPOSURE for CDS and non-CDS companies. Not surprisingly, the coefficient estimates for most explanatory variables are fairly unchanged. The main finding of this second-stage regression is that the relationship between distance to default and the new instrument of excess CDS exposure is negative and statistically significant for CDS companies, while it is positive and statistically significant for their much smaller non-CDS peers. The negative coefficient indicates that CDS firms with positive CDS_EXPOSURE become riskier as they experience a decrease in distance to default. It is also important to note that the negative relationship between CDS_EXPOSURE and distance to default for CDS firms continues to be strong when we use Moody's KMV implied distance to default to measure firm default (model 2 in table 11).

To analyze the time-varying effect of excess CDS exposure, table 12 decomposes again the effect across the years. The relationship of CDS_EXPOSURE to CDS firms remains negative and significant over the entire span of the sample period. Consistent with our previous findings, suggesting a higher correlation between CDS and default over the last few years, we continue to observe a stronger negative effect in 2007 and 2008. These yearly coefficients are again significant for the Moody's KMV specification. Given that the EDF scores are adjusted by Moody's KMV to present a more time-consistent "through the cycle" risk profile, the pattern of more negative coefficients on CDS_EXPOSURE in the more recent period is now more subtle.

It is difficult to assign economic significance to our empirical findings because the scale of the excess exposure measure is somewhat arbitrary. Nevertheless, the regression results imply that a one-standard-deviation increase in CDS exposure leads to about a 20 percent decrease in distance to default for CDS companies. A simple way to make the results more intuitive is to transform the distance-to-default measures into implied-default probabilities, assuming normality. Under this more intuitive scale, the average implied probability of default of CDS firms is roughly 1.15 percent. A one-standard-deviation increase in CDS exposure would raise the implied-default probability to 1.45 percent, or about 26 percent.

9. FINANCIAL SYSTEM FRAGILITY AND FIRM DEFAULT

The final phase of our investigation explores more closely a set of alternative explanations for the rise in default among CDS firms. As noted earlier, several studies emphasize the role of asset fire sales and deleveraging mechanisms in contributing to the unprecedented severity of the recent financial crisis. Under these scenarios, higher implied default among CDS firms may not necessarily be triggered by agency problems but could be traced to a shift in investor behavior during a financial turmoil. To illustrate the magnitude of this significant relocation in risk perceptions in the most recent crisis, figure 5 contrasts the distribution of the distance to default over the period 2001–06 to that of 2008 (the crisis period). While the profile of the distribution for non-CDS firms also becomes more risky (lower panel of figure 5), the magnitude of the shift is nowhere near that experienced by larger CDS firms. This leftward shift in the distribution of distance to default of CDS firms is consistent with their higher incidence of bankruptcy in 2008, documented by the hazard analysis. Yet this rapid convergence in distance to default between these two groups is paradoxical because it implies that investors discriminated less between smaller, risky non-CDS and larger, and presumably more solvent, CDS companies.

Shleifer and Vishny (2011) argue that large-scale fire sales of financial assets during a crisis could systemically transmit distress, adversely affecting both large and small firms. Firms that rely on shorter-term financing, such as the commercial paper or repo markets, will be more exposed to the refinancing pressures that stem from these fire sales and are likely to experience greater credit pressures. Indeed, we find that a cluster of large corporations with outstanding CDS contracts relies more on the commercial paper market than smaller firms. Based on information from Capital IQ, we estimate that about 30 percent of the CDS firms in our sample are issuers of commercial paper, compared to less than 1 percent for the subset of non-CDS firms.

To analyze the importance of these shorter-term refinancing pressures faced by firms during a financial crisis, we added a variable controlling for the potential commercial paper funding dependence (CP_FUNDING) to the default regression. The capacity to issue commercial paper is measured by the commercial paper ratio in year (t), minus the average commercial paper ratio over the previous five-year sample period, in which the commercial paper ratio is defined simply as commercial paper outstanding divided by total assets.

In addition to addressing funding problems, the literature examining liquidity spirals and fire sales asserts that publicly traded companies will be exposed to serious selling pressures from large institutional investors (for example, Shleifer and Vishny 2011; Brunnermeier and Pedersen 2009). Coval and Stafford (2007) demonstrate that outflows from large mutual fund investors triggered fire sales that caused significant stock price declines, which persisted for a considerable period.

Expectedly, the nature of the financial turmoil dictated which companies or industries would suffer the most. During the dot-com bust, we witnessed massive selling of high-technology stocks that suffered the brunt of the damage. In the most recent crisis, financial firms with significant exposures to the subprime mortgage market came under intense pressure from institutional investors and short sellers. While financial stocks represented only about 15 percent of the market capitalization in United States before the onset of the crisis, Hau, Lai, and Chua (2011) find that the implosion of this sector eventually led to a 50 percent decrease in the value of nonfinancial stocks as well. Their analysis reveals that mutual funds, which were exposed to greater investor redemptions, had to resort to massive liquidation of both their financial and their nonfinancial stock holdings. These selling pressures were more intense on those funds with a heavy concentration in financial stocks.

The fire sales and deleveraging theories provide an alternative mechanism under which financial problems can be transmitted to nonfinancial companies, resulting in significant stock price declines and, more important for our premise, greater equity volatility and higher implied default. To explore the relationship between the recent massive outflows from the stock market and firm default, we introduce in the regression model a control measuring the degree of these selling pressures faced by the nonfinancial companies. We use data from the 13F holdings reports available from Reuters Thomson Financial to estimate the institutional ownership of each firm over time.

Analogous to CDS exposure, a firm's institutional ownership is endogenously related to firm distress. Simply put, investors who anticipate systemic or firm-specific financial problems may unwind their holdings and thus create a spurious relationship between default and institutional ownership. Again, this endogeneity problem can be corrected by using a variation of the instrumental variable approach described in the previous section. The first phase involves constructing a model for institutional ownership (the ratio of shares owned by institutions divided by the firm's total number of shares). Our specification borrows from several studies in the finance and accounting literature that analyze institutional ownership (see, for example, Gompers and Metrick 2001; and Chen and Cheng 2005). For the sake of brevity, we do not report the results of this first-stage regression in this paper. As expected, the institutional ownership ratio has several key determinants. Foremost, larger firms attract considerable interest from investors. In addition, institutional ownership is positively correlated with implied distance to default and negatively with firm volatility, indicating a preference for safer assets. Consistent with Ackert and Athanassakos (2003), we find a strong link between financial visibility (measured by the number of analysts following a firm) and ownership.

This first-stage estimation allows us to construct an orthogonal instrument of institutional ownership control (INST_CONTROL) that gauges the unanticipated level of investor interest. The unanticipated institutional interest is measured by the regression residual (firm institutional ownership minus predicted ownership). A positive (negative) value of INST_CONTROL indicates that the firm attracts higher (lower) interest from investors compared to its peers. To better understand the importance of institutional ownership, we interacted the variable INST_CONTROL with the binary indicator CDS.

Table 13 presents the regression results that examine the impact of firm funding problems and financial system fragility. The negative coefficient estimate of CP_FUNDING implies that the firm's capacity to issue commercial paper is weakly related with distress. Nevertheless, considering the statistical insignificance of this variable, it is obvious that the rapid credit deterioration of CDS firms was not greatly influenced by the difficulties in funding commercial paper during the recent financial crisis. Arguably, this result is not very surprising, given that nonfinancial companies do not rely heavily on the commercial paper market to meet their funding needs. In comparison, we observe that INST_CONTROL is negative and statistically significant, signifying that greater institutional interest amplified implied default. Notably, the impact is significantly higher for CDS firms. The results imply that a one-standard-deviation increase in INST_CONTROL would reduce Merton's distance to default by close to 25 percent for CDS firms, compared to just 6 percent for non-CDS firms.

Based on Moody's implied-default-regression estimates presented in the second column of table 13, the parameter estimate of INST_CONTROL continues to be negative and statistically significant, although now the effect of institutional ownership is similar across all companies. Given that Moody's KMV EDFs are shaped to convey a more stable risk profile consistent with its coveted letter ratings, this result is not surprising. In comparison, our own raw measure of Merton's distance to default is more responsive to the unusual fluctuation of stock price volatility.

