信用违约互换与公司创新

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Abstract: We show that credit default swap (CDS) trading on a firm's debt positively influences its technological innovation output measured by patents and patent citations. This positive effect is more pronounced in firms relying more on debt financing or being more subject to continuous monitoring by lenders prior to CDS trade initiation. Moreover, after CDS trade initiation, firms pursue more risky and original innovations and generate patents with higher economic value. Further analysis suggests that CDSs improve borrowing firms' innovation output by enhancing lenders' risk tolerance and borrowers' risk taking in the innovation process rather than by increasing R&D investment. Taken together, our findings reveal the real effects of CDSs on companies' investments and technological progress.

Keywords: Credit Default Swaps; Corporate Innovation; Risk Taking

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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 Chair of the Federal Reserve*

1. Introduction

Technological innovation is vital for companies' competitiveness and long-term growth, but financing it with debt is difficult. 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 of 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, prior studies (e.g., Stiglitz, 1985; Hall and Lerner, 2010) have regarded debt as a less-than-favorable source of financing for innovation relative to equity. Furthermore, among the various types of debt financing, bank debt is viewed as less suitable for financing innovation than public debt because banks are less tolerant of risky experimentation and early innovation failure than public debt investors (Rajan and Zingales, 2003; Atanassov, 2015).

As an important *financial* innovation in recent decades, credit default swaps (CDSs) are credit-derivative contracts in which CDS sellers offer CDS buyers protection against credit events of underlying reference entities in exchange for periodic premium payments by CDS buyers.[1] If CDSs are traded on a borrowing firm's debt, the lenders can buy CDSs to hedge the credit risk associated with their investments (such as loans or bonds) while retaining legal ownership of these investments.[2] Even

[1] A reference entity can be a corporation, a government, or a legal entity that issues debt of any kind. Credit events mainly include defaults on interest or principal payments and borrowers' bankruptcy filing; in some CDS contracts, they may also include debt restructuring and credit-rating downgrades. 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, depending on the terms agreed upon at the onset of the contract. According to the International Swaps and Derivatives Association, the size of the CDS market has reached a peak of $62.2 trillion in notional value at the end of 2007, making CDSs a major financial innovation for managing credit risk in global financial markets.

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

if lenders do not purchase CDSs, the existence of CDS markets provides them with a valuable option to hedge against credit risks (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' (i.e., reference firms') technological innovation? If so, is the CDS effect on innovation stronger for firms relying on the types of debt that are less compatible with innovation? By addressing these questions, we aim to reveal the real effects of CDSs on companies' investments and technological progress.

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

[Insert Figure 1 Here]

Furthermore, 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 evaluations of borrowers' investment decisions, imposing stringent financial covenants to constrain borrowers' investment and financing policies, and influencing borrowers' managerial turnover. However, monitoring borrowing firms' innovation investments is particularly costly because of the uncertainties surrounding innovative projects and the difficulty of negotiating and implementing covenants. Recent studies (e.g., Morrison, 2005) show that the onset of CDS trading weakens lenders' incentives to engage in costly monitoring and to intervene in borrowers' governance because lenders' claims can be insured via CDSs. Shan, Tang, and Winton (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 potentially have more opportunities to direct their efforts and resources toward more 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 CDSs to foster borrowing firms' innovation by enhancing lenders' risk tolerance and allowing borrowing firms to take more risk in the innovation process. We label this mechanism the risk-taking channel.

Prior studies also suggest several other economic forces that could potentially discourage borrowing firms from taking risks in innovation upon CDS trade initiation. For example, in response to CDS-insured lenders' reduced monitoring, a borrowing firm's uninsured lenders may increase their monitoring efforts to control the borrower's risk taking. Moreover, CDS sellers may fully anticipate the incentives of CDS-insured lenders and price them into the CDS premium. To lower protection prices or avoid the reputation costs arising from adverse credit events due to reduced monitoring, CDS-insured

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

lenders may continue intensively monitoring borrowers in the post-CDS period.[4] Finally, Hu and Black (2008) note that lenders can separate their cash flow rights from control rights by purchasing CDS protection, thereby turning themselves into "empty creditors". As a result, CDS-insured lenders can be tougher in debt renegotiation; they 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 tough CDS-insured lenders, borrowing firms might have weaker *ex ante* incentives to undertake risky innovative projects to avoid defaults and covenant violations that trigger debt renegotiation. 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 projects, thereby weakening the risk-taking channel outlined above. Thus, the net effect of CDSs 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. Following previous studies (e.g., Hirshleifer, Low, and Teoh, 2012), we use the number of patents granted by the U.S. Patent and Trademark Office (USPTO) to measure the quantity of borrowing firms' innovation output, and use the number of patent citations to capture the quality of innovation output.

Our CDS firms are not randomly assigned. Some factors that determine a borrowing firm's innovation output plausibly also drive its likelihood of being selected into CDS trading. For example, a firm's investment opportunities 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 use the

[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 attribute *ex post* borrowers' defaults to *ex ante* lenders' reduced monitoring. An easier-to-implement and more cost-efficient protection method is to diversify credit risk exposure by selling CDSs referenced to companies in different industries. In doing so, the 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.

propensity score matching procedure to conduct a matched-sample analysis. We include both treated (CDS) firms and control (matched non-CDS) firms in the regressions. Our baseline specification is a difference-in-differences (DiD) model with firm and year fixed effects, which essentially compares the change in CDS firms' innovation output around CDS trade initiation with that of non-CDS firms.

