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Abstract

We document that credit default swaps (CDS) trading on a firm's debt positively influences its technological innovation measured using patents and patent citations. The positive effect is more pronounced for firms relying more on debt financing, using more bank debt, borrowing from fewer lenders, having more restrictive debt covenants, or using more short-term debt prior to CDS introduction. Further analysis shows that firms' innovation strategies become more risky and long-term oriented after the advent of CDS trading. These results suggest that CDS foster borrowing firms' innovation via enhancing lenders' risk tolerance and borrowers' risk taking in the innovation process. Taken together, our findings reveal the real effects of financial innovation (i.e., CDS) on companies' investment and technological progress.

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"*I wish somebody would give me some shred of evidence linking financial innovation with a benefit to the economy.*"

Paul Volcker (*2010*)*, former Chairman of the Federal Reserve*

I. Introduction

Companies' *technological* innovation is vital for their competitiveness and long-term growth, but it is difficult to finance with debt. Unlike conventional investments such as capital expenditures and acquisitions, corporate innovation produces intangible assets and involves a long-term and risky process that has both a high likelihood of failure and some prospects for extraordinary positive returns (e.g., Holmstrom, 1989). Thus, fostering innovation requires strong risk-taking incentives, substantial tolerance for early failure, and rewards for long-term success (Manso, 2011). Compared with shareholders, lenders are generally more risk averse, more short-term oriented, and less likely to benefit from firms' innovation success. As such, debt has been regarded by prior studies (e.g., Stiglitz, 1985; Hall and Lerner, 2010) as a disfavored source of finance for innovation relative to equity. Further, amongst various types of debt financing, bank debt is viewed as less suited to financing innovation than public debt (Rajan and Zingales, 2003; Atanassov, 2015), and short-term debt is shown to be less conducive to innovation than long-term debt (Hasan, O'Brien, and Ye, 2013).

As one of the most important *financial* innovations since the turn of the century, credit default swaps (CDS hereafter) are credit derivative contracts, in which CDS sellers offer CDS buyers protection against default or other credit events of underlying reference entities in exchange for a periodic premium payment from CDS buyers.[1] If CDS are traded on a borrowing

[1] A reference entity bears the credit risk of the CDS contract, and can be a corporation, government, or other legal entity that issues debt of any kind. Credit events mainly include defaults on interest or principal payments and the bankruptcy filing of the debtor, and may also include debt restructuring and credit-rating downgrades in some CDS contracts. If a credit event occurs, CDS sellers should make the payment equal to the face value of the debt due. In return, CDS buyers should deliver either the current cash value of the debt or the actual bonds to CDS sellers,

firm's debt, the lenders can buy CDS and thus hedge the credit risk associated with their investment (such as a loan or a bond), while retaining legal ownership of the investment.[2] Even if lenders do not purchase CDS, the existence of CDS markets provides them with a valuable option to hedge against credit risk (Saretto and Tookes, 2013).

Does the existence of such hedging products influence the compatibility between debt financing and corporate innovation? In other words, does the availability of CDS trades to lenders affect borrowing firms' technological innovation? Through addressing these questions, this paper aims to reveal the real effects of innovation in financial markets on companies' investment and technological progress.

We develop our main hypothesis based on prior literature examining the effects of CDS trading on payoffs, incentives, and behaviors of contractual parties (i.e., lenders and borrowers) to existing debt. In particular, we posit that CDS positively influences innovation through promoting borrowing firms' risk-taking behaviors. While risk taking is essential for innovation, lenders are generally averse to it because their payoff is a concave function of borrowing firms' value (Jensen and Meckling, 1976). Specifically, as shown in Figure 1, lenders' payoff is linear and upward sloping in the region of default and fixed in the region of repayment. As such, for lenders, higher risk-taking of borrowing firms implies a higher probability of losses without the same potential for gains that shareholders would capture. With CDS protection, lenders' *net* payoff increases in the region of default and slightly decreases in the regional of repayment after deducting CDS premium, which increases with borrowing firms' default risk. Essentially, CDS

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depending on the terms agreed upon at the onset of the contract. According to the International Swaps and Derivatives Association (ISDA), the size of the CDS market has reached a peak of $62.2 trillion of notional outstanding value at the end of 2007, making CDS one of the most important financial derivatives for managing credit risk in the debt market.

[2] CDS sellers have no control rights with respect to the underlying loan and typically have no direct contractual involvement with borrowers.

protection weakens concavity of lenders' payoff function, thus enhancing lenders' tolerance towards borrowing firms' risk taking.

[Insert Figure 1 Here]

Further, a salient feature of the traditional lender-borrower relationship is that lenders, especially banks, protect themselves against default risk by continuously monitoring borrowers' investment choices even outside the payment default states (e.g., Fama, 1985; Nini, Smith, and Sufi, 2012). Lenders' continuous monitoring may involve hands-on evaluation of borrowers' investment decisions, imposing stringent financial covenants to constrain borrowers' investment and financing policies, and exerting influence on borrowers' managerial turnover. However, it is particularly costly to monitor borrowing firms' innovation investment because of the uncertainties that innovative projects involve and the difficulty of negotiating and implementing covenants. Recent studies, such as Morrison (2005) and Parlour and Winton (2013), show that the onset of CDS trading weakens lenders' incentives to engage in costly monitoring and intervene in borrowers' governance because their claims can be insured via CDS. Shan, Tang, and Yan (2015) find that covenants on a borrower's debt become less strict if there are CDS contracts referencing the borrower's debt at the time of loan initiation. In response to reduced lender monitoring, borrowing firms can have more opportunities to direct their efforts and resources towards higher-quality innovative projects that are riskier by nature.[3] Additionally, as laxer debt covenants reduce the probability of covenant violations, borrowing firms can achieve greater flexibility and tolerance to experimentation, which results in higher-quality innovations (Atanassov, 2015). Taken together, we expect CDS to foster borrowing firms' innovation via

[3] While borrowing firms do not necessarily observe their lenders' purchase of CDS contracts, they can observe CDS trade initiation on their debt (Martin and Roychowdhury, 2015). In addition, Arping (2014) argues that managers at borrowing firms can typically detect any weakening of lenders' monitoring intensity in general.

enhancing lenders' risk tolerance and allowing borrowing firms to take more risk in the innovation process. We refer to this mechanism as the risk-taking channel.

Prior studies also suggest several other economic forces that could potentially discourage borrowing firms from taking risk in their innovation investment upon CDS trade initiation. For example, in response to CDS-insured lenders' reduced monitoring, uninsured lenders of a borrowing firm may increase their monitoring efforts to constrain the borrower's risk taking. Moreover, it is possible that CDS sellers can fully anticipate the incentives of CDS-insured lenders and price it into the CDS premium. To lower protection prices or avoid reputation costs arising from adverse credit events caused by reduced monitoring, CDS-insured lenders may continue monitoring borrowers intensively in the post-CDS period.[4] Finally, Hu and Black (2008) point out that lenders can separate their cash flow rights from control rights through the purchase of CDS protection, turning themselves into "empty creditors". As a result, CDS-insured lenders can be tougher in debt renegotiations, and might even be better off pushing financially distressed borrowers into inefficient bankruptcy or liquidation for the CDS settlement (e.g., Bolton and Oehmke, 2011).[5] Anticipating this, borrowing firms might have weaker ex ante incentives to undertake risky innovative projects in order to avoid defaults and covenant violations that trigger debt renegotiations. In sum, all these factors (i.e., uninsured lenders' monitoring efforts, CDS-insured lenders' cost concerns, and CDS-insured lenders' superior bargaining power in financial distress) might limit borrowing firms' incentives and opportunities to pursue risky innovative

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[4] In principle, CDS sellers, many of which are large insurance companies, can price-protect themselves by charging a higher premium if they can infer reduced lender monitoring based on heightened defaults of borrowers after CDS trade initiation. However, in practice, it is difficult to always attribute ex post borrower defaults to ex ante lenders' reduced monitoring. Thus, CDS sellers typically price-protect only on average across all CDS buyers. An easier-to-implement and more cost-efficient protection method is to diversify credit risk exposure through selling CDS referenced to companies in different industries. By doing so, losses generated by one contract can be compensated by premiums earned from other contracts (Martin and Roychowdhury, 2015).

[5] Gopalan, Nanda, and Yerramilli (2011) show that relationship banks of severely distressed firms bear substantial reputational costs. Thus, lenders' reputation concerns may prevent them from being excessively tough in debt renegotiations.

projects, thereby weakening the risk-taking channel outlined above. Thus, the net effect of CDS on innovation should reflect the tension among various forces, and should be best determined empirically.

In this paper, we identify 782 U.S. listed firms on which CDS trading was introduced between 1997 and 2008. We follow previous studies (e.g., Hirshleifer, Low, and Teoh, 2012; Chang et al., 2015) and measure the quantity of borrowing firms' innovation output using the number of patents granted by the U.S. Patent and Trademark Office (USPTO). In addition, we use the number of patent citations to capture the quality of innovation.

Our CDS firms are not randomly assigned. It is plausible that some factors determining a borrowing firm's innovation output may also drive the likelihood of the firm to be selected into CDS trading. For example, a firm's investment opportunity may affect both innovation output and the onset of CDS trading. To address this selection concern, we follow prior studies (e.g., Ashcraft and Santos, 2009) and implement a matched-sample analysis using the propensity score matching procedure. We include both treated (CDS) firms and control (matched non-CDS) firms in the regression analyses. Our baseline specification is a difference-in-differences (DiD) model with firm and year fixed effects, which essentially compares the change in innovation output around CDS trade initiation for CDS firms with that for non-CDS firms.

Our main results are that CDS firms, compared with the non-CDS firms, create significantly more patents and their patents generate more citations after the introduction of CDS trading on their debt. The positive impact of CDS trade initiation on innovation outcome is both statistically and economically significant. Specifically, after CDS trading is introduced, an average CDS firm generates 14.8% more patents and 20.2% more citations than their non-CDS counterparts. We perform various checks and confirm that our main findings are robust to alternative matching methods, model specifications, and variable definitions.

An important concern of our analysis is that the timing of CDS introduction is endogenous. For instance, unobservable factors correlated with both corporate innovation and CDS trade initiation could bias our results (i.e., the omitted variable concern). Further, in response to a borrowing firm's increased risk taking in innovation, its lenders may initiate hedging contracts and CDS markets emerge (i.e., the reverse causality concern). We perform a number of tests to alleviate endogeneity concerns. Among these tests, we follow Saretto and Tookes (2013) and employ lenders' hedging activities on foreign exchange as the instrumental variable for CDS trading. The instrument choice is based on Minton, Stulz, and Williamson's (2009) finding that banks using foreign exchange derivatives to hedge currency risk are more likely to use CDS to hedge credit risk. Further, lending banks' decision to hedge currency risk should be exogenous to a borrowing firm's innovation output. The main results still hold, suggesting a causal effect of CDS trading on innovation.

Having established the sign of and causality for the CDS trading-innovation relation, we further explore its potential mechanisms. To support the risk-taking channel through which CDS trading positively affects innovation, we examine how firm specific characteristics interact with CDS trading to affect corporate innovation by partitioning our sample in several ways. First, we find that CDS trading has a stronger impact on firms' innovation output when firms are more dependent on debt financing, which confirms the role of CDS as a debt market instrument to help improve the compatibility between debt financing and innovation. We also find that the effect of CDS trading on firms' patents and patent citations is more evident when firms are more likely to use bank debt versus public debt in debt financing and when firms have fewer bank lenders and greater debt covenants. These findings are consistent with our argument because banks are more risk averse and exert more influence on firms' risk-taking activities by imposing strict covenants, which are more harmful to firms' innovation (Rajan and Zingales, 2003; Atanassov, 2015). In addition, we find that our results are more pronounced for firms with more short-term debt versus long-term debt in debt financing prior to CDS introduction. Since short-term bondholders are more myopic and are more likely to pursue safe investments, which have an adverse effect on firms' innovativeness (Hasan, O'Brien, and Ye, 2013), the findings provide additional supports to our argument that CDS trading improves lenders' tolerance towards risk taking.

To further substantiate the risk-taking channel, we present evidence on the effect of CDS trading on firms' innovation strategies, which play an essential role in maintaining corporate technological advantages (Hall, 1993; Cockburn, Henderson, and Stern, 2000). Generally, we find that firms' innovation strategies become more risky and long-term after CDS trade initiation. Specifically, we find that CDS trading has a positive effect on firms' exploratory innovation that departs from existing knowledge and builds on new knowledge a negative effect on firms' exploitative innovation that arises from existing knowledge with a short development cycle and less uncertainty. In addition, we find that firms create more production patents that usually lead to more creative products rather than process patents after CDS are introduced on these firms. Finally, we find that firms apply for patents that cite other patents in a wide array of technology classes. Overall, these findings lend further support to our argument that CDS trading promotes corporate innovation through encouraging managers' risk-taking incentives and motivating managers' to take long perspectives.

Although our findings are consistent with the view that CDS trading encourages firms' innovation via the risk-taking channel, these findings are also consistent with the notion that

CDS trading mitigates firms' financing constraints through increasing borrowing firms' debt capacity (e.g., Saretto and Tookes, 2013) and allowing more innovative projects to be financed by debt. To examine this alternative channel, we conduct three tests. First, we include additional controls for the changes in debt capacity around CDS trading ignition and find the results are not affected. Second, we investigate the effect of CDS trading on R&D expenditures and find that CDS trading does not significantly increase firms' spending on R&D. Third, we partition the sample according to various measures of financial constraints. The financing channel predicts that financially constrained firms benefit more from the relaxed borrowing constraint and thus exhibit greater increase in innovation output. However, we find that the effect of CDS trading on firms' innovative outcomes does not depend on their financial constraints. Collectively, these results suggest that our findings are not driven by CDS trading relaxing borrowers' financial constraints.