As indicated above, Hau, Lai, and Chua (2011) argue that the recent implosion of stock prices was caused primarily by massive institutional selling of financial assets. To investigate the magnitude of the fire sale of financial assets, the default regression model controls for a firm's underlying exposure to institutional holders with a larger concentration of financial stocks. To derive this financial concentration variable, we first measured an institutional investor's fraction of financial stocks and subsequently calculated the weighted fraction of the institutional holdings of each firm. The average financial ownership implied by this financial exposure variable is around 14 percent, remarkably very similar to the 15 percent estimate of the financial sector's share of total market capitalization in United States. Unfortunately, this financial exposure measure may not fully reflect the actual vulnerability of institutional investors to the recent financial crisis because it is solely based on U.S. stock holdings. It is possible that some institutional investors may have large unobserved financial positions in corporate bond holdings or may have hedged some of these exposures in the credit derivatives market. With this caveat in mind, we included in the regression specification this financial exposure control as well as its interactions with the INST_CONTROL. For the sake of brevity, these results are not tabulated. Overall, we find that some of the effect of institutional ownership for non-CDS firms is absorbed by the interaction of INST_CONTROL and financial exposure, indicating that smaller non-CDS firms were slightly more exposed to the collapse of the financial sector caused by the subprime mortgage crisis.

The key finding of this regression analysis is that the influence of excess CDS exposure remains unchanged even after controlling for these additional pressures of financial fragility. Therefore, our investigation has unveiled several culprits for the rise in implied default among firms with traded CDS positions. Firms with higher-than-normal institutional ownership suffer a larger increase in implied default, perhaps reaffirming a company's vulnerability to systemic risk. Moreover, throughout the different facets of empirical investigation, time and again we observe that firms with higher exposure to CDS trading experienced greater default.

10. CONCLUSION

This paper investigates whether CDS trading amplifies corporate distress risks. The empty-creditor hypothesis formalized by Hu and Black (2008b) argues that credit derivatives engender agency problems between creditors and debtholders and thus increase the likelihood of corporate bankruptcy. We develop a formal econometric model of bankruptcy, using survival analysis to assess a firm's likelihood of filing for reorganization over its entire public life cycle. The hazard regression analysis reveals no significant link between a firm-specific indicator of CDS and the probability of bankruptcy over the entire sample period 2001-08. When we decompose the effect of the CDS indicator over time, we discover that the presence of CDS is associated with a significant jump in bankruptcy risks in 2008.

The next phase of the investigation analyzes the relationship between credit derivatives and measures of implied default derived from Merton's contingent claims model. Our analysis uses two related measures of default. We begin with our own raw estimates of Merton's implied default, but we subsequently consider formal proprietary estimates provided by Moody's KVM. Looking at our own constructed measures of distance to default, we continue to find that CDS firms experienced a significant increase in default over the last few years. These results are reinforced by the Moody's KMV EDF estimates, which show a statistically significant positive link between CDS and implied default during 2004–08. To address possible endogeneity problems, we constructed a firm-specific CDS exposure index designed to eliminate these reverse-causality problems. Our regression analysis continues to indicate a strong positive link between the firm-specific index of CDS exposure and implied default.

While this evidence is consistent with the empty-creditor hypothesis, we also present evidence supporting alternative interpretations that focus on the aftermath of the recent financial crisis. We find that firms with higher-than-normal exposure to institutional holders experience greater default. These results suggest that the intensity of the fire sales of financial assets caused by the unusual ferocity of the recent financial turmoil could have indiscriminately wreaked havoc on large and small firms alike. Although the empirical analysis controls for several competing explanations for the higher implied default that firms experienced over the last few years, it is notable that CDS exposure remains a strong contributing factor.

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Table 1. Summary Statistics for Explanatory Variables, 2001-08

Explanatory Variable	Definition	CDS Firms	Non-CDS Firms
MARKET_CAP	Market capitalization (in $ millions)	16,656	866
ASSETS	Total Assets (in $ millions)	15,838	660
STOCK_VOLATILITY	Annualized standard deviation of daily stock returns (percent)	2.19	4.18
STOCK_RETURN	Firm stock return minus the value-weighted market return (percent)	3.04	9.67
AGE	Age of company (in years)	25.6	12.9
WORKING_CAP	Working capital divided by total assets	0.088	0.296
EBITDA_RATIO	EBITDA divided by total assets	0.096	-0.057
MARKET_BOOK	Market-to-book ratio	3.09	2.81
SALES_ASSETS	Total sales divided by assets	1.02	1.07
DEBT_ASSETS	Debt-to-assets ratio	0.301	0.177
CASH_ASSETS	Cash assets divided by total assets	0.071	0.165
Number of Firm-Year Observations		3,580	25,670

NOTES: The number of firm-year observations is based on total assets. This value may vary over the different explanatory variables. All market-based variables are computed from CRSP. The source of the remaining financial ratios is Compustat.

Table 2. Number and Asset Size of CDS and Non-CDS U.S. Firms, 2001-08

Year	Number of Firms	Mean Assets	Median Assets
		Non-CDS Firms	
2001	4,214	899	142
2002	3,758	735	145
2003	3,359	649	155
2004	3,198	623	165
2005	3,079	608	176
2006	2,987	634	199
2007	2,908	674	208
2008	2,677	705	227
		CDS Firms	
2001	228	20,840	10,278
2002	308	17,907	7,977
2003	428	15,853	5,986
2004	519	14,626	5,363
2005	531	14,861	5,098
2006	543	15,326	5,446
2007	548	16,245	5,981
2008	527	16,289	6,070

NOTES: This table presents the number of firms with and without existing CDS contracts on their debt. CDS firms were identified using information from Markit.

Table 3. Bankruptcy Rate for CDS and Non-CDS Firms

Year	Number of Firms	Bankruptcies	%Bankrupt	%Cumulative Default
		A. Non-CDS Firms		
2001	4,214	130	3.08%	3.08%
2002	3,758	87	2.32%	5.40%
2003	3,359	59	1.73%	7.13%
2004	3,198	39	1.22%	8.35%
2005	3,079	34	1.07%	9.42%
2006	2,987	41	1.37%	10.79%
2007	2,908	60	2.03%	12.82%
2008	2,677	34	1.23%	14.05%
		480		
		B. CDS Firms		
2001	228	4	1.75%	1.75%
2002	308	0	0.00%	1.75%
2003	428	1	0.47%	2.22%
2004	519	3	0.58%	2.80%
2005	531	3	0.75%	3.55%
2006	543	6	1.10%	4.66%
2007	548	5	1.09%	5.75%
2008	527	17	3.42%	6.37%
		43		

NOTES: This table summarizes the number of bankruptcies filed by publicly traded nonfinancial U.S. companies included in Compustat. The list of corporate bankruptcies was compiled primarily from SDC Platinum and Capital IQ. These two primary sources were also supplemented with information available from Moody's Default Database and the CRSP delisting header file.

Table 4. Determinants of Corporate Bankruptcy: Hazard Regression Estimates, 2001-08
Dependent Variable: Conditional Bankruptcy Rate

Explanatory Variables	(1)	(2)
log (MARKET_CAP)	0.620***	0.594***
	(28.49)	(25.98)
log (MARKET_CAP) ^{2}	-0.055***	-0.052***
	(21.59)	(18.70)
STOCK VOLATILITY	9.485***	9.463***
	(47.82)	(47.09)
STOCK RETURN	-0.572***	-0.582***
	(40.08)	(40.62)
WORKING CAP	-0.575***	-0.588***
	(9.10)	(9.54)
EBITDA RATIO	-0.052	-0.060
	(0.17)	(0.23)
MARKET BOOK	-0.084***	-0.083***
	(13.85)	(13.51)
SALES ASSETS	0.050	0.052
	(0.78)	(0.82)
DEBT ASSETS	1.889***	1.884***
	(58.35)	(57.74)
CASH ASSETS	-0.410	-0.418
	(1.21)	(1.25)
CDS	0.097	
	(0.23)	
CDS × 2001		0.223
		(0.17)
CDS × 2002		-12.083
		(0.00)
CDS × 2003		-1.058
		(1.08)
CDS × 2004		-0.296
		(0.23)
CDS × 2005		-0.387
		(0.38)
CDS × 2006		0.345
		(0.59)
CDS × 2007		-0.538
		(1.20)
CDS × 2008		0.945***
		(8.84)
Likelihood Ratio	1,537	1,554
Number of Observations	29,157	29,157
Censored Observations	28,634	28,634
CDS Bankruptcies	480	480
Non-CDS Bankruptcies	43	43

NOTES: The dependent variable in the hazard regression is the probability that a firm will file for bankruptcy given that it has not done so until that point in time. The explanatory variables are defined in Table 1. The variable CDS is a binary indicator for firms with CDS contracts. The hazard regression controls for year time variation, one-digit industry effects and major exchange listing. The firm-year observations are treated as recurring censored events until the firm files for bankruptcy (the terminal event). The symbols (***), (**), and (*) indicate statistical significance at the 1-, 5-, and 10-percent level, respectively. The numbers in parentheses represent chi-square statistics.