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

We perform a few tests to alleviate the concern that the timing of CDS introduction is endogenous. Among others, 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 CDSs to hedge credit risk. Furthermore, a lending bank's decision to hedge currency risk should not directly impact borrowing firms' innovation output. The instrumental variable regressions generate results consistent with the main results discussed above. Further, we adopt an additional identification strategy based on the passage of state-level anti-recharacterization laws that strengthen creditor rights over collateral (e.g., Mann, 2016). To the extent that these laws improve the suitability of debt financing for innovation, the CDS effect on innovation should be less pronounced after they are enacted. Our analysis confirms this prediction. Collectively, our endogeneity tests support a causal effect of CDS trading on innovation, although we cannot completely rule out endogeneity as a potential confounding factor.

Having documented the positive CDS effect on innovation, we further investigate the mechanisms that plausibly account for our main results. We divide our sample in several ways to examine how the CDS effect on innovation varies according to several firm characteristics measured prior to CDS trade initiation. We find that the CDS effect is more pronounced for borrowing firms that are more dependent on debt financing for investment or more subject to continuous lender monitoring (i.e., firms that use bank debt, borrow from fewer banks, or have bank loan contracts with secured debt and net worth covenants). These results confirm the role of CDSs as a debt market instrument in improving the compatibility between debt financing and corporate innovation. They also support our arguments that CDS trading promotes innovation by encouraging risk taking and reducing the monitoring imposed by lenders. In addition, we document that the CDS effect on innovation is stronger for borrowing firms with lower probabilities of debt renegotiation, indicating that borrowing firms engage in more risk taking in innovation when they are less concerned about tough CDS-insured lenders in debt renegotiation. Moreover, consistent with the risk-taking channel, our further analysis reveals that after CDS trade initiation, firms generate more patents that depart from existing knowledge, result in the creation of new products, or have high originality scores. These findings indicate that CDS trading shifts the trajectory of corporate innovation toward high-risk, radical, and original inventions.

Although our findings are consistent with the view that CDS trading encourages borrowing firms' innovation via the risk-taking channel, they can also be consistent with the mechanism that CDS trading relieves borrowing firms' financial constraints (e.g., Bolton and Oehmke, 2011; Saretto and Tookes, 2013) and allows them to issue more debt to finance more research and development (R&D) investments, resulting in greater innovation output. We label this mechanism the financing channel. We design several tests to examine the implications of the financing channel; however, the results do not support this alternative explanation. In particular, while more financially constrained firms should gain more from the relaxation of borrowing constraints, we find that the positive CDS effect on innovation is not stronger for such firms. We also document that the CDS effect on innovation is not stronger for firms where debtholders are less willing to finance innovation investments because of their conflicts with shareholders. Moreover, we find that CDS firms do not increase R&D more than their non-CDS counterparts after CDS trade initiation. Collectively, these results imply that CDS trading primarily affects technological innovation by shaping borrowing firms' incentives to pursue novel and risky projects rather than by relieving their financial constraints. In other words, CDSs promote innovation not by increasing R&D investments but by changing the way in which R&D investments are deployed. To further confirm this implication, we investigate how CDS trading affects borrowing firms' innovation efficiency, which is measured using the ratio of innovation output (i.e., patents and citations) to innovation input (i.e., R&D spending). The results suggest that after CDS trade initiation, CDS firms become more efficient in converting R&D investments into innovation output.

Finally, we study the CDS effect on innovation using three additional measures for the importance of corporate innovation. They are the number of citations per patent, citation-weighted patents, and Kogan et al.'s (2017) economic value of patents, which is estimated using movements in stock prices in response to news about patents granted by the USPTO. Our analysis reveals that these measures significantly increase after CDS trade initiation, suggesting that CDS trading enhances both the scientific value (measured using citations) and the economic value of patents.

Our study contributes to the extant literature in two ways. First, our paper adds to the literature on finance and innovation. While most prior studies (e.g., Hall, 2002) suggest that corporate innovation should primarily rely on internal funds and equity financing, several recent studies (e.g., Nanda and Nicolas, 2014; Kerr and Nanda, 2015) reveal the increasing importance of debt financing for innovation, especially for large firms. We extend this literature by showing that the risk-transferring function of CDSs can improve the compatibility between innovation and debt financing. 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 financial and real effects of CDSs. On the one hand, previous studies have shown that CDSs facilitate credit risk transfer, promote risk sharing, and relax credit supply constraints (e.g., Saretto and Tookes, 2013). On the other hand, Warren Buffet has referred to CDSs as "financial weapons of mass destruction".[6] Subrahmanyam, Tang, and Wang (2014) reveal a dark side of CDS trading in terms of increasing borrowing firms' probabilities of default and credit rating downgrades. We demonstrate that CDSs can encourage borrowing firms to engage in risky experimentation and to improve the efficiency of R&D investments, thereby spurring corporate innovation. In doing so, our analysis uncovers a specific micro-level channel through which CDSs can positively impact economic growth.