Last, we investigate how CDS trading affects firms' innovation efficiency and also the economic value from innovation. We find that firms have higher number of patents and citations per R&D dollars after CDS trade initiation, suggesting that CDS firms are more efficient in converting R&D investments into innovation outputs. The finding reconciles the results that CDS trading increases innovation output but do not have significant impact of R&D input. Further, we find that the market valuation of patents increases after CDS trade initiation, suggesting that in addition to scientific value, CDS firms are also better able to produce patents with higher economic value.

Our study contributes to the extant literature in two ways. First, our paper adds to the literature on the financing of innovation. While most prior studies (e.g., Hall, 2002; Brown, Fazzari, and Petersen, 2009) suggest that innovation should primarily rely on internal funds and equity financing, several recent studies (e.g., Nanda and Nicolas, 2014; Kerr and Nanda, 2014) reveal the increasing importance of debt financing for innovation, particularly for large firms. We extend this literature by showing that the risk-transferring function of CDS can improve the compatibility between innovation and debt financing.[6] This finding suggests a useful focus for policymakers who are interested in fostering innovation in the economy. Second, our study contributes to the ongoing debate on the effects of financial innovation. On the one hand, CDS, as a major form of financial innovation, have been shown by previous studies to facilitate credit risk transfer, promote risk sharing, and relax capital supply constraints (e.g., Saretto and Tookes, 2013). On the other hand, Warren Buffett referred to CDS as "financial weapons of mass destruction". Subrahmanyam, Tang, and Wang (2014) reveal a dark side of CDS in terms of increasing the probability of default and credit rating downgrade. We document that CDS encourage borrowing firms to engage in risky experimentation, thereby spurring innovation. By doing so, our analysis discovers a specific micro-level channel through which financial innovation may drive economic growth, and hence complements the macro-level findings of Beck et al. (2014) who show that financial innovation allows countries and industries to better reap growth opportunities and achieve higher economic growth.

The reminder of the paper is organized as follows. Section 2 reviews related literature. Section 3 describes the data, the sample, and the variable construction. Main empirical results are presented in Section 4. Additional tests are reported in Section 5. Section 6 concludes.

2. Related Literature

[6] In response to the global financial crisis of 2007–08, there was a wide-spread debate on the bright and dark sides of financial innovation. In particular, the *Economist* organized an online debate in early 2010 between Ross Levine and Joseph E. Stiglitz regarding the costs and benefits of financial innovation.

Our paper builds on two strands of literature: recent works that focus on the effects of CDS trading on various corporate policies; and research on the financing of corporate innovation.

2.1. CDS trading and corporate policies

CDS provide credit suppliers with an effective tool to hedge their downside risk. CDS protected creditors tend to be more risk tolerant in their lending practices. For example, several studies show that as creditors' exposure to borrowers' default risk is protected by CDS, these creditors' interest is more aligned with that of shareholders and hence their intervention incentive is weakened. Specifically, Morrison (2005) and Parlour and Winton (2013) theoretically model this incentive. Shan, Tang, and Winton (2014) provide empirical evidence that debt covenants imposed by lenders become less restrictive after the initiation of CDS trading on reference firms' debt. As a result, creditors' enhanced risk tolerance encourages these firms' risk-taking. Martin and Roychowdhury (2015) show that a borrowing firm's reporting conservatism declines after CDS trading is introduced on this firm. Karolyi (2013) finds that borrowers increase operational risk taking after the introduction of CDS trading. Furthermore, CDS may affect reference firms' financing policies. For example, Ashcraft and Santos (2009) find that CDS trading decreases the cost of debt for safe and transparent firms. Saretto and Tookes (2013) find that CDS firms are able to maintain higher leverage and longer debt maturity. Shan, Tang, and Yan (2014) find that banks that are active CDS users grant larger amounts of loans to CDS-referenced borrowers.

However, firms may also face "tougher negotiators" in the process of debt restructuring. CDS create "empty creditors" who have control rights of the firm but different risk alignment from other creditors without CDS protection (Hu and Black, 2008). Bolton and Oehmke (2011) formally model the CDS-induced empty creditor problem. Consistent with their model predictions, Subrahmanyam, Tang, and Wang (2014) find increased bankruptcy risk for the reference entities after CDS trading. Subrahmanyam, Tang, and Wang (2015) further find that CDS firms increase precautionary cash holdings in response to the potential threat from tougher "empty creditors".

Different from previous literature that mainly focuses on the effect of CDS trading on firms' financing activities or reporting practice, our study investigates the real effect of CDS trading on the output of firms' innovation investment. Given the huge economic value and strategic importance of corporate innovation, we add to the literature by identifying a unique role of CDS trading in affecting firm value.

2.2. Financing of corporate innovation

Given the importance of technological innovation for growth and competitiveness, a number of papers focus on the determinants of corporate innovation, especially about its financing. Previous studies mainly focus on the role of equity market in affecting corporate innovation. For example, Brown, Martinsson, and Petersen (2013) find that firms in countries with stronger shareholder protections and easier access to equity financing are associated with higher rates of R&D investment. Hsu, Tian, and Xu (2014) show that firms in countries with more developed equity markets are more innovative especially in industries that rely heavily on external finance. Bushee (1998) documents that managers in firms with high institutional ownership are less likely to cut R&D when there is a decline in earnings. However, high short-term institutional ownership pressures managers to cut R&D to boost declining earnings in the short run. Tian and Wang (2014) find that IPO firms backed by more failure tolerant venture capitalists are more innovative after their IPOs. Aghion, Van Reenen, and Zingales (2013) show that greater institutional ownership that alleviates managers' career concern encourages innovation. Fang, Tian, and Tice (2014) present evidence that stock liquidity impedes innovation by increasing the likelihood of hostile takeover as well as the holdings of short-term institutional investors.

Several recent studies also investigate the role of debt financing and find mixed evidence. On the one hand, the enhanced creditor power may impede corporate innovation due to creditors' excessive focus on short-term performance (Acharya and Subramanian, 2009; Hsu, Tian, and Xu, 2014; Chava et al., 2013). On the other hand, different types of debt financing arrangements can have different impacts on the incentives of firms to innovate. For example, Atanassov (2015) finds that that firms that rely more on bank financing generate fewer patents and fewer citations of the patents than those that use arm's length financing because of less flexibility and tolerance to experimentation associated with bank financing. Hasen, O'Brien, and Ye (2013) provide evidence that short-term bondholders, compared with long-term bondholders, discourage firms from making innovations both in quantity and in quality. This is consistent with Manso (2011) who proves that greater tolerance to experimentation is the key to innovation. Moreover, similar to equity financing, debt financing may have a positive effect on innovation due to increased credit supply. Amore, Schneider, and Zaldokas (2013) and Chava et al. (2013) find the positive effect of increased credit supply via bank deregulation on corporate innovation.

We contribute to the literature by documenting the bright side of CDS as an effective instrument to encourage borrowing firms' risk taking, and hence overcome the potential detrimental effect of debt financing on corporate innovation.

3. Data, Variables, and Summary Statistics

3.1. Data and sample selection

We obtain our data from multiple sources. Accurate CDS initiation dates are difficult to obtain from a single data source because CDS are not traded on centralized exchanges. We thus assemble CDS inception and transaction data by combining three data sources used in previous studies: Markit, CreditTrade, and the GFI Group.[7] Our sample starts from 1997, which is the broad inception year of the CDS market for company names (Tett, 2009).

To measure firms' innovation output, we rely on patents granted by the U.S. Patent and Trademark Office (USPTO) between 1976 and 2010.[8] Patent citations are obtained from the Harvard Business School (HBS) Patent Network Dataverse.[9] There is, on average, a two-year lag between the date when inventors file for patents (the application date) and the date when patents are granted. Since the latest year for our patent and citation data is 2010, patents applied for in 2009 and 2010 may not be completely covered by the database as it only includes patents already granted. As suggested by Hall, Jaffe, and Trajtenberg (2001), we end our sample period in 2008 to address this issue.[10] We obtain firm financial information from the Compustat Industrial Annual files. Data on stock prices and returns are retrieved from the Center for Research in Security Prices (CRSP) files. Analyst coverage data are obtained from the Institutional Brokers' Estimate System (IBES) and bank debt and debt covenants data are obtained from S&P Capital IQ and Loan Pricing Corporation's (LPC) DealScan database, respectively.

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[7] For previous studies using different CDS data sources, see among others, Subrahmanyam, Tang, and Wang (2014), Acharya and Johnson (2007), and Blanco, Brennan, and Marsh (2005).

[8] We download the patent data from Noah Stoffman's website (https://iu.app.box.com/patents). A detailed discussion on how the data set is constructed can be found in Kogan et al. (2015) who collect the raw patent data from the USPTO, and identify the company (the assignee), to which each patent belongs. Then they identify company names in the raw patent database and match each of them to firm names in the CRSP using an automated name matching algorithm. In addition, they also validate the accuracy of data extraction and matching by comparing the final database with the National Bureau of Economic Research (NBER) Patent and Citation database.

[9] The database contains all citations of utility patents granted by the USPTO, and is constructed by Lai et al. (2012). We download the data from http://thedata.harvard.edu/dvn/dv/patent.

[10] We use the patent application year rather than the grant year to merge the patent and citation dataset and CDS data since Hall, Jaffe, and Trajtenberg (2001) suggest that the application date is closer to the actual time of inventions than the grant date.

Following common practice (e.g., Hirshleifer, Low, and Teoh, 2012), we exclude firms in any four-digit Standard Industrial Classification (SIC) industries that have no patents between 1976 and 2010 and firms in financial and utility industries (SIC codes 6000-6999 and 4900-4999, respectively). Also excluded are observations with missing values for the variables employed in the regressions. These restrictions result in a sample that consists of 782 firms that have CDS trading initiated between 1997 and 2008.

3.2. Variables

To identify CDS trade initiation for the firms in our sample, we use the first CDS trading date as the CDS initiation date. Panel A of Appendix A presents the distribution by year for the 782 firms on which CDS trading was introduced during the sample period.[11] Panel B reports the distribution by one-digit SIC industry. We find that our CDS firms are mainly from rubber, stone, computer, food, petroleum refining, paper, and transportation industries. Following prior literature (e.g., Saretto and Tookes, 2013), we construct a binary variable, *CDS Trading*, to capture CDS trading activities between CDS buyers and sellers on the referenced borrowing firm. Specifically, *CDS Trading* is equal to one in and after the inception year of CDS trading on a reference firm, and zero prior to it. In addition, we construct several variables measuring the liquidity of CDS trading and the ease of access to the CDS market for investors: the average number of daily CDS quotes during a year (*Daily Quotes*), the average number of distinct dealers providing CDS quotes during a year (*Distinct Dealers*), and the average number of distinct maturities of CDS contracts traded on a firm in a given year (*Distinct Maturities*).

We measure corporate innovation using patents and patent citations. Our first measure of innovation output, *Patent*, is the number of patents that were applied for during each firm-year

[11] Consistent with Martin and Roychowdhury (2015), we also find that the number of CDS trade initiations decreases drastically after 2004, reflecting the effects of the looming financial crisis.

and were eventually granted. Patent counts offer a good indicator of the level of innovation output as patenting is an important means by which firms protect their technological inventions. Nevertheless, patent counts imperfectly capture innovation success because patents vary drastically in their technological and economic significance (Hirshleifer, Low, and Teoh, 2012). We therefore follow Hall, Jaffe, and Trajtenberg (2001, 2005) and use forward citations of a patent to measure its quality (importance).[12] More significant and important patents are expected to be cited more frequently by other patents. The raw citation counts are subject to the truncation bias due to the finite length of the sample. Patents receive citations from other patents over a long period of time, thus patents in the later years of the sample have less time to accumulate citations. To correct for this bias, we follow prior studies (e.g., Hirshleifer, Low, and Teoh, 2012; Chang et al., 2015) and adjust the raw citation counts using the fixed-effect approach, which involves scaling the raw citation counts by the average citation counts of all patents applied for in the same year and in the same technology class. The fixed-effect approach accounts for the differing propensity of patents in different years and in different technology classes to cite other patents. The sum of the adjusted citations in each firm-year (*Citation*) is used as our second measure of innovation output.

To isolate the effect of CDS trading on innovation output, we control for an array of firm characteristics that have been documented as important determinants of innovation by previous studies (e.g., Hirshleifer, Low, and Teoh, 2012; Chang et al., 2015). The first control variable is R&D expenses scaled by total assets (*R&D/Assets*), which captures the observable quantitative input to the innovation process (e.g., Aghion, Van Reenen, and Zingales, 2013). Firm-years with

[12] We include self-citations since Hall, Jaffe, and Trajtenberg (2005) find that self-citations are more valuable than external citations. They argue that self-citations, which come from subsequent patents, reflect strong competitive advantages, less need of technology acquisitions, and lower risk of rapid entry. The robustness check in Section 4.2 shows that excluding self-citations has no material effects on our main results.

missing R&D information are assigned a zero R&D value (Hirshleifer, Low, and Teoh, 2012). Hall and Ziedonis (2001) argue that large firms and capital-intensive firms generate more patents and citations. We thus use the natural logarithm of the book value of assets (*Ln*(*Assets*)) to control for firm size, and use the natural logarithm of the net property, plant, and equipment scaled by the number of employees (*Ln*(*PPE/Employees*)) to account for capital intensity. We employ the natural logarithm of firm age (*Ln*(*Firm Age*)) to capture the effect of a firm's life cycle on its innovation ability. *Firm Age* is the number of years elapsed since a firm enters the CRSP database. Return on assets (*ROA*), which equals EBIT divided by the book value of assets, is included to capture operating profitability. To control for growth opportunities, we included the market-to-book ratio (*MB*) defined as the market value of assets divided by the book value of assets, and *Sales Growth*, which is the logarithm of one plus the annual sales growth rate. *Leverage* (i.e., the ratio of total debt over the book value of assets) and the cash-to-assets ratio (*Cash/Assets*) are added to account for the effects of capital structure and cash holdings on innovation. Further, since Chan, Lakonishok, and Sougiannis (2001) document that investments in innovation are positively related to stock return volatility, we include the standard deviation of daily stock returns over the fiscal year (*Stock Volatility*) as an additional control. Finally, to account for the inverted U-shaped relation between product market competition and innovation documented by Aghion et al. (2005), we include the Herfindahl index (*Herfindahl*), which is calculated as the sum of squared market shares in sales of a firm's three-digit SIC industry, and its squared term ($Herfindahl^2$).