Table 5. Impact of CDS on the Probability of Firm Bankruptcy

$$\text{Bankruptcy Odds Ratio} = \frac{\text{Probability CDS Firm goes bankrupt}}{\text{Probability nonCDS Firm goes bankrupt}}$$

Year	Bankruptcy Odds Ratio	95% Odds Ratio Confidence Limits	
		Lower	Upper
2001	1.249	0.432	3.612
2002	0.798	0.239	3.084
2003	0.347	0.047	2.557
2004	0.744	0.221	2.508
2005	0.679	0.2	2.311
2006	1.413	0.587	3.401
2007	0.584	0.223	1.53
2008	2.573**	1.38	4.797

NOTES: The odds ratio estimates were derived from the proportional hazard model of bankruptcy presented in the last column of Table 4. A bankruptcy odds ratio equal to 1.5 indicates that the CDS firm has a 50% greater chance of filing for bankruptcy. The symbols (***), (**), and (*) indicate statistical significance at the 1-, 5-, and 10-percent level, respectively.

Table 6. The Relationship between Distance to Default and CDS

Dependent Variable: Merton's DD

Explanatory Variables	All Non-Financial Firms (1)	(2)	Non-Financial Firms With Bonds
STOCK_VOLATILITY	-0.618***	-0.608***	-0.533***
	(-12.1)	(-12.0)	(-9.19)
STOCK RETURN	0.621***	0.626***	0.553***
	(3.77)	(3.81)	(3.03)
AGE	0.063	0.062	0.056
	(0.88)	(0.86)	(0.74)
log(MARKET CAP)	0.658***	0.647***	0.604***
	(6.30)	(6.24)	(4.89)
WORKING CAP	0.745*	0.802*	0.458
	(1.81)	(1.96)	(0.92)
EBITDA RATIO	0.917***	0.973***	0.901**
	(3.07)	(3.26)	(2.35)
MARKET BOOK	-0.076**	-0.064*	-0.015
	(-2.10)	(-1.79)	(-0.38)
SALES ASSETS	0.003	0.008	0.046
	(0.017)	(0.049)	(0.20)
DEBT ASSETS	-6.44***	-6.47***	-6.29***
	(-10.6)	(-10.7)	(-9.68)
CASH ASSETS	0.910*	0.885*	2.337***
	(1.79)	(1.75)	(3.28)
CDS	-0.180		
	(-0.40)		
CDS × 2001		0.191	-0.035
		(0.22)	(-0.041)
CDS ×2002		-1.138*	-1.151*
		(-1.74)	(-1.78)
CDS × 2003		-0.059	-0.019
		(-0.10)	(-0.033)
CDS × 2004		1.031*	0.983*
		(1.87)	(1.82)
CDS × 2005		0.850	1.162*
		(1.40)	(1.96)
CDS × 2006		0.750	0.989
		(1.21)	(1.59)
CDS × 2007		-0.815	-0.591
		(-1.35)	(-0.97)
CDS × 2008		-2.343***	-2.527***
		(-4.64)	(-4.94)
Number of Observations	29,011	29,011	20,427
R^2	0.74	0.74	0.68

NOTES: The dependent variable is a model-derived Merton's distance to default. The explanatory variables are defined in Table 1. Models are estimated with robust standard errors. The regression controls for firm fixed effects, yearly time variation, industry effects and major exchange listing. The symbols (***), (**), and (*) indicate statistical significance at the 1-, 5-, and 10-percent level, respectively. The numbers in parentheses represent t statistics.

Table 7. Examining the Link between Moody's KMV default and CDS, 2004-08
Dependent Variable: Moody's KMV Implied DD

Explanatory Variables	(1)	(2)
STOCK_VOLATILITY	-0.063***	-0.063***
	(-7.48)	(-7.47)
STOCK_RETURN	0.299***	0.298***
	(8.41)	(8.36)
AGE	-0.004	-0.004
	(-0.83)	(-0.84)
log(MARKET_CAP)	0.134***	0.134***
	(10.2)	(10.2)
WORKING_CAP	0.247***	0.247***
	(6.05)	(6.08)
EBITDA_RATIO	0.098**	0.098**
	(2.44)	(2.44)
MARKET_BOOK	0.0004	0.0002
	(0.011)	(0.064)
SALES_ASSETS	0.027	0.026
	(1.48)	(1.44)
DEBT_ASSETS	-0.758***	-0.756***
	(-13.5)	(-13.4)
CASH_ASSETS	0.004	0.002
	(0.098)	(0.055)
CDS	-0.074*	
	(-1.94)	
CDS × 2004		-0.096**
		(-2.34)
CDS × 2005		-0.063*
		(-1.66)
CDS × 2006		-0.064*
		(-1.68)
CDS × 2007		-0.062
		(-1.59)
CDS × 2008		-0.093**
		(-2.11)
R^2	0.873	0.874
Number of Observations	16,744	16,744

NOTES: The dependent variable is an estimate distance-to-default derived from the Moody's KMV EDF measure. Specifically, this estimated KMV distance-to-default equals $-\text{probit}(\text{EDF})$ where the probit function is the inverse cumulative distribution function. The explanatory variables are defined in Table 1. Models are estimated with robust standard errors. The regression controls for firm fixed effects, yearly time variation, industry effects and major exchange listing. The symbols (***), (**), and (*) indicate statistical significance at the 1-, 5- and 10-percent level, respectively. The numbers in parentheses represent t statistics.

Table 8. Regression Analysis Conditional on Bankruptcy: The Impact of CDS before Bankruptcy

Explanatory Variables	(1) Merton's DD			(2) Moody's KMV Implied DD		
CONSTANT	4.14**			1.58***		
	(2.80)			(6.32)		
STOCK_VOLATILITY	-0.546***			-0.098***		
	(-8.03)			(-7.92)		
STOCK_RETURN	0.721			0.300		
	(1.04)			(1.89)		
AGE	-0.053***			-0.004***		
	(-5.88)			(-5.31)		
log(MARKET_CAP)	0.359***			0.128***		
	(3.71)			(8.70)		
WORKING_CAP	0.700			0.144*		
	(1.16)			(2.66)		
EBITDA_RATIO	0.040			0.028		
	(0.07)			(0.51)		
MARKET_BOOK	0.063			0.037***		
	(1.52)			(5.66)		
SALES_ASSETS	0.016			-0.028		
	(0.13)			(-0.91)		
DEBT_ASSETS	-2.785***			-1.003***		
	(-4.80)			(-12.43)		
	CDS Firms	Non-CDS Firms	F-test	CDS Firms	Non-CDS Firms	F-test
BANKRUPTCY	-1.493	-1.178***	0.09	-0.336	-0.285	0.91
	(-1.19)	(-3.98)		(-1.89)	(-1.59)	
BANKRUPTCY-1	-1.010	-1.107***	0.05	-0.336	-0.159	1.15
	(-1.80)	(-3.54)		(-1.58)	(-0.86)	
BANKRUPTCY-2	-1.393	-0.440	2.3	-0.169	-0.041	6.15*
	(-1.78)	(-0.91)		(-0.92)	(-0.21)	
BANKRUPTCY-3	-1.944**	0.272	4.9	-0.208	-0.152	0.53
	(-2.43)	(0.55)		(-1.07)	(-0.70)	
BANKRUPTCY-4	-1.588***	0.244	3.46*	-0.262	-0.208	2.83
	(-3.85)	(0.34)		(-1.32)	(-1.04)	
BANKRUPTCY-5	-1.716***	1.040*	64.1***			
	(-4.13)	(1.90)				
F-test: All Bankruptcy Effects			7.7***			3.18
Adjusted R^2	0.304			0.612		
Observations	1,667			687		

NOTES: The variable BANKRUPTCY- (j) is 1 for (j) year before bankruptcy, 0 otherwise; BANKRUPTCY is a binary indicator for year of bankruptcy. All other explanatory variables are defined in Table 1. Models are estimated with robust standard errors. The regression controls for year time variation, one-digit industry effects and major exchange listing. The symbols (***), (**), and (*) indicate statistical significance at the 1-, 5- and 10-percent level, respectively. The numbers in parentheses represent t-statistics. The F-tests investigate the equality of CDS and non-CDS bankruptcy variable coefficients.