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

2. Related Literature

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

2.1. CDSs and corporate policies

CDS contracts enable lenders to transfer the credit risk of borrowers, i.e., the reference entities, to CDS sellers, which include insurance companies, hedge funds, and other financial institutions. CDS sellers typically diversify credit risk exposure by selling CDSs referenced to companies in different industries (Martin and Roychowdhury, 2015). The risk-transferring function of CDSs can also benefit lenders, particularly banks, with respect to regulatory capital management because they can assign the risk weight to a loan based on the credit rating of the counter-party in the CDS contract instead of the original borrower (Martin and Roychowdhury, 2015). Thus, banks have increasingly used CDSs to

[6] Letter from Warrant Buffet to shareholders of Berkshire Hathaway, Inc. (February 21, 2003).

hedge the credit exposures arising from their lending business (Ashcraft and Santos, 2009). For corporate CDSs, the underlying reference assets can be the bonds or loans of the reference firms. While senior unsecured bonds are the most commonly used CDS underlying reference assets, banks often use the bond-linked CDSs to hedge the credit risk of their loan portfolios because bonds and loans typically face default in the same states of the world under the standard cross-default clauses (Shan, Tang, and Winton, 2015).[7]

The credit risk transfer via CDSs induces changes in the lender-borrower relationship. Morrison (2005) and Parlour and Winton (2013) model that CDSs weaken insured lenders' monitoring and intervention incentives. Shan, Tang, and Winton (2015) reveal that lenders impose less restrictive debt covenants after CDS trade initiation, suggesting that CDSs substitute covenants for creditor protection. Bolton and Oehmke (2011) note that CDSs can turn insured lenders into "empty creditors", thereby increasing their bargaining power in debt renegotiation. Bolton and Oehmke's (2011) analysis reveals two effects of CDSs. On the one hand, CDSs can serve as a commitment device for borrowing firms to increase pledgeable cash flows and reduce the incidence of strategic default, which effectively enhances borrowing firms' debt capacities and enables more positive net present value projects to be financed. On the other hand, lenders in equilibrium tend to over-insure with CDSs, thus becoming excessively tough in debt renegotiation and potentially pushing distressed borrowing firms into inefficient bankruptcy.

Corporate CDSs trade over the counter (OTC). Oehmke and Zawadowski (2017) document that both hedging and speculative motives determine trading and positions in CDS markets. In particular, the positive link between insurable interest and net notional CDS positions suggests that market participants use the CDS market to hedge their debt or counterparty exposure. Although borrowing firms essentially have no control over whether there are CDS contracts traded on their debt, CDS

[7] Although some "loan-only" CDSs (LCDSs) contracts are linked to secured loans, CDS buyers typically use bond-linked CDS contracts because of the relative illiquidity of the LCDS market (Amiram et al., 2017).

trading affects their corporate policies. Saretto and Tookes (2013) investigate the impact of CDS trading on borrowing firms' capital structure. They find that CDS-insured lenders are more willing to lend, resulting in an increase in credit supply. As a result, borrowing firms increase leverage after the inception of CDS trading.[8] Consistent with Bolton and Oehmke's (2011) predictions, Subrahmanyam, Tang, and Wang (2014) report that the likelihood of borrowing firms' bankruptcy and credit rating downgrades surges after the start of CDS trading. Furthermore, Subrahmanyam, Tang, and Wang (2017) find that borrowing firms increase cash holdings for precautionary motives after CDS trade initiation to avoid negotiations with exacting empty creditors. Martin and Roychowdhury (2015) discover that CDS trade initiation results in a decline in borrowing firms' reporting conservatism, consistent with the view that CDSs reduce lenders' incentives to continuously monitor borrowers and their demand for conservative accounting.

Unlike prior studies that mainly focus on the financial or accounting effects of CDS trading, we are among the first to show that CDS trading can have real effects on the output and the nature of firms' innovation investments. By doing so, we add to the literature that examines the real effects of financial development (e.g., Rajan and Zingales, 1998; Beck and Levine, 2002; Hsu, Tian, and Xu, 2014; Nanda and Nicholas, 2014; Beck et al., 2016) by revealing an important micro-level channel (i.e., corporate innovation), through which the financial sector could affect economic growth.

2.2. Financing corporate innovation

Financing plays a critical role in corporate innovation, as it enables companies to conduct research, to adopt technologies, and to develop and commercialize inventions. Many earlier studies on financing and innovation argue against the role of debt in financing innovation (Kerr and Nanda, 2015).

[8] Relatedly, Shan, Tang, and Yan (2016) find that banks that use CDSs actively grant larger loans to CDS-referenced borrowers. Ashcraft and Santos (2009) document that the onset of CDS trading does not reduce the cost of capital for the average firm but leads to a small decrease in the cost of debt for safer and more transparent firms. Amiram et al. (2017) provide evidence that CDSs reduce the effectiveness of a lead arranger's stake in the loan as a mechanism to address the information asymmetry problems in syndicated loans. The introduction of CDS trading increases the share of loans retained by the lead arrangers and increases loan spreads.