3.3. Matched control firms

By no means are firms randomly assigned to be treated with or without CDS trading. Instead, there are many factors determining the likelihood of a firm being selected into CDS trading (e.g., Ashcraft and Santos, 2009). To the extent that these factors are also correlated with corporate innovation, our estimated effect of CDS trading on innovation is subject to selection biases. To mitigate this concern, we match each treated firm (CDS firm) with a control firm with no CDS traded on it (non-CDS firm) in the sample period, and use both treated and control firms in the matched sample throughout our regression analyses.

To construct the matched sample, we first follow prior studies (e.g., Subrahmanyam, Tang, and Wang 2014; Martin and Roychowdhury, 2015) and model the firm-level probability of CDS trade initiation in a given year as a function of borrowing firms' characteristics. Specifically, we estimate the following probit model using our CDS firms and all non-CDS firms that are in the Compustat database during the period 1997-2008 and have non-missing values for the variables used in the model:

$$Prob(CDS\ Trading_{i,t} = 1) = \Phi(\alpha_0 + \alpha_1 X_{i,t-1} + \alpha_2 Industry_{i,t} + \alpha_3 Year_t), \qquad (1)$$

where Φ is the cumulative distribution function of the standard normal distribution and *CDS* $Trading_{i,t}$ is the binary variable for CDS firm *i* in year *t*. It equals zero for non-CDS firms in all years. Because our focus here is on predicting the likelihood of CDS trade initiation, we follow Subrahmanyam, Tang, and Wang (2014) and exclude from the estimation post-initiation years for CDS firms. For the array of borrowing firms' characteristics (*X*), we follow Martin and Roychowdhury (2015) and include four proxies for borrowing firms' credit risk (i.e., *Credit Rating*, *Investment Grade*, *Leverage*, and *ROA*), and three variables (i.e., *Ln*(*Assets*), *Stock Volatility*, and *MB*) that account for the effects of information environment and growth opportunities on the demand and supply of CDS contracts. *Credit Rating* is an indicator variable that equals one if a borrowing firm has a debt rating assigned by Standard & Poor's, and zero otherwise. *Investment Grade* is an indicator variable that equals one if a borrowing firm has a credit rating assigned by Standard & Poor's above BB+, and zero otherwise. To further alleviate the concern that the determinants of innovation output may also affect the likelihood of CDS trade initiation, we include in X all control variables that affect innovation output (defined in Section 3.2).[13] To ensure that no outcome variable is included as a regressor, all independent variables are lagged by one year. *Industry* and *Year* represent two-digit SIC industry and year fixed effects.

The probit regression results of estimating Eq. (1) are tabulated in Panel A of Table 1. The pseudo-R^2 of 0.465 indicates that the onset of CDS trading can be reasonably well predicted by the explanatory variables. The coefficients of the explanatory variables are generally consistent with those in previous studies (e.g., Martin and Roychowdhury, 2015). For example, we find that larger and more mature firms and those with higher leverage and better credit ratings are more likely to have CDS trading initiated during the sample period.

[Insert Table 1 Here]

We then calculate the predicted probability (p) of CDS trade initiation based on the estimation results of Eq. (1). The propensity score is computed as $\Phi^{-1}(p)$. For each CDS firm in the year prior to the initiation of CDS, we find a matching firm that has the closest propensity score but has no CDS trading throughout our sample period. We utilize the above procedure to identify matched non-CDS firms for those 782 CDS firms which as a result generates a total of 16,636 CDS and non-CDS firm-years between 1997 and 2008. We use this matched sample for our regression analyses in Section 4.

Panel B of Table 1 presents the comparison of characteristics between CDS firms and matched non-CDS firms prior to CDS trade initiation. The results indicate that before the onset

[13] In particular, we include *R&D/Assets*, *Ln*(*PPE/Employees*), *Ln*(*Firm Age*), *Sales Growth*, *Cash/Assets*, *Herfindahl*, and *Herfindahl*^{2}. Robustness checks (untabulated) show that our main results are unaffected if we exclude them from the matching procedure.

of CDS trading, CDS firms and the matched non-CDS firms are close in asset value, firm age, *R&D/Assets*, *MB*, *Leverage*, *Cash/Assets*, stock volatility, and *Herfindahl*, suggesting that these characteristics are unlikely to primarily drive the difference in innovation output after CDS trade initiation. While CDS firms and non-CDS firms are still different in terms of profitability (*ROA*), sales growth, and *Ln*(*PPE/Employees*), they have similar probabilities of CDS trade initiation, as evidenced by the insignificant difference in propensity scores (0.003). At last, we compare innovation output variables (*Patent* and *Citation*), which are not included in the computation of the propensity scores, and find no statistically significant differences between CDS and the matched non-CDS firms before the advent of CDS trading.

3.4. Summary statistics

Table 2 presents the summary statistics of our final sample, which consists of 16,636 firm-year observations of CDS firms and matched non-CDS firms. Dollar values of total assets are converted into 2000 constant dollars using the Gross Domestic Product (GDP) deflator. All variables are winsorized at the 1% level at both tails of their distributions. Not surprisingly, the firms in our sample are larger than an average firm in Compustat since larger firms are more likely to be CDS referenced firms.

[Insert Table 2 Here]

Turing to corporate innovation measures, we find that an average firm in our sample obtains 78.148 patents and receives 63.703 citations for its patents in a year. The distributions of patent and citation counts are highly skewed. Untabulated statistics reveal that approximately 54% (65%) of firms obtain no patents (receive no citations) in a given year, thus the median number of patent (citation) counts is zero. To reduce the skewness of our innovation measures, we use the natural logarithm of one plus these variables (i.e., *Ln*(1+*Patent*) and *Ln*(1+*Citation*)) in the regression analyses. Further, 26.8% of the firm-years in our sample have CDS trading. Among the firm-years with CDS trading, there are on average 236 daily quotes, 6.732 distinct dealers providing CDS quotes, and 7.467 distinct maturities of CDS contracts traded.

4. Main Results

4.1. Univariate analysis

To investigate the relation between CDS trading and corporate innovation, we start with a univariate analysis on the changes in innovation output around CDS trade initiation for CDS firms (treatment group) benchmarked to the matched non-CDS firms (control group). Specifically, we define the year of CDS trade initiation as event year 0, and compute the change in innovation output from one year before CDS trade initiation (i.e., event year -1) to t years (t = 1, 2, and 3) after CDS trade initiation. The event years of non-CDS firms are defined according to their CDS counterparts.

Panel A of Figure 2 plots the changes in the number of patents for the event windows (-1, 1), (-1, 2), and (-1, 3), respectively. On average CDS firms experience an increase in the number of patents by 13.671 from event year -1 to 1. In contrast, the average increase for non-CDS firms is around 3.798. The difference in the increases between CDS and non-CDS firms is not only economically significant but also statistically significant at the 1% level (*p-value* = 0.003). The changes in the number of patents for event windows (-1, 2) and (-1, 3) display larger gaps between CDS and non-CDS firms, indicating that the positive effect of CDS trading on innovation is persistent and increasing over time. This finding is also consistent with the fact that many innovative projects involve long gestation periods.

[Insert Figure 2 Here]

Panel B of Figure 2 presents the results for the number of patent citations. For CDS firms, the number of citations on average increases by 14.510, 17.646, and 18.976 for event windows (-1, 1), (-1, 2), and (-1, 3), respectively. The corresponding increases are only 3.796, 0.313, and 0.556 for non-CDS firms. The differences between CDS and non-CDS firms in the citation increases are statistically significant (*p-value* = 0.002, 0.003, and 0.027 for t = 1, 2, and 3, respectively). Overall, the patterns in Figure 2 suggest that compared with matched non-CDS firms, CDS firms experience larger increases in both the quantity and quality of innovation output after the CDS initiation year. Since these two groups of firms are *ex ante* similar in fundamentals and the propensity of having CDS traded on their debt, the univariate results are consistent with our conjecture that CDS trading stimulates corporate innovation. Collectively, these findings provide preliminary evidence for the positive relation between CDS trading and corporate innovation output. Although interesting, these unconditional relations require more refined multivariate tests, which we turn to next.

4.2. The baseline model

We conduct multivariate regression analysis using a difference-in-differences (DiD) approach. Our baseline regression specification is written as follows:[14]

$$Ln\left(1 + Innovation_{i,t}\right) = \beta_0 + \beta_1 CDS\ Trading_{i,t-1} + \gamma Y_{i,t-1} + \delta Firm_i + \theta Year_t + \varepsilon_{i,t}, \quad (2)$$

where $Innovation_{i,t}$, represents our innovation output measures (*Patent* and *Citation*) of firm i in year t. The key independent variable is $CDS\ Trading_{i,t-1}$, which equals one if firm i has CDS trading on its debt during year t-1. β_1 captures the difference-in-differences effect due to CDS

[14] For our setting, a typical DiD approach estimates the following regression using the Ordinary Least Squares (OLS) estimation: $Innovation = \beta_0 + \beta_1 \times CDS\ Firm \times Post + \beta_2 CDS\ Firm + \beta_3 Post + \gamma Y + \varepsilon$. *CDS Firm* is the treatment variable that equals one if a firm has a traded CDS contract on its debt at any time during our sample period, and zero otherwise. The post-treatment indicator (*Post*) equals one in the post-CDS period, and zero otherwise. When year and firm fixed effects are included, there is no need to include the non-interacted *Post* and *CDS Firm* dummy variables. Then the DiD model is reduced to Eq. (2), because by construction, *CDS Trading* = *CDS Firm* × *Post*.

trade initiation. As we have logarithmically transformed the innovation measures to reduce skewness of the dependent variables, β_1 yields the percentage of innovation differential that can be attributed to CDS trading. *Y* represents the set of control variables described in Section 3.2. Except for *Stock Volatility*, which are measured between year *t*-1 and *t*, all control variables are measured at *t*-1 in the regressions. We include firm fixed effects to control for the impact of unobservable time-invariant firm characteristics. Year fixed effects are included to account for the aggregate time variation in innovation output. The standard errors of the estimated coefficients allow for clustering of observations by firm but our conclusions are not affected if we allow clustering by both firm and year.

The baseline regression results are presented in Table 3. Columns (1) and (2) present the results on patent count and citation count, respectively. In both columns, the coefficients on *CDS Trading* are positive and statistically significant (*t*-statistics = 3.3 in both columns), suggesting that compared with non-CDS firms, CDS firms experience a greater increase in the number of patents and patent citations after CDS trade initiation. Economically, the coefficient of *CDS Trading* in column (1) implies that after the initiation of CDS trading, on average the annual increase in the number of patents for CDS firm is 9.883 more than that for non-CDS firms.[15] This difference-in-differences effect is approximately 14.8% of the mean value of *Patent* (78.148). Column (2) indicates that after CDS trade initiation, on average, the annual increase in the number of patent citations for CDS firms is 11.493 more than that for non-CDS firms. The citation differential amounts to 20.2% of the average number of citations (63.703) across firms.

[15] Specifically, because $d[Ln(1+y)]/dx = [1/(1+y)]\ dy/dx$, $dy = d[Ln(1+y)]/dx \times (1+y)dx$. For example, when quantifying the effect of the change in *CDS Trading* (dx) on the change in *Patent* (dy), we increase *CDS Trading* from zero to one, so $dx = 1$. The change in *Patent* (dy) from its mean value (78.148) is then equal to $0.147 \times (1+78.148) \times 1 = 11.63$, which amounts to 14.8% of the mean value of *Patent*.

Untabulated statistics show that the mean Variance Inflation Factor (VIF) is below 2, suggesting that multicollinearity is not a major issue in our setting.

[Insert Table 3 Here]

The coefficients of control variables are largely consistent with prior literature (e.g., Hirshleifer, Low, and Teoh, 2012; Chang et al., 2015). For instance, larger and older firms and those with higher capital intensity have more patents and citations. Further, firms investing more in R&D generate greater innovation output. Firms with lower leverage, higher market-to-book ratio, more cash holdings, or greater stock volatility are more innovative.