Table 9. Linear Probability Model for Firms with Existing CDS Contracts
Dependent Variable: A binary indicator for firms with outstanding CDS contracts

Explanatory Variables	Parameter Estimates
CONSTANT	-0.354***
	(-14.46)
DD	-0.0017***
	(-8.77)
log(ASSETS)	0.074***
	(28.35)
log (MARKET_CAP)	0.0185***
	(7.23)
AGE	0.0045***
	(31.22)
STOCK_RETURN	0.0105**
	(2.11)
WORKING_CAP	-0.065***
	(-8.94)
EBITDA_RATIO	-0.090***
	(-10.54)
MARKET_BOOK	0.005***
	(4.54)
SALES_ASSETS	0.0078***
	(3.46)
DEBT_ASSETS	0.048***
	(4.68)
CASH_ASSETS	0.057***
	(5.06)
ROA	-0.038***
	(-5.89)
CAPX_ASSETS	-0.179***
	(-7.11)
GOODWILL	-0.045***
	(-3.93)
Adjusted R^2	0.53
Number of Observations	29,016

NOTES: The dependent variable in the linear probability model is a binary indicator for firms with existing CDS contracts. Variable definitions: DD=Distance to default; ROA = return-on-assets ratio; CAPX_ASSETS = capital expenditure divided by assets; GOODWILL = goodwill divided by assets. The remaining explanatory variables are defined in Table 1. The linear probability regression includes year dummy controls, one-digit industry effects and major exchange listing indicators. The symbols (***), (**), and (*) indicate statistical significance at the 1-, 5-, and 10-percent level, respectively. The numbers in parentheses represent t statistics.

Table 10. Summary Statistics for the Excess CDS Exposure Instrument

Size Quintile Group	Number of observations	CDS_EXPOSURE			Merton's DD
		Mean	Maximum	Minimum	
		A. Non-CDS Firms			
1	5,500	0.963	0.406	-0.283	5.49
2	5,816	0.019	0.429	-0.303	8.91
3	5,862	-0.071	0.338	-0.347	10.76
4	5,657	-0.201	0.099	-0.489	11.93
5	2,615	-0.344	-0.087	-0.844	13.35
All Non-CDS Firms	25,450	-0.210	0.429	-0.844	9.72
		B. CDS Firms			
1	16	1.127	1.207	1.091	6.24
3	31	0.864	1.022	0.711	11.55
4	236	0.718	0.935	0.482	11.31
5	3,283	0.485	0.826	-0.064	13.86
All CDS Firms	3,566	0.506	1.207	-0.064	13.64
All Firms	29,016	0	1.207	-0.844	10.20

NOTES: The variable CDS_EXPOSURE is an index gauging a firm's excess volume of CDS interest over what it would normally be expected to attract from market participants. A positive (negative) value for CDS_EXPOSURE indicates that the firm is overexposed (underexposed) to CDS trading. The total number of observations in this table is lower than those reported in Table 1 because CDS_EXPOSURE is not observable for observations with missing explanatory variables.

Table 11. The Relationship between Merton’s Default Risk and Excess CDS Exposure

Explanatory Variables	(1) Model Derived DD	(2) Moody’s KMV Implied DD
STOCK_VOLATILITY	-0.569***	-0.061***
	(-11.6)	(-25.15)
STOCK_RETURN	0.398***	0.262***
	(2.76)	(21.65)
AGE	0.110	-0.0001
	(1.54)	(-0.03)
log(MARKET_CAP)	1.427***	0.197***
	(10.2)	(28.41)
WORKING_CAP	-0.451	0.120***
	(-1.02)	(4.85)
EBITDA_RATIO	-0.405	-0.010
	(-1.21)	(-0.46)
MARKET_BOOK	-0.060*	0.003
	(-1.65)	(1.49)
SALES_ASSETS	-0.1168	0.011
	(-0.63)	(1.00)
DEBT_ASSETS	-4.620***	-0.585***
	(-7.16)	(-18.44)
CASH_ASSETS	1.378***	0.059**
	(2.74)	(2.10)
CDS $\times$ CDS_EXPOSURE	-0.088***	-0.009***
	(-6.63)	(-15.66)
(1-CDS) $\times$ CDS_EXPOSURE	0.170***	0.015***
	(9.04)	(22.19)
R^2	0.75	0.878
Number of Observations	29,011	16,712

NOTES: The dependent variable in Specification (1) is a model-derived distance to default. The dependent variable in Specification (2) is a normalized measure of Moody’s KMV EDFs defined by the $-\text{probit}\left(\text{EDF}\right)$. Specification (2) is only estimated for the period 2004-08. The variable CDS_EXPOSURE is an index gauging a firm’s excess volume of CDS interest over and above what it would normally be expected to attract from market participants. The explanatory variables are defined in Table 1. Models are estimated with robust standard errors. The regression controls for firm fixed effects, yearly time variation, industry effects and major exchange listing. The symbols (***), (**), and (*) indicate statistical significance at the 1-, 5-, and 10-percent level, respectively. The numbers in parentheses represent t statistics.

Table 12. Impact of Excess CDS Exposure on Merton's Default Risk by Year

Explanatory Variables	(1) Model-Derived DD	(2) Moody's KMV Implied DD
STOCK_VOLATILITY	-0.507***	-0.057***
	(-10.5)	(-7.20)
STOCK_RETURN	0.361**	0.252***
	(2.53)	(7.27)
AGE	0.119	-0.0004
	(1.63)	(-0.10)
log(MARKET_CAP)	1.544***	0.205***
	(10.5)	(12.7)
WORKING_CAP	-0.517	0.108**
	(-1.17)	(2.52)
EBITDA_RATIO	-0.486	-0.006
	(-1.40)	(-0.15)
MARKET_BOOK	-0.044	0.004
	(-1.24)	(1.08)
SALES_ASSETS	-0.111	0.011
	(-0.60)	(0.64)
DEBT_ASSETS	-4.428***	-0.573***
	(-6.87)	(-9.86)
CASH_ASSETS	1.519***	0.071*
	(3.07)	(1.72)
CDS × CDS_EXPOSURE × 2001	-0.047***	
	(-2.99)	
CDS × CDS_EXPOSURE × 2002	-0.083***	
	(-5.91)	
CDS × CDS_EXPOSURE × 2003	-0.081***	
	(-5.22)	
CDS × CDS_EXPOSURE × 2004	-0.070***	-0.008***
	(-4.48)	(-6.14)
CDS × CDS_EXPOSURE × 2005	-0.083***	-0.008***
	(-4.79)	(-5.92)
CDS × CDS_EXPOSURE × 2006	-0.090***	-0.008***
	(-5.18)	(-6.05)
CDS × CDS_EXPOSURE × 2007	-0.134***	-0.009***
	(-7.83)	(-5.93)
CDS × CDS_EXPOSURE × 2008	-0.161***	-0.010***
	(-10.3)	(-6.81)

Table 12 continued.

(1-CDS) × CDS EXPOSURE × 2001	0.180***	
	(8.57)	
(1-CDS) × CDS_EXPOSURE × 2002	0.211***	
	(10.2)	
(1-CDS) × CDS_EXPOSURE × 2003	0.159***	
	(7.49)	
(1-CDS) × CDS_EXPOSURE × 2004	0.145***	0.015***
	(6.77)	(6.45)
(1-CDS) × CDS_EXPOSURE × 2005	0.176***	0.015***
	(6.99)	(6.62)
(1-CDS) × CDS_EXPOSURE × 2006	0.187***	0.015***
	(8.39)	(6.76)
(1-CDS) × CDS_EXPOSURE × 2007	0.232***	0.016***
	(9.16)	(7.06)
(1-CDS) × CDS_EXPOSURE × 2008	0.254***	0.018***
	(12.2)	(7.93)
R^2	0.751	0.879
Number of Observations	29,011	16,712***

NOTES: The dependent variable in Specification (1) is a model-derived distance to default. The dependent variable in Specification (2) is a normalized measure of Moody's KMV EDFs defined by the -probit$\left(\text{EDF}\right)$. Specification (2) is only estimated for the period 2004-08. The variable CDS_EXPOSURE is an index gauging a firm's excess volume of CDS interest over and above what it would normally be expected to attract from market participants. The explanatory variables are defined in Table 1. Models are estimated with robust standard errors. The regression controls for firm fixed effects, yearly time variation, industry effects and major exchange listing. The symbols (***), (**), and (*) indicate statistical significance at the 1-, 5-, and 10-percent level, respectively. The numbers in parentheses represent t statistics.