For example, Brown, Fazzari, and Petersen (2009) document that young and publicly traded U.S. firms in high-tech industries finance their R&D investments almost entirely with internal cash flows and external equity. They argue that "information problems, skewed and highly uncertain returns, and lack of collateral value likely make debt a poor substitute for equity finance". Subsequent research reveals that shareholder protections, equity market development, and long-term and failure-tolerant institutional shareholders foster corporate innovation.[9]

Recently, a growing body of work has focused on the role of debt financing in corporate innovation. For example, Acharya and Subramanian (2009) find that creditor-friendly bankruptcy codes lead to excessive liquidations, thereby causing leveraged companies to shun innovation. Hsu, Tian, and Xu (2014) provide cross-country evidence that credit market development discourages innovation in high-tech industries. Chava et al. (2013) show that U.S. intrastate (interstate) banking deregulation in the 1980s and 1990s increased (decreased) the local market power of banks, thereby decreasing (increasing) the level and risk of innovation in young, private firms. Furthermore, Amore, Schneider, and Zaldokas (2013) find that interstate banking deregulation enhances corporate innovation by increasing the credit supply and alleviating the financial constraints of bank-dependent firms. Kerr and Nanda (2015) note that bank financing can be an important source of financing for innovation, particularly for large firms with tangible and intangible assets that can be pledged as collateral.

Several studies investigate which types of debt are relatively more conducive to innovation. Atanassov (2015) investigates how the choice between public and bank debt influences corporate innovation. He argues that compared with arm's-length public debtholders, banks have more private information about borrowers, are more likely to include stricter covenants in debt contracts, are more likely to continuously monitor the development of borrowers' investment projects because bank financing is often provided in tranches, and have lower tolerance of borrowers' risky experimentation

[9] See, among others, Brown, Martinsson, and Petersen (2013), Hsu, Tian, and Xu (2014), Aghion, Van Reenen, and Zingales (2013), Tian and Wang (2014), and Fang, Tian, and Tice (2014).

and early investment failures.[10] As such, bank debt may be ill-suited to novel innovations. By contrast, public debt investors come from a variety of backgrounds and independently assess borrowing firms' innovative projects. Thus, by issuing public debt, firms can tap a wider range of investors and be better able to convince some investors of the merits of a novel technology (Rajan and Zingales, 2003). Moreover, public debt investors can benefit more from the upside of risky and innovative projects than banks through the warrants and the conversion options often embedded in public debt. Against this backdrop, Atanassov (2015) documents that firms relying on bank debt innovate less and have lower quality innovations than those relying on public debt. Furthermore, focusing on bank financing, he shows that firms are less innovative if they borrow from fewer banks or if their loans have more stringent debt covenants.

Taken together, prior studies imply a pecking order for financing innovation. By nature, debt is generally less compatible with innovation than equity. Among the different types of debt, bank debt is less suitable for innovation than public debt. Our study adds to the literature by documenting that CDSs mitigate incompatibility issues between debt financing and innovation, and thus shape both the rate and the trajectory of corporate innovation.

3. Data, Variables, and Summary Statistics

3.1. Data and sample selection

Accurate CDS initiation dates are difficult to obtain from a single data source because CDSs 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. Our sample starts in 1997, which is the broad inception year of the CDS market for company names (Tett, 2009).

[10] Fama (1985) describes bank debt as inside debt because banks have great access to private information and are more likely to monitor borrowing firms closely after loan initiation. Atanassov (2015) also notes that bank loan officers normally lack the necessary knowledge and skills to properly evaluate novel technologies and that they are inherently conservative in financing innovative projects due to substantial reserve requirements and lending restrictions.

To measure firms' innovation output, we rely on patents granted by the USPTO between 1976 and 2010.[11] Patent citations are obtained from the Harvard Business School (HBS) Patent Network Dataverse.[12] On average, a two-year lag exists 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, the database may not completely cover the patents applied for in 2009 and 2010. As suggested by Hall, Jaffe, and Trajtenberg (2001), we end our sample period in 2008 to address this issue.[13] 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. Bank debt and debt covenants data are obtained from the S&P Capital IQ platform and Loan Pricing Corporation's DealScan database, respectively.

In line with 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). Observations with missing values for the variables employed in the regressions are also excluded. 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 initiations 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. Panel B reports the distribution by one-

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[11] 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. (2017), who collect raw patent data from the USPTO and identify the company (the assignee) to which each patent belongs. They then identify company names in the raw patent database and match each 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.

[12] Constructed by Lai et al. (2014), the database contains all citations of utility patents granted by the USPTO. We download the data from http://thedata.harvard.edu/dvn/dv/patent.

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

digit SIC industry. We find that our CDS firms are mainly from manufacturing industries and industries providing transportation, communications, electric, gas, and sanitary services. Following prior research (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 first year of CDS trading on a reference firm and zero prior to it. In addition, we construct several variables to measure the liquidity of CDS trading and the ease of access to the CDS market for investors: the average number of daily CDS quotes in a year (*Daily Quotes*), the average number of distinct dealers providing CDS quotes in a year (*Distinct Dealers*), and the average number of distinct maturities of CDS contracts traded on a firm in a year (*Distinct Maturities*).