We perform a number of additional tests to ensure that our baseline results are robust to alternative matching methods, model specifications, and variable definitions. For brevity, we only tabulate the coefficients of CDS-related variables in Appendix B. In particular, none of the following has a major effect on our results: (*a*) using an alternative matching method requiring a CDS firm and the matched non-CDS firm to be in the same two-digit SIC industry to alleviate the concern that our results are driven by the industry differences between the two groups of firms;[16] (*b*) running negative binomial regressions (instead of OLS regressions) to address the issue that patent and citation counts are non-negative and discrete;[17] (*c*) using innovation output measures at t+2 (rather than at t) as the dependent variables to account for the possibility that it may take more than one year for CDS trading to have effects on innovation;[18] (*d*) excluding

[16] In untabulated tests, we use another two matching criteria and obtain similar results. First, when matching each CDS firm with a non-CDS firm, we require the difference in the propensity score between the two firms to be less than 0.01. This reduces the sample to 11,420 firm-year observations since some CDS firms do not have very close matches. Second, we match each CDS firm with two non-CDS firms that have the closest propensity scores with the CDS firm. The inclusion of additional matching firms increases our sample size to 33,272 firm-year observations.

[17] For this test, the dependent variables are the numbers of patents and adjusted citations, rather than their log values. To control for the time-invariant firm characteristics that can be correlated with innovation output, we use a mean scaling approach (Aghion, Van Reenen, and Zingales, 2013), which involves including the pre-sample average of patents and citations between 1976 and 1997 in the negative binomial model.

[18] The results remain qualitatively the same if we use innovation output measured at t+1 or t+3 as dependent variables.

firm-years with zero patents and citations; (*e*) excluding self-citations when defining *Citation* to address the concern that the number of citations can be inflated by firms continuously citing their own patents; (*f*) using as dependent variable, the average citations per patent (rather than total citations) that measure the average importance or quality of patents; (*g*) excluding firms engaging in mergers and acquisitions (identified using the Securities Data Company Mergers & Acquisitions database) in the previous two years, to address the concern that firms may acquire patents and citations through takeovers rather than via in-house innovation activities incentivized by CDS trading; (*h*) excluding the period of the technology boom (1998–2000) to address the concern that the presence of highly risky new-economy firms drives both innovation output and CDS trade initiation.

4.3. Tests on endogeneity

While we have documented a robust positive relation between CDS trading and corporate innovation, its causal interpretation remains hypothetical. Apart from the selection issue discussed in Section 3.3, our main results are potentially subject to two types of endogeneity. The first type is omitted variable bias. Although in Eq. (2) we have controlled for a standard set of variables that have been shown by previous studies to affect corporate innovation, the CDS-innovation relation may be spurious if our model omits any variables affecting both innovation and the presence of CDS on a firm's debt. The other plausible endogeneity issue is reverse causality running from corporate innovation to CDS trade initiation. For instance, if lenders observe borrowing firms' increasing levels of risky investment in innovation, they may initiate CDS trading to hedge their exposure to these borrowers. To alleviate these endogeneity concerns (i.e., selection bias, omitted variables, and reverse causality), our first strategy is to explicitly describe the issues that we can think of, and design specific tests to address them. In our second strategy, we use the instrumental variable approach to mitigate any remaining endogeneity concerns. We tabulate the results of the endogeneity tests in Table 4. While all control variables in Eq. (2) are still included in the new tests, we only report the coefficients of *CDS Trading* and the newly added variables for brevity.

[Insert Table 4 Here]

4.3.1. Tests on selection issues

Our matched-sample analysis is designed to address the selection concern that CDS firms are different from non-CDS firms in ways that are systematically related to innovation output. To further alleviate this concern, we conduct two additional analyses. First, we follow Subrahmanyam, Tang, and Wang (2014) and add to our baseline model a binary variable (*CDS Firm*) that equals one if a reference firm has CDS trading on its debt at any time during the entire sample period, and zero otherwise. *CDS Firm* is used to capture the unobservable differences that may drive the differences in innovation output between CDS and matched non-CDS firms. Because *CDS Firm* is a time-invariant variable, we replace firm fixed effects with two-digit SIC industry fixed effects. The regression results reported in Panel A of Table 4 show that our main results still hold.

Second, we avoid selection concerns by conditioning the sample on firm-years that have CDS trading (i.e., firm-years for which *CDS Trading* = 1). Using this sub-sample, we relate corporate innovation to the three CDS liquidity measures defined in Section 3.2 (i.e., *Daily Quotes*, *Distinct Dealers*, and *Distinct Maturities*). Saretto and Tookes (2013) argue that more liquid CDS contracts are easier and less costly to trade, thereby increasing the likelihood of lenders using CDS contracts as hedging instruments. We thus expect the CDS effect on innovation to be stronger when the CDS market referencing borrowers' debt is more liquid. Panels B1-B3 of Table 4 report the regression results obtained by replacing *CDS Trading* in Eq. (1) with our three CDS liquidity measures, respectively. Despite that the sample is reduced to 4,330-4,579 firm-years, the coefficients of the three CDS liquidity measures are positive and statistically significant with *t*-statistics ranging from 2.1 to 3.9. In terms of economic significance, for example, a one-standard-deviation rise in *Daily Quotes* increases *Patent* (*Citation*) by 6.1% (12.1%) from its mean value.[19] These results not only reveal the positive effect of CDS contract liquidity on corporate innovation, but also suggest that our main finding is robust to this alternative procedure of controlling for selection bias.

4.3.2. Tests on omitted variables

We conduct several tests to tackle the omitted variables problem. First, we augment the baseline model by replacing year fixed effects with two pairs of fixed effects, i.e., the location state-by-year and industry-by-year fixed effects. We include state-by-year fixed effects to account for unobserved, time-varying state-level factors, such as political economy or local business cycles. For instance, prior studies (e.g., Amore, Schneider, and Zaldokas, 2013; Cornaggia et al., 2015) document that the staggered banking deregulation across U.S. states affects corporate innovation output through enhancing state-level credit supply. As such, deregulation of state-level banking and branching may drive both corporate innovation and the demand/supply of CDS for credit protection. We determine a firm's location state based on the location of its headquarter, which is usually where its major operations and plants are located (Gormley and Matsa, 2016). We include industry-by-year fixed effects to control for potential

[19] The standard deviation of *Daily Quotes* is 59.742, thus a one-standard-deviation rise in *Daily Quotes* is associated with a 0.001 × (1+78.148) ×59.742 = 9.45 increase in *Patent*, which is equivalent to 6.1% of its mean (78.148).

differential trends in patenting activities and CDS trading across industries over time. Panel C of Table 4 suggests that our main results continue to hold after including both state-by-year and industry-by-year fixed effects.

Second, the key variable of our interest, *CDS Trading*, is constructed using the actual CDS trade initiation dates, which exhibit a clustered pattern (Panel A of Appendix A). Thus, it is possible that the concentration of CDS trade initiations around particular time periods could give rise to spurious results. We employ the methodology of Bekaert, Harvey, and Lundblad (2005) to address this concern. Specifically, we draw 782 uniform random numbers and randomly assign one of the actual CDS initiation dates to each of the 782 CDS firms in our sample. We then re-estimate Eq. (2) using CDS and matched non-CDS firms with randomly assigned initiation dates, and repeat the simulation procedure one thousand times. Because the distribution of actual CDS initiation dates is preserved in simulated data, if our main results are driven by event clustering, many of the replications should yield coefficients close to those obtained using the actual initiation dates. The results reported in Panel D of Table 4 indicate that this is not the case. Both the mean and the median of the coefficients for *CDS Trading*, which is constructed using randomized CDS initiation dates, are very close to zero. The coefficients reported in Table 3 (0.147 and 0.199) are very far out in the right tail of the distribution (i.e., higher than the 99th percentiles), implying that assigning the initiation date to the right firm really matters and that our results are not merely a statistical artifact reflecting certain time trends or event clustering.

In Panel E we augment Eq. (2) by including a set of additional control variables that proxy for corporate governance, which may affect both CDS trade initiation and corporate innovation. For instance, on the one hand, prior studies (e.g., Bhojraj and Sengupta, 2003) document that poor governance mechanisms can increase default risk by aggravating agency costs and information asymmetry between a firm and its lenders, thereby increasing the likelihood of lenders using CDS for hedging. On the other hand, Chemmanur and Tian (2011) show that firms shielded with a larger number of anti-takeover provisions generate better innovative outcomes because anti-takeover provisions alleviate the short-term pressure on managers from the corporate control market. To ensure our findings are not driven by corporate governance, we include as additional controls the governance index (*G*-index) compiled by Gompers, Ishii, and Metrick (2003), board size, and institutional ownership. Because of missing values for these additional controls, we perform our analysis with a much smaller sample of 5,317 firm-year observations. Our main results, however, are unaffected.[20]

4.3.3. Tests on reverse causality

Next, we conduct two tests to alleviate the reverse causality concern. First, we examine the dynamics of innovation differentials between CDS and non-CDS firms over the years surrounding CDS trade initiation. If reverse causality drives our results, we should observe increases in innovation output prior to CDS trade initiation. To detect this possibility, we use the method of Bertrand and Mullainathan (2003) and replace *CDS Trading* in Eq. (2) with five year indicators, namely, $Year^{-2}$, $Year^{-1}$, $Year^{0}$, $Year^{+1}$, and $Year^{\geq+2}$. $Year^{j}$ equals one in the j^{th} year relative to the year of CDS trade initiation, and zero otherwise. $Year^{\geq+2}$ captures the CDS effects from the second year after CDS trade initiation onwards. The results presented in Panel F of Table 4 show that the coefficients of $Year^{-2}$, $Year^{-1}$, and $Year^{0}$ are statistically insignificant, suggesting that compared with the matched non-CDS firms, CDS firms do not have greater

[20] In untabulated tests, we also find that results are robust to controlling for alternative proxies for corporate governance (e.g., the percentage of independent directors), an proxy for management quality (Milbourn, 2003), which is abnormal stock returns (CAPM adjusted) accumulated over the period [*t*-3, *t*-1], or the measures of financial constraints (e.g., Kaplan and Zingales' (1997) and Whited and Wu's (2006) indices).

innovation output before and during the year of CDS trade initiation. This finding to a large extent ameliorates the reverse causality concern. Further, the coefficients of $Year^{+1}$ and $Year^{\geq +2}$ are positive and significant (*t*-statistics ranging from 2.2 to 3.2), indicating that the innovation differentials appear only *after* the advent of CDS trading. Interestingly, the coefficients of $Year^{\geq +2}$ (0.204 and 0.15) are larger than those of $Year^{+1}$ (0.106 and 0.099), indicating that while the CDS effect on innovation manifests immediately (i.e., one year after CDS trade initiation), it becomes much stronger subsequently. This result is consistent with the patterns in Figure 2.

Second, we incorporate into Eq. (2) several additional variables to explicitly account for reverse causality that a borrowing firm' innovative activities increase its risk profile and thus increase its lenders' needs for CDS trading. Specially, to control for the level of innovation investment, we measure past innovation investment (past innovation success) as the rolling average *R&D/Assets* (number of patents or citations) during the previous five years, i.e., from year *t*-2 to *t*-6.[21] Moreover, we use forward looking implied volatility to capture borrowing firms' perceived risk by CDS market participants. Hilscher, Pollet, and Wilson (2015) show that information in equity markets leads information in CDS markets, thus forward looking implied volatility, which is estimated using stock and option prices, should help gauge investors' risk perception in CDS markets. The results, reported in Panel G of Table 4, reveal that the coefficients of *CDS Trading* remain positive and significant, substantiating forward causality running from CDS trading to innovation.

4.3.4. The instrumental variable approach

[21] Alternatively, in untabulated tests, we measure past innovation investment (past innovation success) as the pre-sample five-year average *R&D/Assets* during 1991–1996, and obtain similar results.

To further address endogeneity concerns, especially those not particularly identified previously, we employ an instrumental variable approach similar to that of Subrahmanyam, Tang, and Wang (2014) and Saretto and Tookes (2013). Specifically, we employ lenders' hedging activities on foreign exchange (*Lender FX hedging*) as the instrumental variable for CDS trading. Minton, Stulz, and Williamson (2009) find that banks that hedge tend to hedge more than one component of their portfolios. In particular, they document that banks hedging their currency risk using foreign exchange derivatives tend to hedge their credit risk using CDS as well. Thus, from a relevance perspective, lending banks' foreign exchange hedging activities should be positively correlated with their hedging demand using CDS and the likelihood of CDS contracts being initiated on their borrowers. This instrument is likely to meet exclusion criteria because lenders' foreign exchange derivatives position is a macro hedge rather than a firm-level hedge. Lenders' foreign exchange hedging should not directly drive borrowing firms' innovation output. We define *Lender FX hedging* as the average notional volume of foreign exchange derivatives used for hedging (not trading) purposes relative to the bank's total assets, across all the banks that have served either as lenders or bond underwriters to the firm over the previous five years.[22]

We then follow Saretto and Tookes (2013) and employ Wooldridge's (2002) three-step procedure, which involves using the fitted probability from a probit model for *CDS Trading* as the instrumental variable. In the first step, we predict *CDS Trading* as in Table 1 using *Lender FX hedging* as the instrument. In steps 2 and 3, we use a standard two-stage least squares (2SLS) approach, with the predicted value obtained from step 1 as the instrument.[23] The first-step

[22] We identity firms' lenders using the Dealscan syndicated loan database. Bond underwriters are identified using the Mergent Fixed Income Securities Database (FISD). We then use Federal Reserve call report data to obtain the foreign exchange derivative positions of the lenders and bond underwriters.
[23] Wooldridge (2002) shows that, under fairly general conditions, this procedure provides efficient estimations. In addition, as we use the fitted value of *CDS Trading* as an instrument, the effect of misspecification in the first-step probit model is mitigated.

regression (untabulated) shows that *Lender FX hedging* indeed positively and significantly predicts *CDS Trading* (t-statistic =3.7), suggesting that the instrument meets the relevance criteria econometrically. The weak instrument test (untabulated) generates a p-value less than 0.01, thus rejecting the weak instrument hypothesis. We then replace the actual CDS trading indicator in Eq. (2) with the fitted value of CDS trading from the first-stage regression. The results of the second-stage regressions are presented in Panel H of Table 4. The panel shows that the coefficients of fitted *CDS Trading* are positive and statistically significant at the 5% level in both regression models with patent and citation counts as the dependent variables. This evidence is consistent with a causal interpretation of the CDS effect on corporate innovation.