Table 13. Investigating the Impact of Financial Fragility on Corporate Default

Dependent Variable = Implied Distance to Default

Explanatory Variables	(1) Model-Derived DD	(2) Moody's KMV Implied DD
STOCK_VOLATILITY	-0.552***	-0.063***
	(-11.3)	(-8.12)
STOCK_RETURN	0.507***	0.312***
	(3.65)	(13.7)
AGE	0.126*	-0.002
	(1.74)	(-0.41)
log(MARKET_CAP)	1.208***	0.195***
	(8.98)	(13.5)
WORKING_CAP	0.202	0.159***
	(0.45)	(4.03)
EBITDA_RATIO	0.004	-0.027
	(0.014)	(-0.75)
MARKET_BOOK	-0.067*	0.0002
	(-1.79)	(0.076)
SALES_ASSETS	-0.122	0.018
	(-0.63)	(1.07)
DEBT_ASSETS	-4.894***	-0.536***
	(-7.11)	(-9.53)
CASH_ASSETS	1.216**	0.034
	(2.46)	(0.87)
CDS Controls		
CDS $\times$ CDS_EXPOSURE	-0.053***	-0.008***
	(-4.07)	(-6.31)
(1-CDS) $\times$ CDS_EXPOSURE	0.116***	0.014***
	(6.24)	(7.35)

Table 13 continued next page

Table 13 Continued

Financial Fragility Controls		
CP_FUNDING	-5.943	-0.373
	(-0.76)	(-0.81)
INST_CONTROL $\times$ CDS	-0.085***	-0.003***
	(-4.83)	(-3.19)
INST_CONTROL $\times$ (1-CDS)	-0.019***	-0.005***
	(-4.06)	(-12.8)
R^2	27,831	15,959
Number of Observations	0.744	0.894

NOTES: The dependent variable in Specification (1) is a model-derived distance to default. The dependent variable in Specification (2) is a normalized measure of Moody's KMV EDFs defined by the $-\text{probit}\left(\text{EDF}\right)$. Specification (2) is only estimated for the period 2004-08. CDS_EXPOSURE = index gauging a firm's excess volume of CDS interest over and above what it would normally be expected to attract from market participants; INST_CONTROL = the excess level of institutional investor interest; CP_FUNDING = commercial paper funding dependence. The remaining explanatory variables are defined in Table 1. Models are estimated with robust standard errors. The regression controls for firm fixed effects, yearly time variation, industry effects and major exchange listing. The symbols (***), (**), and (*) indicate statistical significance at the 1-, 5-, and 10-percent level, respectively. The numbers in parentheses represent t statistics.

Figure 1. Growth of CDS Market, 2001-09

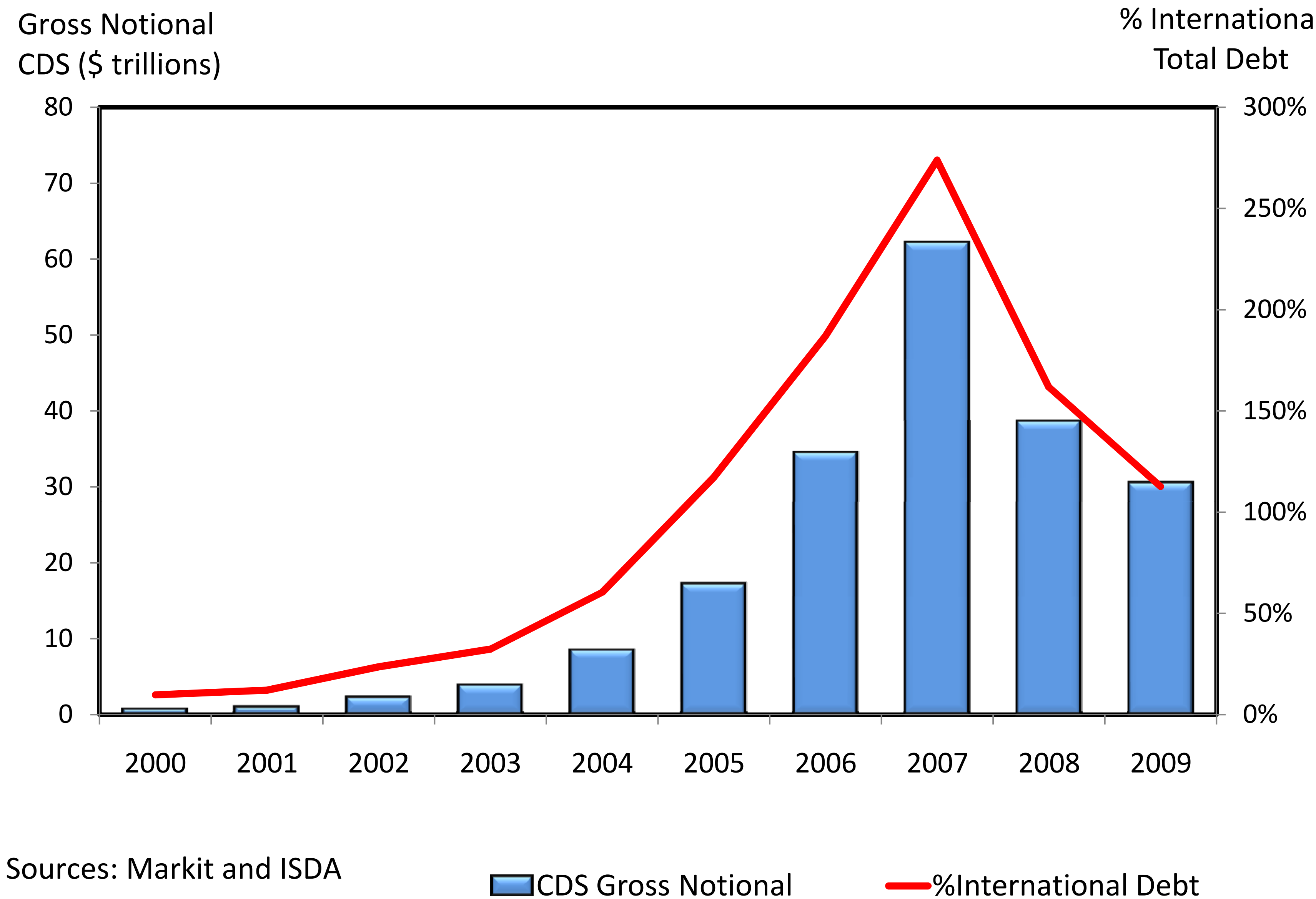
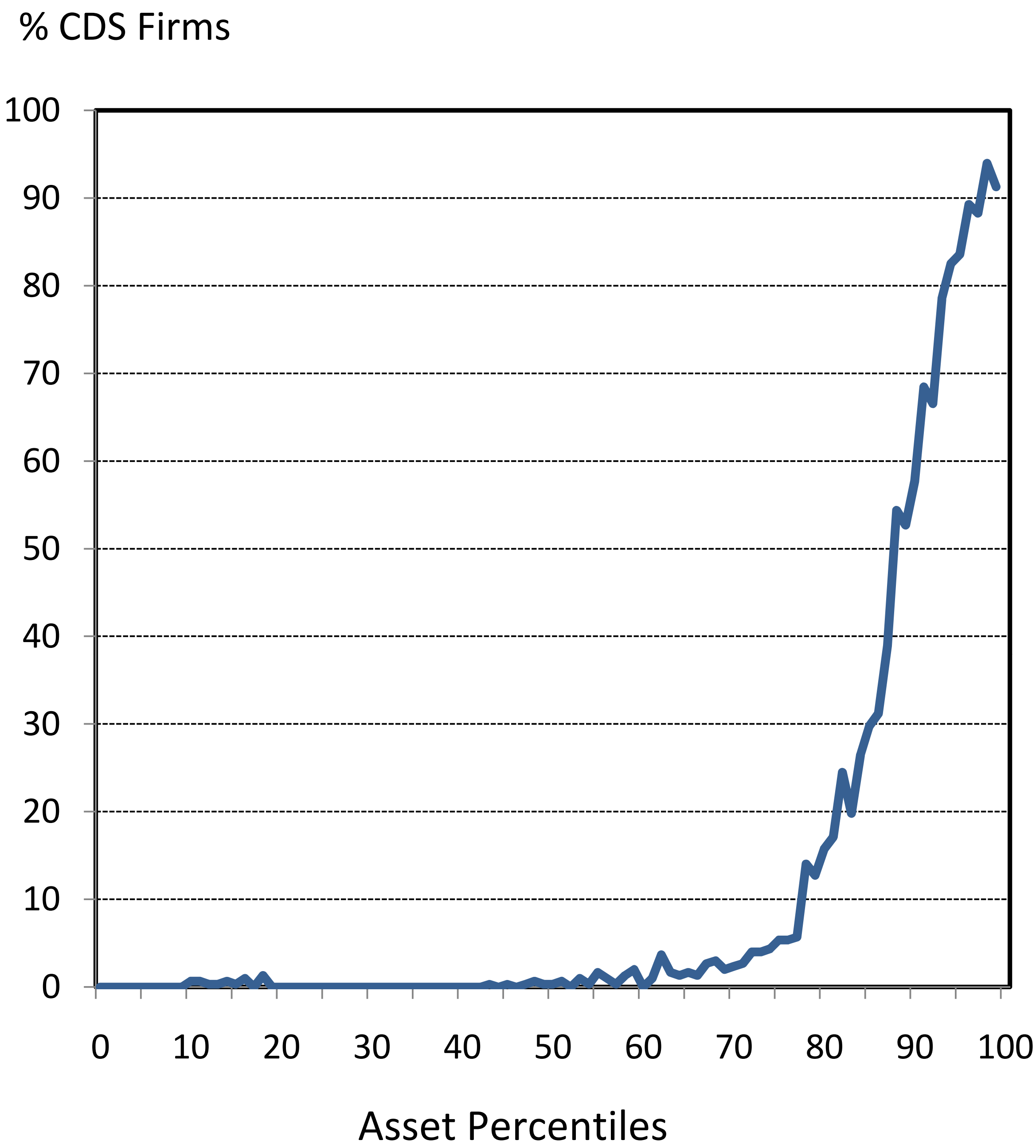