Our first measure of innovation output, *Patent*, is the number of patents that were applied for during each firm-year and were eventually granted. Patent counts are a good indicator of the level of innovation output, as patenting is an important means by which firms can 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). Therefore, we follow Hall, Jaffe, and Trajtenberg (2001, 2005) and use forward citations of a patent to measure its quality or scientific value.[14] More significant and important patents are expected to be cited more frequently by other patents. The raw citation counts are subject to 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., 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

[14] We include self-citations because 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, a reduced need for 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.

patents applied for in the same year and in the same technology class. The fixed-effect approach accounts for the differing propensities 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 previous studies have documented as important determinants of innovation (e.g., 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. We control for 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 missing R&D information are assigned a zero R&D value (Hirshleifer, Low, and Teoh, 2012). Return on assets (*ROA*), which equals earnings before interest and taxes (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*, the logarithm of one plus the annual sales growth rate. *Leverage* (i.e., the ratio of total debt to 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. Furthermore, because Chan, Lakonishok, and Sougiannis (2001) reveal 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 the 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, many factors determine a firm's likelihood of being selected into CDS trading (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 CDSs traded on it (non-CDS firm) 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., 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 in the Compustat database during the 1997–2008 period and have non-missing values for the variables used in the model:

$$Prob\left(CDS\ Trading_{i,t} = 1\right) = \Phi\left(\alpha_0 + \alpha_1 X_{i,t-1} + \alpha_2 Industry_j + \alpha_3 Year_t\right), \quad (1)$$

where Φ is the cumulative distribution function of the standard normal distribution. $CDS\ Trading_{i,t}$ equals zero for non-CDS firms in all years. Because we focus on predicting the likelihood of CDS trade initiation, we follow Subrahmanyam, Tang, and Wang (2014) and exclude post-initiation years of CDS firms from the estimation. 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*) to account for the effects of the information environment and growth opportunities on the demand and supply of CDS contracts. *Credit Rating* is an indicator variable that equals one if the 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 Standard & Poor's credit rating 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.[15] 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 explanatory variables can predict the onset of CDS trading reasonably well. 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 investment grade ratings are more likely to have CDS trading initiated during the sample period. CDS trading is also more likely for firms with better growth opportunities, higher leverage, or less volatile stock returns.

[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 firm in each year. For each CDS firm in the year prior to CDS trade initiation, we find a matching firm that has the closest propensity score but no CDS trading throughout our sample period.[16] We utilize the procedure above to identify matched non-CDS firms for 782 CDS firms, thus generating 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.

[15] In particular, we include *R&D/Assets*, *Ln*(*PPE/Employees*), *Ln*(*Firm Age*), *Sales Growth*, *Cash/Assets*, *Herfindahl*, and *Herfindahl*^{2}. Our main results are unaffected if we exclude them from the matching. Robustness checks described in Section 4.2 show that similar results are obtained if we include additional variables identified by Oehmke and Zawadowski (2017).

[16] The propensity scores are compared in the year prior to CDS trade initiation. A non-CDS firm can be matched to multiple CDS firms (matching with replacement). Our results are robust to alternative matching criteria outlined in Section 4.2.

Panel B of Table 1 compares the characteristics of CDS firms to those of matched non-CDS firms prior to CDS trade initiation. The results indicate that before the onset of CDS trading, CDS firms and matched non-CDS firms are similar in *Credit Rating*, *Investment Grade*, *Ln*(*PPE/Employees*), *R&D/Assets*, *MB*, *Sales Growth, Leverage*, *Cash/Assets*, *Stock Volatility*, and *Herfindahl*, suggesting that these characteristics are unlikely to drive the difference in innovation output after CDS trade initiation. While CDS firms and non-CDS firms still differ in terms of *Ln*(*Assets*), *Ln*(*Firm Age*), and *ROA*, they have similar probabilities of CDS trade initiation, as evidenced by the insignificant difference in propensity scores (0.003). Finally, 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 firms and matched non-CDS firms before CDS trade initiation. In an untabulated test, we again estimate Eq. (1) using the propensity-score matched sample and find that none of the firm characteristics is significant in predicting CDS trade initiation, confirming the effectiveness of our matching procedure.

3.4. Summary statistics

Table 2 presents the summary statistics of our final sample that consists of 16,636 firm-years. All variables are winsorized at the 1% level at both tails of their distributions. On average, the firms in our sample are larger than the average firm in Compustat because larger firms are more likely to become CDS-referenced firms (Li and Tang, 2016).

[Insert Table 2 Here]

Turning to innovation output measures, we find that the average firm in our sample obtains 78.148 patents and receives 63.703 citations for its patents each 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. Furthermore, 26.8% of the firm-years in our sample have CDS trading.

4. Main Results

4.1. Univariate analysis

To investigate the relation between CDS trading and corporate innovation, we start with a univariate analysis of the changes in innovation output around CDS trade initiation for CDS firms (treatment group) benchmarked to matched non-CDS firms (control group). Specifically, we define the year of CDS trade initiation as event year 0 and compute the average changes 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 average changes in the number of patents for the event windows (-1, 1), (-1, 2), and (-1, 3). On average, CDS firms experience a 17.675 increase in the number of patents from event year -1 to 1. By contrast, the average increase for non-CDS firms is 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 increases over time. This finding is also consistent with the long gestation periods of many innovative projects.

[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 increases, on average, by 18.298, 18.844, and 19.085 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 in citation increases between CDS and non-CDS firms 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 CDS firms, compared with matched non-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 in their propensity to have 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 of 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 DiD approach. Our baseline regression specification is written as follows:[17]

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

where $Innovation_{i,t}$ represents our innovation output measures (*Patent* and *Citation*) for firm i in year t. The key independent variable is $CDS\ Trading_{i,t\text{-}1}$, which equals one if firm i has CDSs traded on its debt during year t-1. β_1 captures the DiD effect due to CDS trade initiation. As we have logarithmically transformed the innovation measures to reduce the skewness of the dependent variables, β_1 yields the percentage of innovation differential that can be attributed to CDS trading. Y is the set of control variables described in Section 3.2. 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.