To summarize, while endogeneity is a perennial issue that no empirical test can entirely rule out, we conduct a battery of tests to alleviate these endogeneity concerns, and find that our main conclusion holds. Although each test can be subject to criticism, the balance of evidence points to a causal relation going from CDS trading to corporate innovation.

5. Additional Analysis

Our baseline results imply a positive and causal relation between CDS trading and corporate innovation. In this section, we conduct a number of tests to pin down the channel through which CDS trading enhances borrowing firms' innovation output. If the risk-taking channel plays an important role in shaping the positive CDS trading-innovation relation, the effect of CDS trading on innovation should be more pronounced for firms where debt financing is less compatible with borrowing firms' risk taking in innovation. Furthermore, after the advent of CDS trading, borrowing firms' innovation efforts should be directed towards more risky innovation projects. Also, we use several tests to examine the possibility that CDS trading promotes innovation through alleviating borrowing firms' financing constraints and allowing more innovative projects to be financed by new debt issuance. Finally, we examine the effect of CDS trading on firm innovation efficiency to reconcile our findings that CDS trading improves innovation output but do not have significant impact on R&D input. We further investigate whether patents generated after CDS trading have higher economic values, instead of simply scientific values in terms of citations.

5.1. Cross-section differences in results

Our regression results so far show that CDS trading enhances corporate innovation. In this section, we conduct a number of cross-section tests to identify the channels through which CDS trading impacts corporate innovation. Following the practice of the difference-in-differences approach (e.g., Low, 2009), we use variables one year prior to the initiation of CDS trading to partition the sample and examine the cross-sectional difference in our regression results. Again, we only report the coefficient on CDS trading, the key variable of interest for brevity.

We first examine the effect of firms' debt financing dependence on the results. Since CDS is a debt market financial derivative, we expect that the effect of CDS trading on innovation is stronger when firms are more dependent on debt financing. To test this prediction, we divide our sample firms into two groups according to the sample median of industry debt financing dependence, where firm level debt financing dependence is calculated as sum of net amount of debt issued over the past decade divided by the sum of capital expenditures over the past decade according to Rajan and Zingales (1998) and Duchin, Ozbas, and Sensoy (2010), and perform the regression in Eq. (2) on the two subsamples of firms with high and low values separately. The results are presented in Panel A of Table 5. The results show that the coefficient of *CDS trading* is positive and significant only for the subsample of firms in industries with higher dependence on debt financing, suggesting that CDS trading mainly affects innovative output of firms in industries that are more dependent on debt. This finding is consistent with the view that CDS trading mitigates the agency problem in debt market resulting in more risk-tolerant creditors, and thus is beneficial for firms' innovative output.

Second, we examine the impact of bank debt on the relation between CDS trading and innovative output. Compared with public bondholders, banks are usually more conservative (e.g., impose more restrictions through covenants) and are more likely to exert active intervention on firms' operation, and thus are likely to be more harmful to corporate innovation (Rajan and Zingales, 2003; Atanassov, 2015). Hence we expect that the positive effect of CDS trading on innovative output is stronger for firms with bank debt. To test this prediction, we partition the sample into two groups of firms with and without bank debt. We then perform the regression in Eq. (2) for the two groups, respectively. The results are presented in Panel B of Table 5. Consistent with our expectation, the results indicate that the positive relations between CDS trading and both patent and citation counts are mostly driven by the subsample of firms with bank debt.

[Insert Table 5 Here]

Third, we examine how the number of bank lenders affects the relation between CDS trading and corporate innovativeness. The firm-lender relationship tends to be stronger if a firm has fewer bank lenders (Carvalho, Ferreira, and Matos, 2013). Relationship lenders are more likely to constrain their borrowers due to their information advantage and strong bargaining power (Rajan, 1992; Petersen, 1999; Pinkowitz and Williamson, 2001). Hence we expect the effect of CDS trading on corporate innovation to be stronger for firms with fewer bank lenders. To test the prediction, we partition a subsample of firms with bank debt into two groups with low and high number of lending banks according to the sample median. Then, we perform the regression in Eq. (2) for the two groups and present the results in Panel C of Table 5. The results show that the positive relation between CDS trading and patent or citation counts is stronger for firms with a smaller number of lending banks.

Fourth, we examine how the relation between CDS trading and corporate innovation varies depending on debt covenant intensity. To protect their own interest, banks lenders usually include debt covenants in the loan agreement to limit firms' ability to engage in risky investment projects, which are detrimental to innovation. Hence we would expect the effect of CDS trading on corporate innovation to be stronger for firms with debt covenants.[24] To test the prediction, we partition firms with bank debt into two groups according to covenant intensity. Specifically, high covenant intensity group includes firms with at least one of the above two types of covenants, while low covenant intensity group includes firms neither of the two types of covenants. We estimate the regression in Eq. (2) on the two groups separately and present the results in Panel D of Table 5. The results show that the effect of CDS trading on corporate innovation is positive and significant for firms with high covenant intensity but insignificant for firms with low covenant intensity.

Fifth, we examine how the effect of CDS trading on corporate innovation differs according to debt maturity. Hasan, O'Brien, and Ye (2013) argue that short-term bondholders are more myopic and are more likely to pursue safe investments, which may have an adverse effect on corporate innovative success. Thus we expect the effect of CDS trading on firms' innovative outcome to be more pronounced in firms that have more short-term debt. To examine this

[24] We focus on two types of loan covenants that directly affect firm investments, namely, secured debt and financial ratio covenants. Secured debt covenant requires that the borrowing firm protect the loan with a collateral asset that is at least of the same value as the face value of the loan. Financial ratio covenant is based on various common accounting ratios that the firm must maintain while the debt is outstanding.

prediction, we split the sample firms into two groups of firms with shorter and longer maturity debt according to the sample median, where debt maturity is defined as the proportion of debts that will mature within 3 years.[25] We then estimate the regression in Eq. (2) for the two groups separately and present the results in Panel E of Table 5. The results show that the coefficient of CDS trading is positive and significant for the subsample of firms with higher proportion of short-term debt but statistically insignificant for the subsample of firms with low proportion of short-term debt. Collectively, the findings in Panels A to E provide further support to our arguments that CDS trading enhances creditors' risk-taking incentive and debtholders' myopia by alleviating their concern on borrowing firms' default risk.

Last, we examine the role of financial distress in the relation between CDS trading and corporate innovation. Since financial distress increases the likelihood of firms' debt renegotiations, CDS-insured creditors might become tougher in firms' debt renegotiations because they have more bargaining power and require better conditions in order to agree on a renegotiation (Bolton and Oehmke, 2011).[26] If CDS-insured creditors become tougher in case of financial distress, firms that anticipate this incentive may choose to adopt conservative corporate policies ex ante at the expense of shareholders, which offsets the positive role of CDS trading in aligning the interests of creditors and shareholders. Alternatively, CDS-insured creditors may restrict firms' risk taking ex ante to avoid higher premiums charged by CDS sellers on risky reference entities (Shan, Tang, and Winton, 2015). Either way, we would expect that the positive effect of CDS trading on innovation is weaker for financially distressed firms.

[25] We obtain similar results if we define short-term debt as the proportion of debt that will mature within 1 year.
[26] As supporting evidence, Subrahmanyam, Tang, and Wang (2014) and Danis (2015) document an increased bankruptcy risk after CDS introduction.

To test this prediction, we partition firms into financially undistressed firms and distressed firms according to Altman's *Z*-score.[27] Specifically, financially undistressed firms are those with *Z*-score in the top quartile for two consecutive years prior to CDS introduction, while financially distressed firms are those with *Z*-score in the bottom quartile for two consecutive years prior to CDS introduction. We then perform the regression in Eq. (2) for the two groups separately and present the results in Panel F of Table 5. The results show that the coefficient of CDS trading is positive and significant for the subsample of financially undistressed firms but negative for the subsample of financially distressed firms despite an insignificant sign. The findings are consistent with the notion that financially distressed firms are indeed concerned about CDS-insured creditors becoming tougher in the debt renegotiation. However, it is less likely to be a dominant force for our results.

5.2. Innovation strategies

In this subsection, we explore the effect of CDS trading on firms' innovation strategies. Corporate innovation strategies are highly heterogeneous and play an essential role in maintaining corporate competitive advantages (Hall, 1993; Cockburn, Henderson, and Stern, 2000). We focus on three types of innovation strategies, i.e., exploratory versus exploitative innovation, production innovation versus process innovation as well as patent originality and generality.

First, we examine the effect of CDS trading on firms' strategic choice between exploratory innovation and exploitative innovation.[28] Exploratory innovation involves a high level of radical

[27] The results are similar if we use Ohlson's *O*-score as an alternative measure of financial distress.

[28] Prior literature has identified two innovation strategies with distinct impact on firm performance. See Levinthal and March (1993), McGrath (2001), Benner and Tushman (2002), and Smith and Tushman (2005) for detailed description of the two strategies, and Katila and Ahuja (2002), He and Wong (2004), Uotila, Maula, Keil, and Zahra (2009) for a discussion of the distinct impact of the two strategies on firm performance.

innovation outside of the firm's knowledge base and thus takes longer time to realize and is more risky, while exploitative innovation is based on firms' existing business activity and knowledge and thus has a short development cycle and less uncertainty. We define exploratory and exploitative patents following Benner and Tushman (2002) and Gao, Hsu and Li (2014). Specifically, a patent is categorized as exploratory if 60 percent or more of its citations are based on new knowledge outside of a firm's existing expertise (i.e., not citing the firm's existing patents or the citations made by those patents), while a patent is categorized as exploitative if 60 percent or more of its citations are based on a firm's existing expertise (i.e., the firm's existing patents and the citations made by those patents). We then divide the number of patents falling into each category by the total number of patents applied by each firm in each year. We perform the same regression specification as in Eq. (1), with the dependent variables being the proportion of exploitative and exploratory patents, respectively. The results presented in columns (1) and (2) of Table 6 show that CDS trading is positively and significantly related to the proportion of exploratory patents, while negatively related to the proportion of exploitative patents.

[Insert Table 6 Here]

Second, we test how CDS trading affects firms' production and process innovation output. According to Chava et al. (2013), production innovation, compared with process innovation, helps create new products, and thus is more risky but potentially more beneficial. We follow Chava et al. (2013) and define patents that fall into the International Patent Classification (IPC) category B01 as process patents and defined all other patents as product patents.[29] We then estimate the regression model in Eq. (1) with dependent variables being the logarithm of one plus product patent counts and process patent counts, respectively. The results are reported in columns (3) and (4) of Table 6. These findings indicate that CDS trading has a positive and

[29] IPC category B01 mainly focuses on Physical and Chemical Process.

significant association with product innovation but an insignificant association with process innovation.

Third, we investigate the role of CDS trading in affecting the distribution of citations by employing a patent-based measure, i.e., patent originality. Patent originality reflects how far a patent is away from the extant technology class, and thus indicates the impact of innovation. Following Hall, Jaffe, and Trajtenberg (2001), we define originality as the mean of the originality scores of a firm's patents, where the originality score of each patent is calculated as one minus the Herfindahl index of the three-digit technology class distribution of all the patents that this patent cites. We estimate the same regression specification as in Eq. (2) by replacing patent and citation counts with patent originality. The results are reported in columns (5) of Table 6. These findings show that CDS trading is positively and significantly related to both patent originality scores.

Taken together, the findings in Table 6 provide more supportive evidence to our argument that CDS trading promotes corporate innovation through encouraging managers' risk-taking incentives and motivating managers' to take long perspectives.

5.3. Testing the financing channel

CDS trading may also affect corporate innovation through a financing channel: CDS trading increases firms' debt capacity (Saretto and Tookes, 2013), and thus enables firms to make more innovation investment that is financed with additional debt issuance. We develop three tests to examine this channel. First, we control for the possible increase in firms' debt financing capacity associated with the CDS introduction. Specifically we estimate the regression in Eq. (2) with two additional controls, namely, the change in firms' leverage ratio from year t-1 to year t+1 and firms' total net debt issuance from year t-1 to year t+1. The results are presented in Panel A of Table 7. The panel shows that the coefficient on *CDS trading* remains positive and significant in the regression of both patent and citation counts at the 1% level, suggesting that the positive effect of CDS trading on corporate innovation is not driven by the increase in firms' debt financing.

[Insert Table 7 Here]

Second, we examine the effect of CDS trading on firms' R&D investments, the input of innovative projects. If CDS trading fosters corporate innovation through improving the funding of innovative projects, we would expect an increase in R&D investments after the CDS introduction. We estimate the regression in Eq. (1) with the dependent variable being R&D investments, which is defined as the ratio of firm's R&D expenditure over book assets. The results are presented in Panel B of Table 7, showing that the coefficient on *CDS trading* is statistically insignificant with or without controlling for lagged R&D investments. The findings suggest that CDS trading does not enhance the funding of innovative projects, but rather aligns the interests of creditors and shareholders and thus fosters innovation.