Figure 2. Fraction of CDS Firms by Asset Percentiles



Source: Markit and Compustat

Figure 3. Kernel Density Estimate of Distance to Default and Implied Default Probability

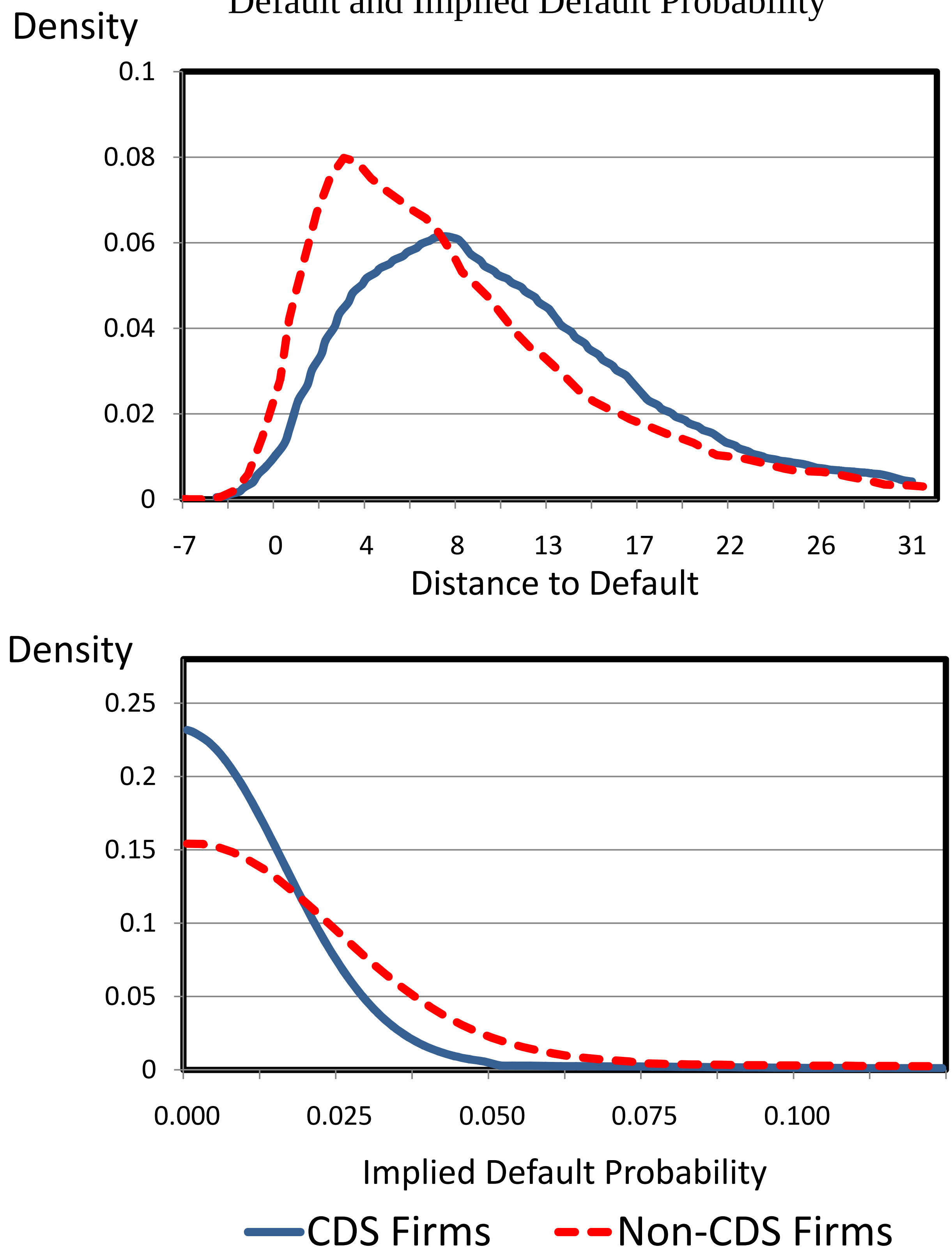


Figure 4. Default Risk for CDS and Non-CDS Firms by Year, 2001-08