[17] For our setting, a typical DiD approach estimates the following regression using the ordinary least squares (OLS) regression: $Ln(1 + Innovation) = \beta_0 + \beta_1 \times CDS\ Firm \times Post + \beta_2 CDS\ Firm + \beta_3 Post + \gamma Y + \varepsilon$, where *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, the inclusion of the non-interacted *Post* and *CDS Firm* dummy variables is unnecessary. The DiD model is then reduced to Eq. (2) because by construction *CDS Trading* = *CDS Firm*×*Post*.

The baseline regression results are presented in Table 3, where columns (1) and (2) present the results for the patent count and the citation count, respectively. In both columns, the coefficients of *CDS Trading* are positive and statistically significant (*t*-statistics = 2.8 and 3.0 in columns (1) and (2), respectively), 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 firms is 11.63 more than that for non-CDS firms.[18] This DiD effect is approximately 14.8% of the mean *Patent* value (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 12.88 more than that for non-CDS firms. The citation differential amounts to 20.2% of the average number of citations (63.703) across firms. Untabulated statistics show that the mean variance inflation factor (VIF) is less than 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 the prior literature (e.g., Hirshleifer, Low, and Teoh, 2012). For instance, larger and older firms and those with higher capital intensity have more patents and citations. Firms with lower leverage, higher market-to-book ratios, 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 that requires a CDS firm and the matched non-CDS firm to be in the same two-digit SIC industry to alleviate the concern that

[18] 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 $0.147\times(1+78.148)\times1 = 11.63$, which amounts to 14.8% of the mean value of *Patent*.

our results are driven by the industry differences between the two groups of firms;[19] (*b*) including additional variables identified by Oehmke and Zawadowski (2017) to predict the introduction of CDS trading in Eq. (1);[20] (*c*) running negative binomial regressions (instead of OLS regressions) to address the issue that patent and citation counts are non-negative and discrete; (*d*) using innovation output measures at t+2 (rather than at t) as dependent variables to account for the possibility that CDS trading may take more than one year to have effects on innovation; (*e*) excluding firm-years with zero patents and citations; (*f*) 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; (*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 obtain patents 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 we have controlled for a standard set of variables in Eq. (2) that

[19] In untabulated tests, we use two other 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, which reduces the sample to 12,536 firm-year observations because some CDS firms do not have very close matches. Second, we match each CDS firm with two non-CDS firms whose propensity scores are closest to that of the CDS firm. The inclusion of additional matching firms increases our sample to 24,954 firm-year observations.

[20] Oehmke and Zawadowski (2017) thoroughly analyze the determinants of CDS trading over the period 2008-2012 using the CDS data from the Depository Trust & Clearing Corporation. They find that hedging motives, speculation motives, and the frictions in the underlying bond market are important determinants of CDS positions. In this robustness check, we follow Oehmke and Zawadowski (2017) and include in Eq. (1) the amount of bonds outstanding and accounts payable to proxy for hedging motives, analyst earnings forecast dispersion to capture speculative trading motives, and bond fragmentation and the contractual heterogeneity of corporate bonds to account for trading frictions in the bond market. See Oehmke and Zawadowski (2017) for detailed definitions of these variables. In addition to these variables, we also include *Bank Size* (defined in Section 4.3.3) to account for firms' relationship with large banks.

previous studies have shown to affect corporate innovation, the CDS–innovation relation may be spurious if our model omits any variables affecting both innovation and the presence of CDSs on a firm's debt. The other plausible endogeneity issue is reverse causality running from corporate innovation to CDS trade initiation. 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 and a quasi-natural experiment 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 the sake of brevity.

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 exclude non-CDS firms and restrict the sample to firm-years that have CDS trading (i.e., firm-years for which *CDS Trading* = 1). Using this subsample, 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 that references borrowers' debt is more liquid. Panels A.1–A.3 of Table 4 report the regression results obtained by replacing *CDS Trading* in Eq. (2) with our three CDS liquidity measures. Although the sample is reduced to 4,330–4,579 firm-years, the coefficients of the three CDS liquidity measures are positive and statistically significant. In terms of economic significance, for example, a one-standard-deviation rise in *Daily Quotes* increases *Patent* (*Citation*) by 6% (12%). 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 the political economy or local business cycles. For instance, prior studies (e.g., Amore, Schneider, and Zaldokas, 2013) reveal that the staggered banking deregulation across U.S. states affects corporate innovation output by enhancing state-level credit supply. As such, deregulation of state-level banking and branching may drive both corporate innovation and the demand/supply of CDSs for credit protection. We determine a firm's location state based on the location of its headquarters, which is usually where its major operations are located (Gormley and Matsa, 2016). We include industry-by-year fixed effects to control for potential differential trends in patenting activities and CDS trading across industries over time. Panel B of Table 4 suggests that our main results continue to hold after including both state-by-year and industry-by-year fixed effects.