Third, we examine the cross-sectional difference in results depending on firms' financial constraints by partitioning the sample according to Hadlock and Pierce's (2010) financial constraint index (HP index), firms' tangibility ratio, and whether the firm has investment-grade credit rating, respectively.[30] Specifically, a firm is defined as financially constrained if its HP index is above the sample median, if its tangibility is below the sample median, or if it does not have the investment-grade bond rating, and a firm is defined financially unconstrained if its HP index is below the sample median, if its tangibility is above the sample median, or if it has the

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[30] Hadlock and Pierce's (2010) index is defined as -0.737 × *Ln* (*Assets*) + 0.043 × *Ln* (*Assets*)^2 - 0.04 × *Firm age*. Hence a higher HP index indicates more financial constraint. Tangibility ratio is defined as the natural logarithm of net property, plant, and equipment over the number of employees. In addition, firms with higher tangibility or investment grade rating have better access to external finance and thus are less likely to be financially constrained.

investment-grade bond rating. Similar to the tests of cross-sectional difference in Section 5.1, we use partitioning variables one year prior to the initiation of CDS trading to split the sample.

We estimate the regression in Eq. (2) for the financially constrained and unconstrained subsamples separately. The regression results are presented in Panel C of Table 7. These results show that the effect of CDS trading on innovative outcomes is not affected by firms' financial constraint status, suggesting that the argument that CDS trading relaxes financial constraint through increasing firms' debt financing capacity is less likely to be a dominant explanation to our findings.

5.4. Innovation efficiency and value creation from innovation

Our baseline results in Table 3 show that firms' number of patents and citations increase significantly after CDS trading, suggesting that CDS trading enhances innovative output. Nevertheless, the results in Panel B of Table 7 show that R&D investments which are innovative inputs do not experience any significant change around CDS trading. To reconcile these findings, we examine the effect of CDS trading on firms' innovation efficiency, i.e., how efficiently firms are able to utilize R&D investment and converting them into patents, Specifically, we follow Hirshleifer, Hsu, and Li (2013) and construct innovation efficiency measures as the natural logarithm of one plus the number of patents and citations over the average R&D expenditures in the past five years. We then replace the dependent variables in Eq. (2) with the two innovation efficiency measures and re-estimate the regressions. The results are reported in Columns (1) and (2) of Table 8, showing that the coefficients on CDS trading are positive and significant. These findings suggest that CDS trading enhance innovative output through improving firms' innovation output per dollar R&D expenditures, instead of increasing R&D expenditures itself.

[Insert Table 8 Here]

Since firms direct innovation efforts to more risky innovation projects and are more efficient in generating patents after CDS trading, we further examine, in addition to higher scientific values in terms of citations, whether patents generated after CDS trading also have higher economic values. We follow Kogan et al. (2015) and measure the economic value of patents as measured as the stock market reaction to the announcement of a patent being granted to a public firm by the USPTO. Specifically, we estimate patent value as the increase in market valuation of the firm in the three-day period of patent announcements after adjusting for benchmark return, idiosyncratic stock return volatility, and various fixed-effects.[31] For firms with more than one patent in a fiscal year, we sum the value of all patents filed for that year. Then, we take the natural logarithm of one plus the patent value to mitigate the skewness in patent value. Last, we replace the dependent variables in Eq. (2) with the patent value measures and rerun the regressions. The regression results are reported in Columns (3) and (4) of Table 8. The results show that CDs trading is positively and significantly related to patent value, suggesting that CDS trading enhances the value of the firm through increasing the value creation from innovation.

6. Conclusion

Does financial innovation impede or enhance technological innovation? We address this question via investigating the impact of CDS trading on corporate innovative activities. Using a sample of U.S. listed firms covered by the USPTO from 1997 to 2008, we find evidence that the introduction of CDS trading on a firm' debt increases the firm's innovative output. Firms' patents and patent citations, on average, increase by 17% and 23%, respectively. These findings are robust to various model specifications and variable definitions, and are less likely to be

[31] We download the patent value data from Dimitris Papanikolaou's website (https://dl.dropboxusercontent.com/u/7796025/Website/default.html).

driven by endogeneity issues and a general upward time trend of firms' patenting activities. We further show that the positive effect of CDS trading on innovation is more pronounced for firms that are more dependent on debt financing and for firms with bank debt, fewer bank lenders or greater debt covenant intensity, and for firms with more short-term debt prior to the CDS introduction. Moreover, firms tend to focus on the risky exploratory innovation strategy rather than the relatively safe exploitative innovation strategy, and create more product patents rather than process patents after the inception of CDS trading. In the meanwhile, after CDS is introduced on a firm both the originality and generality of its patents are enhanced. These findings are consistent with the argument that CDS-protected creditors tend to be more tolerant to firms' risk taking and thus encourage firms' innovative activities.

Our study provides new evidence on the real effect of financial innovation, particularly CDS. Recent papers document that CDS relax firms' borrowing constraint, but also create tougher creditors and increase firms' bankruptcy risk. Firms respond by changing their corporate policies. For example, firms borrow more but increase precautionary cash holdings due to the tougher CDS-protected creditors, especially for financially constrained firms. In this paper, we further find that firms, after the introduction of CDS trading on their debt, adjust their innovative activities, which are important to maintain the future growth and competitiveness.

Our findings also contribute to the debate on the impact of debt market on corporate innovation. While previous literature documents the negative effect of debt financing on firms' innovative activities because of the concave payoff structure of creditors, our results suggest that CDS may change creditors' incentive and mitigate the problem. Given a less concave payoff structure from their CDS position, CDS-protected creditors are more tolerant to firms' risk taking and tend to be more long-term focused. As a result, CDS mitigates the negative effect of debt financing on corporate innovation and enhances corporate innovation.

Appendix A: Distributions of CDS firms over time and by industry

The sample consists of firms jointly covered in the CreditTrade, the GFI Group and Markit CDS database, CRSP, and the USPTO patent and citation database between 1997 and 2008. The CDS initiation year is defined as the first year in which a firm has CDS trading on its debt. Panel A reports the distribution of CDS firms by initiation year. Panel B reports the distribution of CDS firms by one-digit SIC industry.

Panel A: Distribution of CDS firms by initiation year

Year	(1) Number of new CDS firms	(2) Percentage of all CDS firms
1997	21	2.7%
1998	41	5.2%
1999	35	4.5%
2000	77	9.8%
2001	207	26.5%
2002	124	15.9%
2003	94	12.0%
2004	80	10.2%
2005	38	4.9%
2006	31	4.0%
2007	26	3.3%
2008	8	1.0%
Total	782	100%

Panel B: Distribution of CDS firms by one-digit SIC industry

Industry	(1) Number of CDS firms	(2) Percentage of all CDS firms
Mining and construction	82	10.5%
Food, petroleum refining, and paper	208	26.6%
Rubber, stone, and computer	213	27.2%
Transportation	99	12.7%
Retail and wholesale	78	10.0%
Business and personal services	80	10.2%
Public services	22	2.8%
Total	782	100.0%

Appendix B: Robustness checks

The sample consists of CDS firms that initiated CDS trading between 1997 and 2008 and the matched non-CDS firms. $\overline{Citation}$ is the average citation counts per patent. All regressions include the same control variables as those in Table 3, but their coefficients are not tabulated. Detailed variable definitions are in the legend of Table 3. The *t*- or *z*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic-consistent errors, which are also corrected for correlation across observations for a given firm. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Matching within the same industry (N = 16,636)

	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
CDS Trading	0.082**	0.076***
	(2.5)	(2.9)

Panel B: Negative binomial regressions (N = 16,636)

	# *of* $Patent_t$	
CDS Trading	0.235**	
	(2.0)	

Panel C: Using corporate innovative output measured at t+3 (N = 13,543)

	$Ln(1+Patent)_{t+2}$	$Ln(1+Citation)_{t+2}$
CDS Trading	0.233***	0.204**
	(3.0)	(2.2)

Panel D: Excluding firm-years with zero patents or citations (N_{patent} = 7,501; $N_{citation}$ = 5,710)

	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
CDS Trading	0.207**	0.244**
	(2.1)	(2.5)

Panel E: Excluding self-citations

		$Ln(1+Citation)_t$
CDS Trading		0.174***
		(3.0)

Panel F: Using average citations per patent as dependent variables (N = 16,636)

		$Ln(1+\overline{Citation})_t$
CDS Trading		0.016*
		(1.8)

Panel G: Excluding firms engaging in M&A transactions in the previous two years (N = 13,320)

	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
CDS Trading	0.169***	0.249***
	(3.3)	(3.7)

Panel H: Excluding the tech bubble period (1998-2000) (N = 12,647)

	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
CDS Trading	0.171***	0.237***
	(3.0)	(3.2)

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Figure 1: Lenders' net payoff with and without CDS protection

The figure shows lenders' net payoffs with and without CDS protection. The horizontal axis denotes the value of borrowing firms' assets and the vertical axis denotes lenders' net payoff. The dashed (solid) line indicates lenders' net payoffs with (without) the CDS protection. With CDS protection, lenders' net payoff is the face of debt minus CDS premiums, which increases with borrowing firms' default risk.

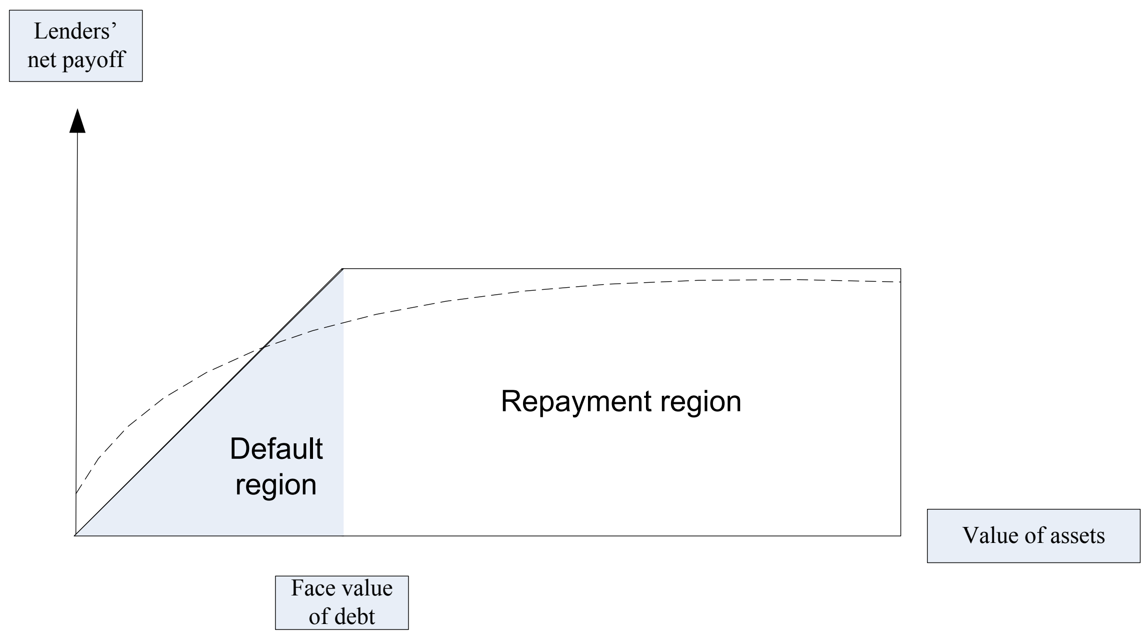
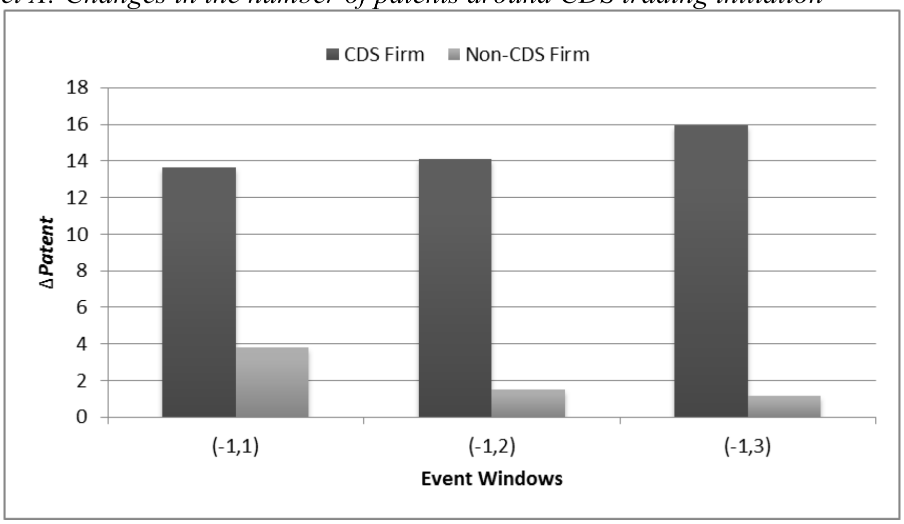


Figure 2: Changes in innovation output around CDS trade initiation

The sample consists of CDS firms that initiated CDS trading between 1997 and 2008 and the matched non-CDS firms jointly The matched non-CDS firms is selected based on the nearest one propensity score matching method, which is estimated using the probit model reported in Panel A of Table 1. *Patent* is the number of patents applied for, during the current year, which are eventually granted. *Citation* is the total number of citations arising from patents. The citations are adjusted using the time-technology class fixed effect. Panel A (B) plots the change in the number of patents (citations) around CDS trade initiation for CDS firms and the matched non-CDS firms separately. For CDS firms, the year of CDS trade initiation is denoted as event year 0. The changes in innovation output are computed from one year before CDS trade initiation (i.e., year -1) to *t* years (*t* = 1, 2, and 3) after CDS trade initiation. The event years of non-CDS firms are defined according to their CDS counterparts.