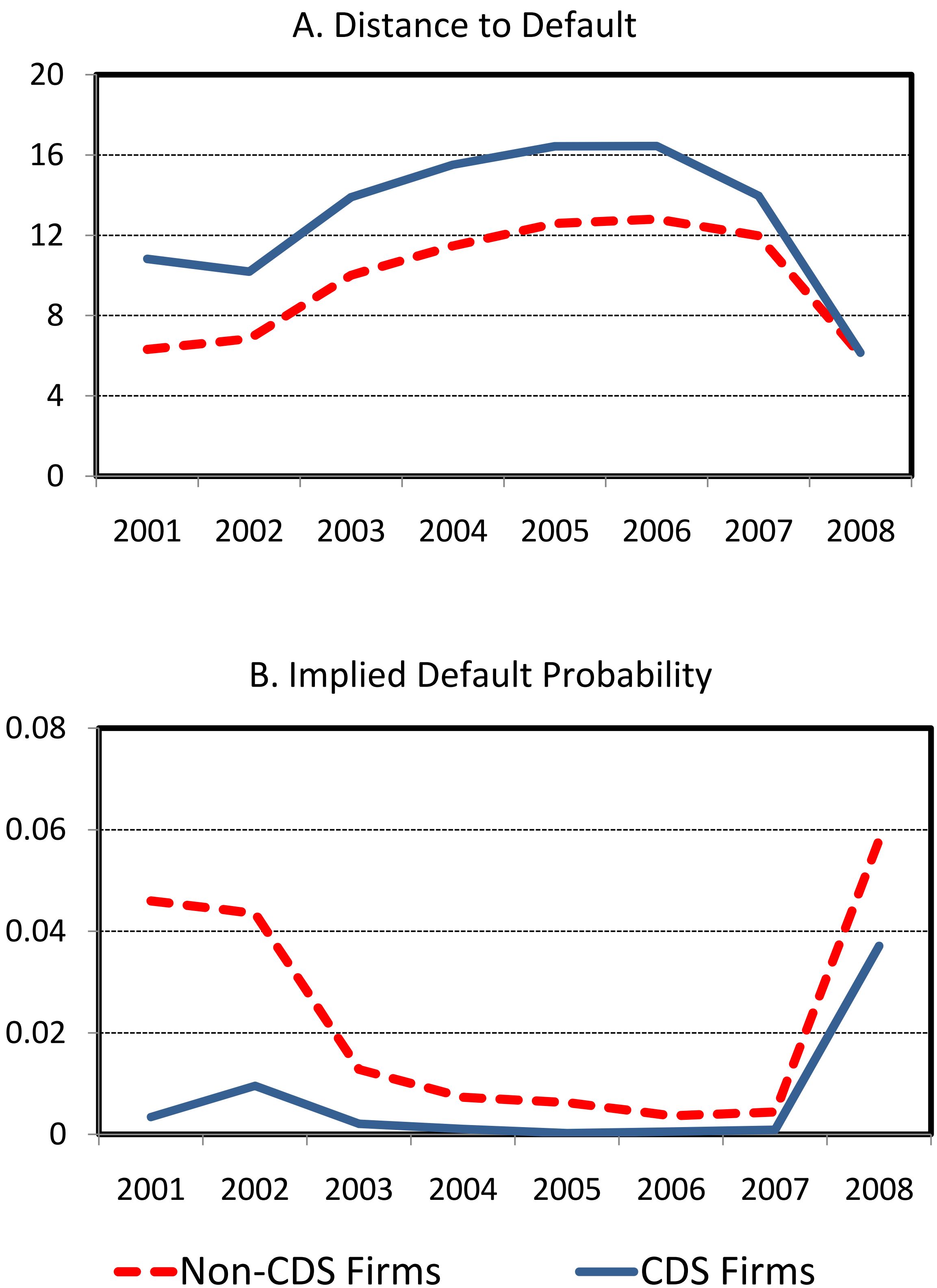


Figure 5. Kernel Density Estimate of Distance to Default Over Time

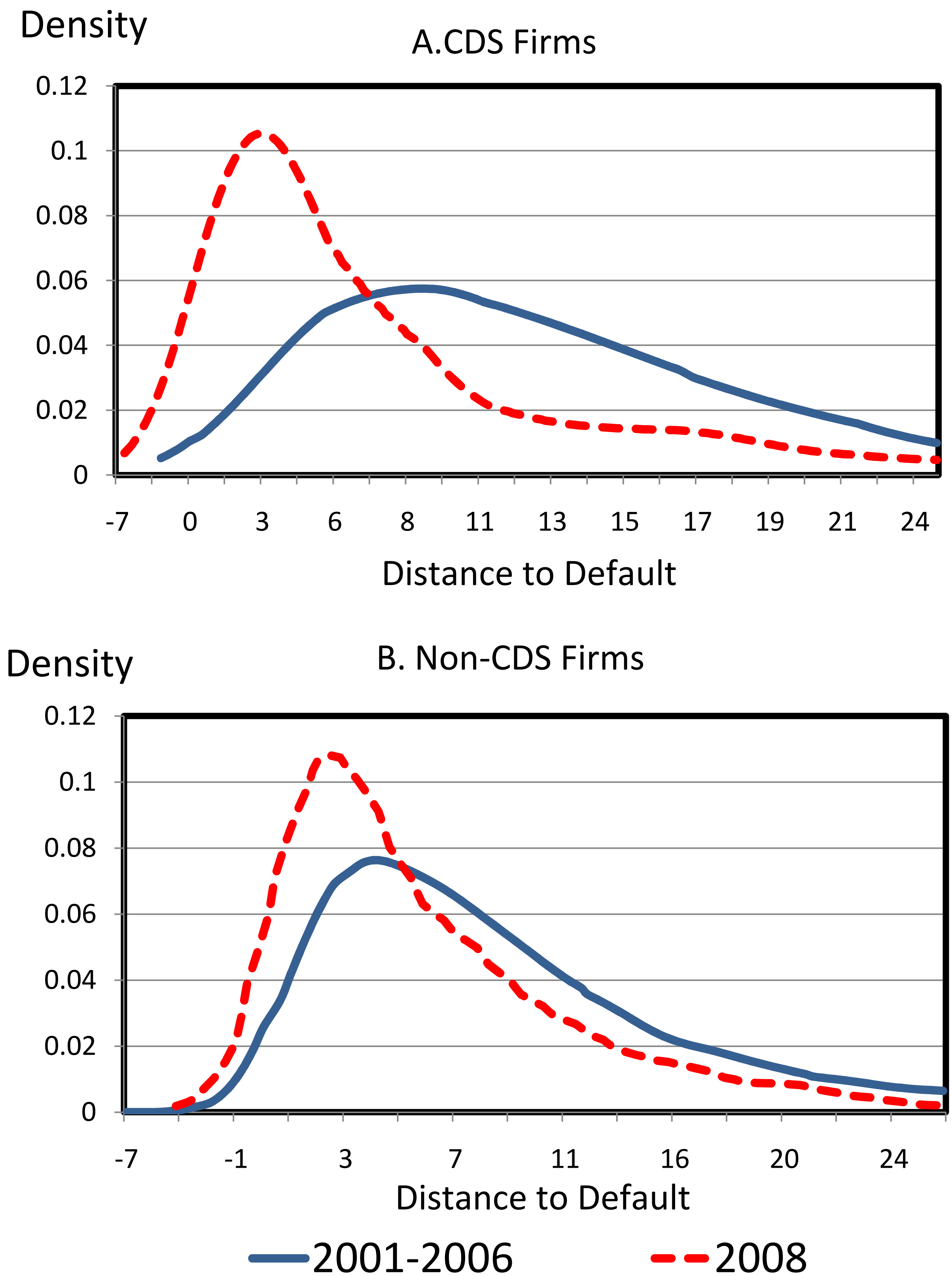


Figure 6. Moody's KMV One-Year Horizon EDFs
by Year, 2004-08

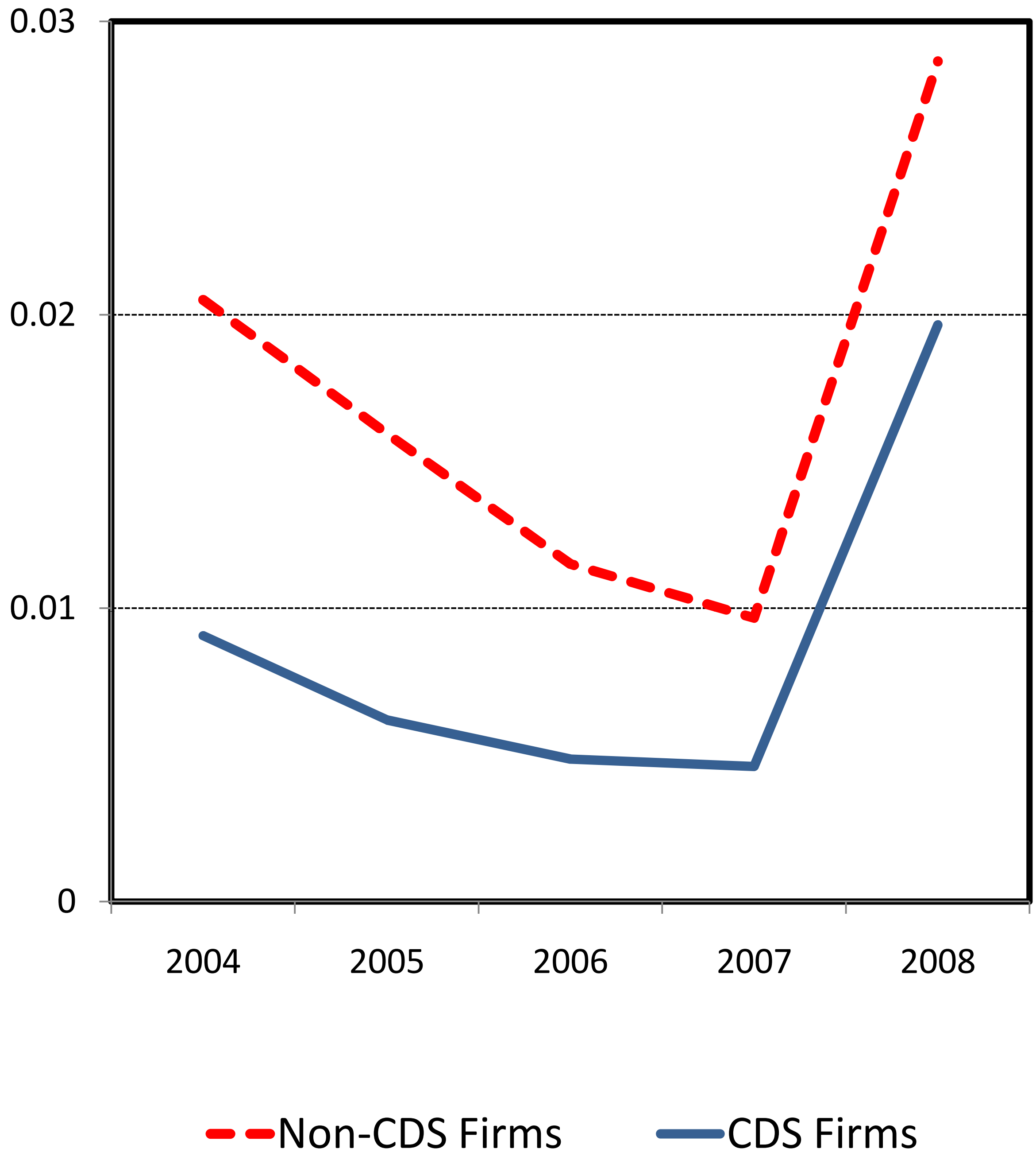