[Insert Table 4 Here]

Second, our key variable of interest, *CDS Trading*, is constructed using the actual CDS trade initiation dates, which exhibit a clustered pattern (Panel A of Appendix A). Thus, 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 firms 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 replications should yield coefficients close to those obtained using the actual initiation dates. The results reported in Panel C 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 close to zero. The coefficients reported in Table 3 (0.147 and 0.199) are 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.[21]

Third, there is a significant amount of recent corporate loans that are covenant-light (a.k.a. cov-lite). Compared with customary loans, cov-lite loans have weaker covenant enforcement, and thus may allow borrowing firms to make riskier investment in innovation. Further, Becker and Ivashina (2017) suggest that cov-liteness is a predominant feature of leveraged loans, a risky segment of the syndicated loan market primarily involving borrowers of low credit quality. Given that cov-lite loans are widely syndicated to banks and institutional investors, such as collateralized loan obligations (CLOs) and loan mutual funds, if these investors hedge against credit risks using CDSs, there should be a coincidence between the issuance of cov-lite loans and CDS trading at the firm level. Therefore, the issuance of cov-lite loans can be an important omitted variable affecting both corporate innovation and CDS trade initiation. To address this concern, we collect loan level data from the S&P Leveraged Commentary and Data (LCD) database, and classify loans as cov-lite (cov-heavy) if the enforcement of financial covenants is incurrence-based (maintenance-based).[22] We find that roughly 3% of CDS firms issue

[21] The inception year (i.e., 1994) of the CDS market is an important milestone, after which it becomes possible for investors to trade credit risk of any company in the CDS market. Thus, one may expect the inception of CDS market in 1994 to have a general effect on all firms' innovation. In untabulated tests, we find that it indeed has some positive effects on innovation output of debt-dependent companies, but its economic significance is much weaker than those obtained using firms' actual CDS trade initiation dates, confirming that firm-specific CDS initiation dates are highly important in driving our results.

[22] Cov-lite loans do not necessarily have fewer covenants than other loans (Becker and Ivashina, 2017). Instead, cov-lite loans typically involve incurrence provisions that require borrowing firms to comply with financial covenants only when they pursue an active event, such as a new debt issuance or a merger. In contrast, cov-heavy loans typically include maintenance provisions that require borrowers to maintain compliance at all points in time with contractual financial covenants (e.g., the interest coverage ratio).

cov-lite loans during our sample period. We conduct three regression analyses and report the results in Panel D of Table 4. In Panel D.1, we explicitly control for the effects of cov-lite loans by including a binary variable, *Cov-Lite*, which equals one in and after the first year of a firm borrowing in the cov-lite loan market, and zero prior to it. In Panel D.2, we augment Eq. (2) by adding two variables, *Inflow_CLO* and *Inflow_MF*, which account for the exogenous variation in the cov-lite loan market arising from net fund inflows to CLOs and loan mutual funds, respectively.[23] In Panel D.3, we exclude firms with CDS trading initiated after the first quarter of 2005, which corresponds to the start of the rapid growth of the cov-lite loan market (Becker and Ivashina, 2017). The coefficients of *CDS Trading* remain positive and significant at the 5% level in all three tests, suggesting that our results are not primarily driven by the rise of the cov-lite loan market.

Finally, 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 that lenders use CDSs for hedging. On the other hand, Chemmanur and Tian (2016) show that firms shielded with a larger number of anti-takeover provisions generate better innovation outcomes because anti-takeover provisions alleviate the short-term pressure on managers from the corporate control market. To ensure that our findings are not driven by corporate governance, we include the governance index (*G*-index) compiled by Gompers, Ishii, and Metrick (2003), board size, and institutional ownership as additional

[23] Becker and Ivashina (2017) argue that high inflows to CLOs and loan mutual funds predict higher volumes of cov-lite loans according to the coordination theory. *Inflow_CLO* and *Inflow_MF* are aggregate net fund flows collected from the LCD and measured at the yearly frequency in billions of U.S. dollars. Because the fund flow data from the LCD are only available since 2001, we restrict this analysis to the period 2001-2008.

controls. Because of missing values for these additional controls, we perform the analysis with a much smaller sample of 5,317 firm-year observations. However, our main results are unaffected.[24]

4.3.3. Tests on reverse causality

The causal relation between corporate innovation and CDS trade initiation can be bidirectional. The two directions of causality are not mutually exclusive, and they may be at work simultaneously. While our results suggest that CDS trading stimulates borrowing firms' innovation, innovative borrowing firms may be more likely to have CDS trading initiated on their debt for several reasons unrelated to the innovation enhancement. First, if lenders observe that borrowing firms have increased the level of risky investment in innovation, they may initiate CDS trading to hedge their exposure to these borrowers. Second, even if the lending unit of a bank is unable to provide risky loans to firms with innovative investment opportunities because of regulatory capital requirements, the bank might be large enough to have other units (e.g., a CDS trading desk or a fixed income mutual fund) that are able to take on credit risk through CDS trading. Third, borrowing firms' past innovation success may allow them to pledge their patents as collateral and raise more debt financing, thereby increasing lenders' needs to hedge credit risk using CDSs.[25]

We conduct three tests to alleviate these reverse causality concern, respectively. 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

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

[25] Mann (2016) reports that, in 2013, 40% of patenting firms in the U.S. have pledged their patents as collateral at some point. Furthermore, he shows that patenting companies issue more debt when creditor rights to patents are strengthened.