Panel A: Changes in the number of patents around CDS trading initiation



Panel B: Changes in the number of citations around CDS trading initiation

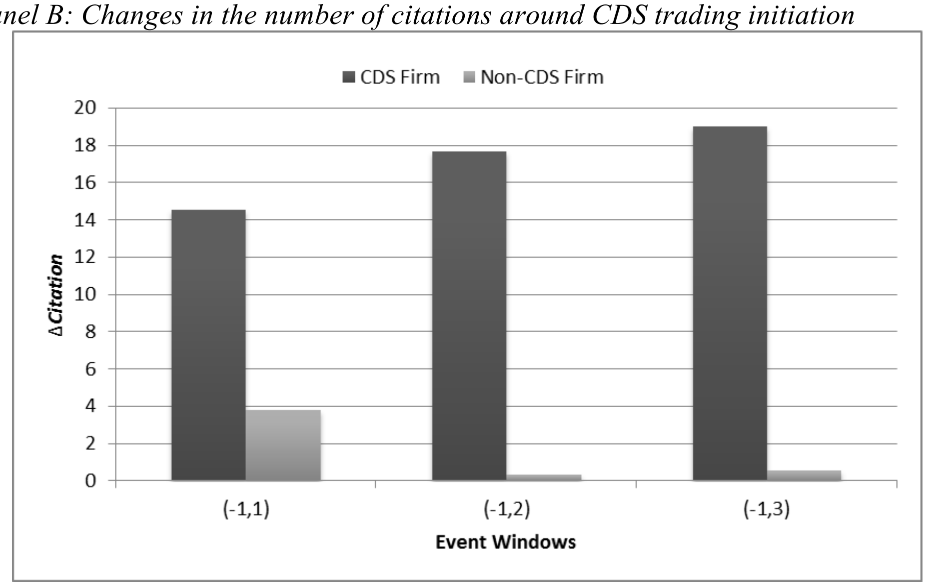


Table 1: The probability of CDS trade initiation and the matched sample

The sample includes our CDS firms and all non-CDS firms that are in Compustat during the period 1997-2008 and have non-missing values for the variables used in the model. Panel A reports the coefficient estimates obtained from estimating a probit model predicting the probability of CDS trade initiation. The dependent variable, *CDS Trading*, equals one in and after the inception year of CDS trading on a reference firm, and zero prior to it. It equals zero for all non-CDS firms. Post-initiation years of CDS firms are excluded from the analysis. *Credit Rating* is an indicator variable that equals one if a borrowing firm has a debt rating assigned by Standard & Poor's, and zero otherwise. *Investment Grade* is an indicator variable that equals one if a borrowing firm has a credit rating assigned by Standard & Poor's above BB+, and zero otherwise. Detailed definitions of other variables are in the legend of Table 2. Constant terms, two-digit SIC industry and year fixed effects are included in the regression, but they are not tabulated. The *z*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic-consistent errors, which are also corrected for correlation across observations for a given firm. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Panel B compares the firm characteristics of CDS firms with those of matched non-CDS firms. *T* tests are conducted to test for differences in mean values between CDS and non-CDS subsamples. The symbols ***, **, and * indicate that subsample means are significantly different from each other at the 1%, 5%, and 10% levels, respectively. Panel C reports the regression results from a probit model predicting the probability of CDS trade initiation using firm characteristics of CDS firms and propensity-score-matched non-CDS firms prior to CDS trade initiation.

Panel A: Probit regression on the probability of CDS trade initiation

Dependent variables	*CDS Trading*
Credit Rating	0.586***
	(9.3)
Investment Grade	0.528***
	(7.8)
Ln(Assets)	0.410***
	(15.6)
Ln(Firm Age)	0.092***
	(3.3)
Ln(*PPE/Employees*)	0.011
	(0.5)
R&D/Assets	0.982
	(1.6)
ROA	-0.157
	(-0.6)
MB	0.036**
	(2.1)
Sales Growth	0.218***
	(4.7)
Leverage	0.853***
	(6.8)
Cash/Assets	-0.338
	(-1.6)
Stock Volatility	-5.583***
	(-3.4)
Herfindahl	1.040*
	(1.8)
Herfindahl^2	-1.014
	(-1.5)
Year FE	X
Industry FE	X
Observations	50,020
Pseudo R-squared	0.465

Panel B: Comparison of firm characteristics prior to CDS trade initiation

Characteristics	(1) CDS firm	(2) Matched non-CDS firm	(3) Difference
Credit Rating	0.898	0.890	0.008
Investment Grade	0.644	0.635	0.009
Ln(*Assets*)	8.615	8.701	-0.086*
Ln(*Firm Age*)	3.000	2.912	0.088*
Ln(*PPE/Employees*)	4.454	4.496	-0.042
R&D/Assets	0.021	0.019	0.001
ROA	0.032	0.018	0.014**
MB	1.967	1.906	0.061
Sales Growth	0.142	0.155	-0.014
Leverage	0.326	0.330	-0.004
Cash/Assets	0.084	0.089	-0.006
Stock Volatility	0.029	0.030	-0.001
Herfindahl	0.155	0.145	0.011
$Herfindahl^2$	0.044	0.038	0.006
Patent	66.973	70.442	-3.469
Citation	50.711	51.888	-1.177
Propensity Score	0.241	0.238	0.003

Panel C: Post-matching Probit regression of CDS trade initiation

Dependent variables	*CDS Trading*
Credit Rating	0.082
	(0.5)
Investment Grade	-0.168
	(-1.1)
Ln(Assets)	0.013
	(0.2)
Ln(Firm Age)	0.059
	(0.8)
Ln(PPE/Employees)	0.028
	(0.4)
R&D/Assets	1.379
	(0.9)
ROA	1.054
	(1.6)
MB	0.036
	(0.6)
Sales Growth	0.023
	(0.2)
Leverage	0.170
	(0.5)
Cash/Assets	-0.320
	(-0.6)
Stock Volatility	-6.709
	(-1.5)
Herfindahl	-1.321
	(-0.9)
Herfindahl^2	1.311
	(0.8)
Year FE	X
Industry FE	X
Observations	1,564
Pseudo R-squared	0.097

Table 2: Summary statistics

The sample consists of CDS firms that CDS trading initiated between 1997 and 2008 and the matched non-CDS firms jointly. *Patent* is the number of patents applied for, during the current year, which are eventually granted. *Citation* is the total number of citations arising from patents. The citations are adjusted using the time-technology class fixed effect. *Ln*(1+*Patent*) is the log of one plus *Patent*. *Ln*(1+*Citation*) is the log of one plus *Citation*. *CDS Trading* is a dummy variable that equals one after the introduction of CDS trading on a reference firm, and zero otherwise. *Daily Quotes* is the average number of CDS daily quotes on a firm in a given year. *Distinct Dealers* is the average number of distinct dealers providing CDS quotes on a firm in a given year. *Distinct Maturities* is the average number of distinct maturities of CDS contract traded on a firm in a given year. *Ln*(*Assets*) is the log of a firm's book value of total assets. *Ln*(*Firm Age*) is the log of the number of years since a firm enters the CRSP database. *Ln*(*PPE/Employees*) is the log of the ratio of net property, plant, and equipment to the number of employees. *R&D* is the R&D expenses scaled by total assets, where missing R&D expenses are treated as zeros. *ROA* is EBIT scaled by total assets. *MB* is the market value of total assets scaled by the book value of total assets. *Sales Growth* is the log of one plus the change in net sales scaled by lagged net sales. *Leverage* is the book value of debts scaled by total assets. *Cash* is the cash holdings scaled by total assets. *Stock Volatility* is the standard deviation of daily stock returns over the fiscal year. *Herfindahl* is the sum of squared market shares in sales of a firm's three-digit SIC industry.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Observations	Mean	Standard deviation	Q1	Median	Q3
<u>Innovation measures</u>						
Patent	16,636	78.148	261.783	0.000	0.000	14.000
Citation	16,636	63.703	240.254	0.000	0.000	7.651
Ln(1+*Patent*)	16,636	1.504	2.136	0.000	0.000	2.708
Ln(1+*Citation*)	16,636	1.251	2.075	0.000	0.000	2.158
<u>CDS variables</u>						
CDS Trading	16,636	0.268	0.443	0.000	0.000	1.000
Daily Quotes	4,579	236	59.742	146	261	262
Distinct Dealers	4,330	6.732	4.588	3.027	5.192	9.828
Distinct Maturities	4,433	7.467	3.451	5.115	8.588	10.485
<u>Control variables in innovation regressions</u>						
Ln(*Assets*)	16,636	8.588	1.526	7.480	8.400	9.789
Ln(*Firm Age*)	16,636	3.061	0.818	2.485	3.178	3.714
Ln(*PPE/Employees*)	16,636	4.454	1.400	3.470	4.291	5.266
R&D/Assets	16,636	0.023	0.046	0.000	0.002	0.028
ROA	16,636	0.088	0.088	0.048	0.084	0.131
MB	16,636	1.863	1.374	1.158	1.465	2.019
Sales Growth	16,636	0.105	0.288	-0.001	0.077	0.168
Leverage	16,636	0.298	0.205	0.152	0.267	0.397
Cash/Assets	16,636	0.105	0.121	0.023	0.063	0.140
Stock Volatility	16,636	0.028	0.015	0.018	0.024	0.033
Herfindahl	16,636	0.159	0.144	0.068	0.108	0.208
Herfindahl^2	16,636	0.046	0.108	0.005	0.012	0.043

Table 3: Effect of CDS trading on innovation output

The sample consists of CDS firms that initiated CDS trading between 1997 and 2008 and the matched non-CDS firms. *Patent* is the number of patents applied for, during the current year, which are eventually granted. *Citation* is the total number of citations arising from patents, which is adjusted using the time-technology class fixed effect. *CDS Trading* equals one if a firm has CDS trading on its debt during a year, and zero otherwise. *Ln*(*Assets*) is the log of a firm's book value of total assets. *Ln*(*Firm Age*) is the log of the number of years since a firm enters the CRSP database. *Ln*(*PPE/Employees*) is the log of the ratio of net property, plant, and equipment to the number of employees. *R&D/Assets* is R&D expenses scaled by total assets. *ROA* is EBIT scaled by total assets. *MB* is the market value of total assets divided by the book value of total assets. *Sales Growth* is the log of one plus the change in net sales scaled by lagged net sales. *Leverage* is the book value of debts scaled by total assets. *Cash/Assets* is the cash holdings scaled by total assets. *Stock Volatility* is the standard deviation of daily stock returns over the fiscal year. Except for *Stock Volatility*, which are measured between year *t*-1 and *t*, all explanatory variables are measured at *t*-1 in the regressions.*Herfindahl* is the sum of squared market shares in sales of a firm's three-digit SIC industry. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic-consistent errors, which are also corrected for correlation across observations for a given firm. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Dependent variables	*Ln*(1+*Patent*)$_t$	*Ln*(1+*Citation*)$_t$
CDS Trading	0.147***	0.199***
	(3.3)	(3.3)
Ln(*Assets*)	0.247***	0.243***
	(5.6)	(4.5)
Ln(*Firm Age*)	0.153	0.297**
	(1.4)	(2.3)
Ln(*PPE/Employees*)	0.286***	0.341***
	(5.1)	(4.9)
R&D/Assets	0.339	0.507
	(0.6)	(0.7)
ROA	0.117	-0.078
	(1.0)	(-0.4)
MB	0.105***	0.156***
	(5.3)	(5.6)
Sales Growth	-0.074	-0.112
	(-1.3)	(-1.4)
Leverage	-0.262*	-0.512***
	(-1.7)	(-2.8)
Cash/Assets	0.723***	0.357
	(2.6)	(0.8)
Stock Volatility	4.823***	8.357***
	(3.4)	(3.5)
Herfindahl	-0.461	0.485
	(-0.8)	(0.6)
Herfindahl^2	0.609	-0.247
	(1.5)	(-0.4)
Firm and year fixed effects	Yes	Yes
N/Adjusted R-squared	16,636/0.895	16,636/0.797

Table 4: Tests on endogeneity

The sample consists of CDS firms that initiated CDS trading between 1997 and 2008 and the matched non-CDS firms. All regressions include the same control variables as those used in Table 3, but their coefficients are not tabulated. *CDS Firm* that equals one if a reference firm has CDS trading on its debt at any time during the entire sample period, and zero otherwise. Detailed definitions of dependent variables and control variables can be found in the legend of Table 2. Panel A presents the regression results using alternative model specification. Panel B presents the regressions results on the effect of CDS liquidity on innovation output. Panel C presents the regression results controlling for state-by-year and industry-by-year fixed effects. Panel D presents the distribution of coefficient estimates of CDS trading and associated t-statistics from regressions by randomizing the years of CDS trading initiation among the sample firms 1000 times. Panel E presents the regression results controlling for other corporate governance measures. Panel F presents the regression results on the test of reverse causality. $Year_{-2}$ ($Year_{-1}$) is a dummy variable that takes the value of one if CDS trading initiates in two (one) years, and zero otherwise. $Year_0$ is a dummy variable that takes the value of one if CDS trading initiates this year, and zero otherwise. $Year_{+1}$ is a dummy variable that takes the value of one if CDS trading initiates one year ago, and zero otherwise. $Year_{\geq+2}$ is a dummy variable that takes the value of one if CDS trading initiates two or more years ago, and zero otherwise. Panel G presents the regression results controlling for pre-sample innovation investments and implied volatility. Panel H presents the second-stage estimation of the two-stage instrumental variable regression results. In the first-stage regression, we predict the probability of CDS trading using *Lender FX Hedging* as the instrument variable. *Lender FX Hedging* is defined as the average of FX derivatives used for hedging purposes, relative to total assets, across the banks that have served as either lenders or bond underwriters for the firm over the previous five years. Detailed definitions of dependent variables and control variables can be found in the legend of Table 2. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by firm. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Using alternative model specification (N =16,636)		
	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
CDS Trading	0.175**	0.221**
	(2.0)	(2.4)
CDS Firm	0.040	0.087
	(0.3)	(0.6)
Panel B: Effect of CDS liquidity on innovation output		
	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
Panel B.1: Number of daily quotes (N = 4,579)		
Daily Quotes	0.001***	0.002***
	(3.9)	(3.8)
Panel B.2: Number of distinct dealers (N = 4,330)		
Distinct Dealers	0.012**	0.029**
	(2.1)	(2.5)
Panel B.3: Number of distinct maturities (N = 4,433)		
Distinct Maturities	0.039***	0.052***
	(2.9)	(2.8)
Panel C: Control for state-by-year and industry-by-year fixed effects (N = 11,605)		
	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
CDS Trading	0.091**	0.091*
	(2.4)	(1.8)
Panel D: Monte Carlo analysis of the effect of CDS trading		
	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
CDS Trading (Mean)	0.003	0.002
	(0.173)	(0.196)
CDS Trading (Median)	0.007	0.008
	(0.155)	(0.116)