Figure 7. Kernel Density Estimate of Moody's KMV EDFs, 2004-08

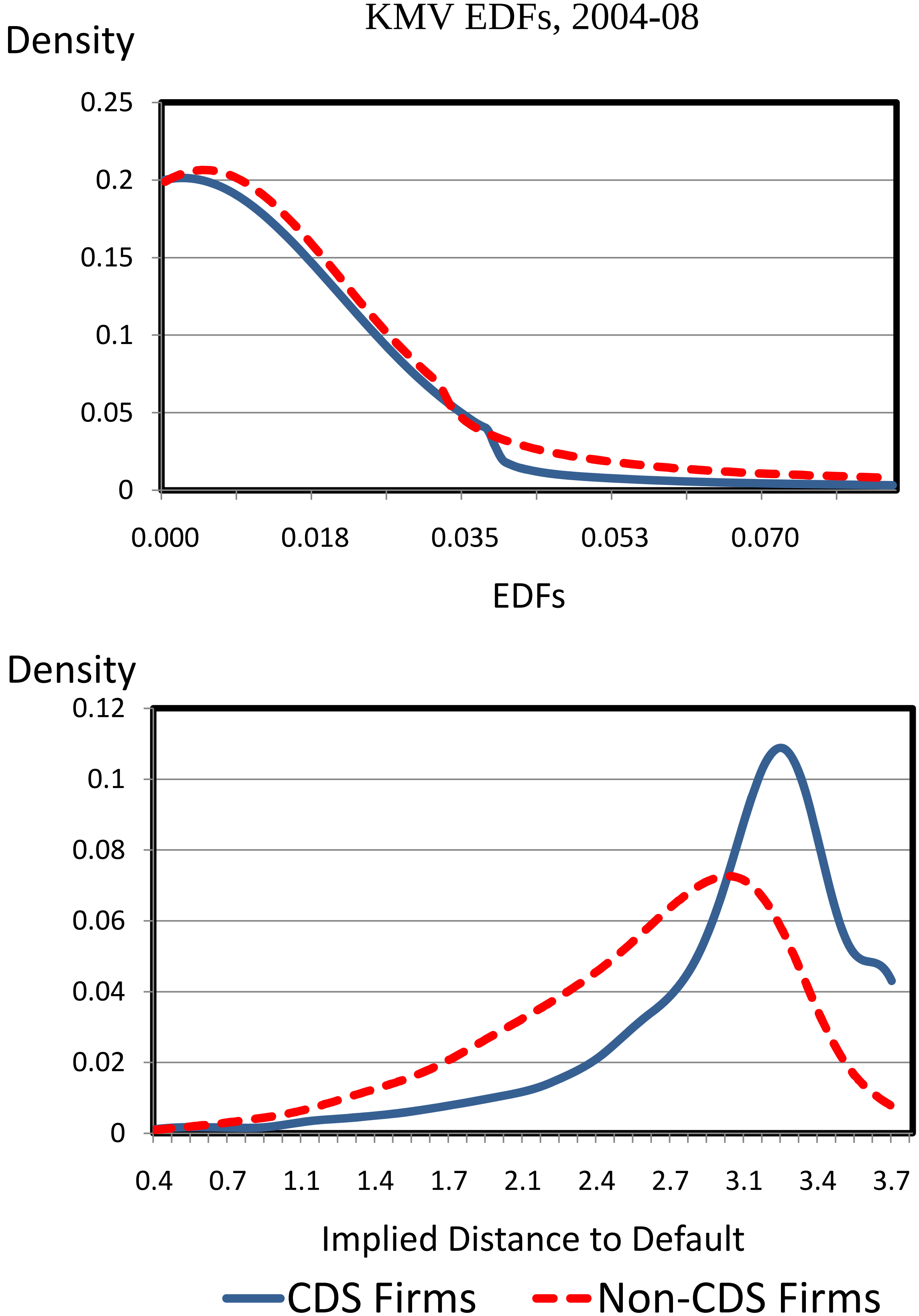
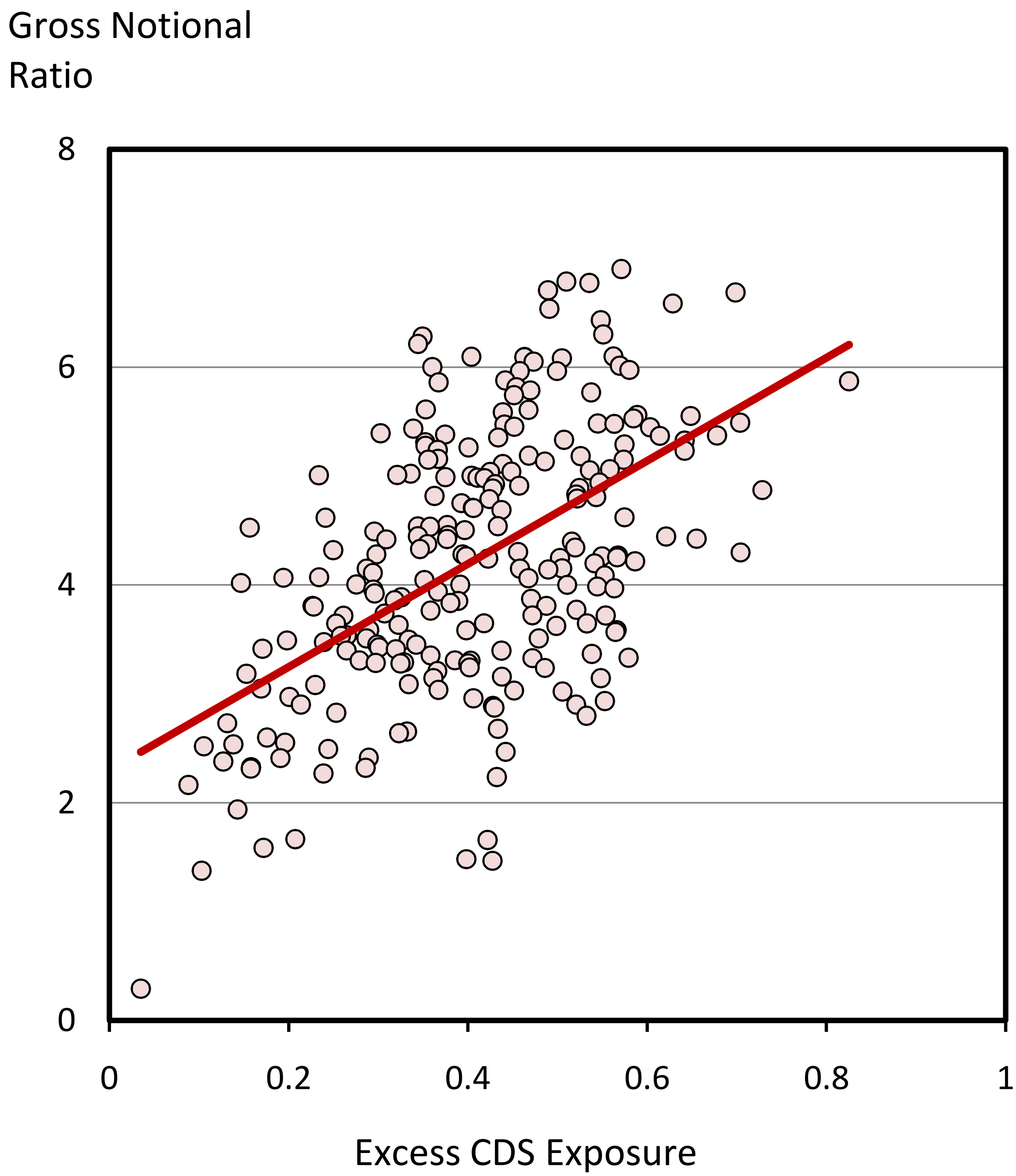


Figure 8. The Relationship between Excess CDS Exposure in 2008 and the Gross Notional Ratio in 2009



Source: DTCC and authors' calculations