CDS Trading (2.5%)	-0.098	-0.162
	(-1.212)	(-1.545)
CDS Trading (10%)	-0.065	-0.084
	(-0.872)	(-1.252)
CDS Trading (90%)	0.064	0.093
	(1.197)	(1.367)
CDS Trading (97.5%)	0.095	0.125
	(1.897)	(1.993)

Panel E: Control for corporate governance measures (N = 5,317)

	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
CDS Trading	0.104***	0.083*
	(3.4)	(1.9)
G-index	0.018	0.020
	(1.2)	(1.0)
Board size	0.026	0.100
	(0.3)	(0.8)
Institutional ownership	0.323***	0.614***
	(2.9)	(3.8)

Panel F: Test of reverse causality (N = 16,636)

	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
$Year_{-2}$	-0.010	-0.052
	(-0.3)	(-1.2)
$Year_{-1}$	0.016	0.011
	(0.5)	(0.2)
$Year_{0}$	0.066**	0.063
	(2.0)	(1.3)
$Year_{+1}$	0.106***	0.099**
	(2.6)	(2.2)
$Year_{\geq+2}$	0.204**	0.150***
	(2.5)	(3.2)

Panel G: Control for pre-sample innovation investments and implied volatility (N = 11,040)

	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
CDS Trading	0.155***	0.227***
	(3.9)	(3.9)
R&D capital	1.266	1.378
	(1.3)	(1.0)
Implied volatility	0.204	0.061
	(1.0)	(0.3)

Panel H: Instrumental variable approach (N = 16,636)

	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
Instrumented CDS Trading	0.258**	0.401**
	(2.0)	(2.3)

Table 5: Cross-sectional differences in the effects of CDS trading on innovation

The sample consists of firms jointly covered in the CreditTrade, the GFI Group and Markit CDS database, CRSP, and the USPTO patent and citation database between 1997 and 2008. In Panel A, the sample is split according to the sample median industry debt financing dependence, where debt financing dependence is defined as the industry median of firms' dependence on debt financing following Rajan and Zingales (1998) and Duchin, Ozbas, and Sensoy (2010). In Panel B, firms' bank debt information is collected from Capital IQ. In Panel C, the sample is split according to the sample median number of banks, where the number of banks is the number of unique banks that lend to the firm. In Panel D, covenant intensity is high (low) if the firm has either collateral requirement or financial ratio covenant in the loan contract (if the firm has neither of the two covenants in the loan contract). In Panel E, the sample is split according to the sample median short-term debt, where short-term debt is defined as the proportion of debts that will mature within three years. In Panel F, financially distressed (undistressed) firms are those with *Z*-score in the bottom (top) quartile for two consecutive years prior to CDS initiation. The same set of control variables as those used in Table 3 is included in all regressions but the coefficient estimates of these variables are not tabulated for brevity. Detailed definitions of other variables can be found in the legend of Table 2. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by firm. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent variables	$Ln(1+Patent)_t$		$Ln(1+Citation)_t$	
Panel A: Partitioning the sample according to industry debt financing dependence (N_{high} = 8,119; N_{low} = 8,517)				
	High	Low	High	Low
CDS Trading	0.303***	0.079	0.342***	0.113
	(3.0)	(0.8)	(3.1)	(0.9)
Panel B: Partitioning the sample according to whether a firm has bank debt (N_{yes} = 5,351; N_{no} = 7,541)				
	Yes	No	Yes	No
CDS Trading	0.158***	-0.005	0.174**	0.036
	(3.4)	(-0.1)	(2.6)	(0.6)
Panel C: Partitioning the sample according to the number of banks (N_{low} = 2,684; N_{high} = 2,667)				
	Low	High	Low	High
CDS Trading	0.227**	0.095	0.298**	0.115
	(2.5)	(1.5)	(2.1)	(1.4)
Panel D: Partitioning the sample according to covenant intensity (N_{high} = 3,136; N_{low} = 2,215)				
	High	Low	High	Low
CDS Trading	0.168**	0.075	0.169*	0.090
	(2.5)	(1.0)	(1.8)	(0.8)
Panel E: Partitioning the sample according to a firm's debt maturity (N_{short} = 8,182; N_{long} = 8,235)				
	Short	Long	Short	Long
CDS Trading	0.183***	-0.013	0.265***	0.001
	(2.8)	(-0.3)	(2.9)	(0.0)
Panel F: Partitioning the sample according to a firm's financial distress ($N_{distressed}$ = 3,112; $N_{undistressed}$ = 2,520)				
	Distressed	Undistressed	Distressed	Undistressed
CDS Trading	-0.093	0.246**	-0.074	0.224*
	(-1.3)	(2.4)	(-1.0)	(1.9)

Table 6: Effect of CDS trading on innovation strategy

The sample consists of firms jointly covered in the CreditTrade, the GFI Group and Markit CDS database, CRSP, and the USPTO patent and citation database between 1997 and 2008. *Exploratory innovation* is the proportion of patents that are exploratory. *Exploitative innovation* is the proportion of patents that are exploitative. A patent is categorized as exploratory if 60 percent or more of its citations are based on new knowledge outside of a firm's existing expertise (i.e., not citing the firm's existing patents or the citations made by those patents), while a patent is categorized as exploitative if 60 percent or more of its citations are based on a firm's existing expertise (i.e., the firm's existing patents and the citations made by those patents). *Process* (*product*) *patent* is the number of patents that fall (do not fall) into IPC 8.0 class B01. *Originality* is defined as the mean of the originality scores of a firm's patents. The originality score of a patent is calculated as one minus the Herfindahl index of the three-digit technology class distribution of all the patents that this patent cites. Detailed definitions of other variables can be found in the legend of Table 2. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by firm. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variables	(1) *Exploratory Innovation*	(2) *Exploitative Innovation*	(3) *Product Innovation*	(4) *Process Innovation*	(5) *Originality Index*
CDS Trading	0.025**	-0.027***	0.149***	0.027	0.029**
	(2.2)	(-2.7)	(3.4)	(0.8)	(2.6)
Ln(*Assets*)	0.012	0.001	0.246***	0.020	0.005
	(1.1)	(0.1)	(5.6)	(1.2)	(0.3)
Ln(*Firm Age*)	-0.182***	0.143***	0.152	0.129**	-0.023
	(-8.9)	(8.0)	(1.4)	(2.1)	(-0.9)
Ln(*PPE/Employees*)	0.046***	-0.055***	0.285***	0.013	0.010
	(3.4)	(-4.8)	(5.1)	(0.9)	(0.5)
R&D/Assets	-0.008	0.092	0.320	-0.002	0.118
	(-0.1)	(0.8)	(0.6)	(-0.0)	(1.4)
ROA	-0.030	0.070	0.118	0.137	-0.011
	(-0.6)	(1.4)	(1.0)	(1.6)	(-0.2)
MB	0.009***	-0.008***	0.105***	0.004	-0.002
	(3.7)	(-3.7)	(5.3)	(0.6)	(-1.1)
Sales Growth	-0.066***	0.047***	-0.072	-0.004	0.013
	(-4.6)	(3.7)	(-1.3)	(-0.2)	(1.0)
Leverage	-0.066*	0.062*	-0.274*	0.096***	0.029
	(-1.8)	(1.9)	(-1.7)	(2.6)	(0.9)
Cash/Assets	-0.162***	0.185***	0.722***	0.222	0.039
	(-3.9)	(4.8)	(2.6)	(1.1)	(1.1)
Stock Volatility	0.513	-0.289	4.871***	0.966	-0.682
	(1.2)	(-0.7)	(3.4)	(1.0)	(-1.4)
Herfindahl	0.149	-0.145	-0.486	-0.071	-0.162
	(0.7)	(-0.8)	(-0.9)	(-0.2)	(-0.8)
Herfindahl^2	-0.204	0.184	0.628	0.126	0.276
	(-1.1)	(1.1)	(1.5)	(0.5)	(1.6)
Year FE	X	X	X	X	X
Firm FE	X	X	X	X	X
Observations	7,775	7,775	16,632	16,632	6,982
Adjusted R-squared	0.580	0.575	0.895	0.707	0.381

Table 7: Testing the financing channel as an alternative explanation

The sample consists of firms jointly covered in the CreditTrade, the GFI Group and Markit CDS database, CRSP, and the USPTO patent and citation database between 1997 and 2008. In Panel A, $\Delta Leverage_{t\text{-}1\ to\ t+1}$ is the change in leverage ratios from $year_{t\text{-}1}$ to $year_{t+1}$. $Net\ Debt\ Issuance_{t\text{-}1\ to\ t+1}$ is the total net debt issued from $year_{t\text{-}1}$ to $year_{t+1}$. Panel B presents the regression results on the effect of CDS trading on R&D investments in $year_{t+1}$. In Panel C, we divide the sample into financially unconstrained subsample (UC) and financially constrained subsample (C) based on the sample median Hadlock and Pierce (2010) index, the sample median tangibility ratio, and whether the firm has investment-grade credit rating or not. The same set of control variables as those used in Table 3 is included in all regressions but the coefficient estimates of these variables are not tabulated for brevity. Detailed definitions of other variables can be found in the legend of Table 2. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by firm. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Controlling for changes in debt financing

	(1)	(2)
Dependent variables	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
CDS Trading	0.149***	0.201***
	(3.4)	(3.3)
$\Delta Leverage_{t\text{-}1\ to\ t+1}$	0.010	-0.036
	(0.1)	(-0.3)
$Net\ Debt\ Issuance_{t\text{-}1\ to\ t+1}$	0.059	0.119
	(0.8)	(1.1)
Other controls	X	X
Year FE	X	X
Firm FE	X	X
Observations	16,628	16,628
Adjusted R-squared	0.895	0.797

Panel B: Effect of CDS trading on R&D investments

	(1)	(2)
Dependent variables	$R\&D_t$	$R\&D_t$
CDS Trading	-0.000	-0.002
	(-0.2)	(-0.8)
$R\&D_t$	0.544***	
	(9.3)	
Other controls	X	X
Year FE	X	X
Firm FE	X	X
Observations	16,636	16,636
Adjusted R-squared	0.871	0.854

Panel C: Partitioning the sample according to a firm's financial constraint status

Table 8: Effect of CDS trading on value creation from innovation

The sample consists of firms jointly covered in the CreditTrade, the GFI Group and Markit CDS database, CRSP, and the USPTO patent and citation database between 1997 and 2008. The dependent variable in column (1) is the natural logarithm of one plus the number of patents over the average R&D expenditures in the past five years. The dependent variable in column (2) is the natural logarithm of one plus the number of citations over the average R&D expenditures in the past five years. The dependent variable in column (3) is the log of one plus the sum of estimated patent value from Kogan, Papanikolaou, Seru, and Stoffman (2015). Detailed definitions of other variables can be found in the legend of Table 2. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by firm. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variables	(1) $Ln(1+Patent/R\&D)_t$	(2) $Ln(1+Citation/R\&D)_t$	(3) $Ln(1+Patent\ Value)_t$
CDS Trading	0.020**	0.026**	0.081**
	(2.0)	(2.0)	(2.4)
Ln(*Assets*)	-0.013**	-0.019***	0.299***
	(-2.5)	(-3.1)	(10.1)
Ln(*Firm Age*)	-0.001	0.007	0.271***
	(-0.1)	(0.7)	(3.9)
Ln(*PPE/Employees*)	0.018*	0.011	0.364***
	(1.7)	(0.7)	(9.6)
R&D/Assets	-0.510***	-0.534***	1.414**
	(-3.2)	(-2.9)	(2.5)
ROA	-0.097	-0.073	0.301*
	(-1.3)	(-0.8)	(1.8)
MB	0.013***	0.016***	0.183***
	(2.9)	(2.8)	(15.5)
Sales Growth	0.117***	0.133***	-0.086***
	(4.1)	(4.0)	(-2.7)
Leverage	-0.121***	-0.124***	-0.255***
	(-3.1)	(-2.7)	(-2.6)
Cash/Assets	0.073	0.068	0.126
	(1.3)	(0.9)	(0.8)
Stock Volatility	-0.093	0.485	8.007***
	(-0.2)	(0.7)	(6.5)
Herfindahl	0.084	-0.035	2.022***
	(0.6)	(-0.2)	(3.7)
$Herfindahl^2$	-0.080	0.026	-1.440**
	(-0.5)	(0.2)	(-2.5)
Year FE	X	X	X
Firm FE	X	X	X
Observations	9,057	9,057	16,636
Adjusted R-squared	0.558	0.543	0.864