CDS trade initiation and zero otherwise. *Year*$^{\geq+2}$ captures the CDS effects from the second year after CDS trade initiation onward. The results presented in Panel F of Table 4 show that the *Year*$^{-2}$, *Year*$^{-1}$, and *Year*^{0} coefficients are largely insignificant, suggesting that, compared with the matched non-CDS firms, CDS firms do not have greater innovation output before and during the year of CDS trade initiation. To a large extent, this finding ameliorates the reverse causality concern. Furthermore, the *Year*$^{+1}$ and *Year*$^{\geq+2}$ coefficients are positive and significant (*t*-statistics ranging from 2.3 to 3.1), indicating that the innovation differentials appear only *after* CDS trading initiation. Interestingly, the *Year*$^{\geq+2}$ coefficients (0.225 and 0.230) are larger than those of *Year*$^{+1}$ (0.087 and 0.134), indicating that while the CDS effect on innovation manifests quickly (i.e., one year after CDS trade initiation), it subsequently becomes stronger. This result is also consistent with the patterns in Figure 2.

Second, to mitigate the concern that innovative firms' relationship with large banks triggers CDS trading on their debt, we include *Bank Size* as an additional control variable in Eq. (2). *Bank Size* is defined as the natural logarithm of bank lenders' average total assets, which are obtained from Compustat Bank. The number of observations is reduced to 4,377 if we focus on firms with bank lenders that are covered by Compustat Bank. However, the results reported in Panel G of Table 4 show that the coefficients of *CDS Trading* remain positive and significant. Similar results (untabulated) are obtained if we estimate the regressions using the whole sample and set *Bank Size* to zero for firms having zero bank debt or having bank lenders not covered by Compustat Bank.

Third, we incorporate several additional variables into Eq. (2) to explicitly account for reverse causality arising from borrowing firms' past innovation investments, past innovation success, and perceived risk profiles, which may increase lenders' hedging needs using CDSs. Specifically, we measure past innovation investments (past innovation success) as the rolling average *R&D/Assets* (the number of patents or citations) from year *t*-2 to *t*-6. Moreover, we use forward-looking implied volatility to capture borrowing firms' risks perceived by CDS market participants.[26] The results, reported in Panel H of Table 4, reveal that the *CDS Trading* coefficients remain positive and significant, substantiating causality running from CDS trading to innovation.

4.3.4. The instrumental variable approach and the quasi-natural experiment

To further alleviate endogeneity concerns, especially those not previously identified, we employ an instrumental variable approach similar to that of Saretto and Tookes (2013). Specifically, we employ lenders' hedging activities on foreign exchange (*Lender FX Hedging*) as an 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 show that banks that hedge their currency risk using foreign exchange derivatives tend to also hedge their credit risk using CDSs. Thus, from a relevance perspective, lending banks' foreign exchange hedging activities should be positively correlated with their hedging demand for CDSs and the likelihood of CDS contracts being initiated on their borrowers. Furthermore, 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 purposes relative to the bank's total assets across all the banks that have served either as lenders or bond underwriters for the firm over the previous five years.[27]

We then implement the instrumental variable analysis using Wooldridge's (2002) three-stage procedure. In the first stage, we estimate the probit model in Eq. (1) with *Lender FX Hedging* as the instrument, and compute the fitted probability of CDS trade initiation. In the second stage, we regress

[26] 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 perceptions in CDS markets.

[27] We identity firms' lenders using the DealScan syndicated loan database. Bond underwriters are identified using the Mergent Fixed Income Securities Database (FISD). We then extract the foreign exchange derivative positions of the lenders and bond underwriters from Federal Reserve call report data.

CDS Trading on the fitted probability of CDS trade initiation and all the control variables in Eq. (2). In the third stage, we regress *Ln*(1+*Innovation*) on all the control variables in Eq. (2) and the fitted value of *CDS Trading* obtained in the second stage.[28] The first-stage regression (untabulated) shows that *Lender FX Hedging* positively and significantly predicts *CDS Trading* (*t*-statistic = 2.1), suggesting that the instrument meets the relevance criteria econometrically. The weak instrument test (untabulated) generates a *p*-value of less than 0.01, thus rejecting the weak instrument hypothesis. The results of the third-stage regression are presented in Panel I of Table 4. The results show that the coefficients of fitted *CDS Trading* are positive and statistically significant at conventional levels in both patent and citation regressions. Similar results (untabulated) are obtained if we control for *Bank Size* in the regressions.

Finally, we use the staggered enactment of state anti-recharacterization laws as a quasi-natural experiment. The laws allow borrowers to transfer collateral to a bankruptcy-remote special-purpose entity so that lenders are not subject to the automatic stay (Mann, 2016), thereby simplifying lenders' claiming process and strengthening their rights and control over collateral.[29] Given that patents are often used as collateral in the debt market, the passage of these laws improves borrowing firms' ability to finance innovation with debt (Mann, 2016; Chava, Nanda, and Xiao, 2017). If the positive effect of CDSs on innovation works through improving the compatibility between debt financing and innovation, the effect should be weaker after the enactment of anti-recharacterization laws by states. To test this implication, we construct an indicator variable (*Post AR*), which equals one after the enactment of anti-recharacterization laws in the state of a firm's headquarter or incorporation, and zero otherwise.[30] We then augment Eq. (2) by including *Post AR* and its interaction with *CDS Trading*, and report the regression results in Panel J of Table 4. We find that the coefficients of *CDS Trading*×*Post AR* are

[28] An important advantage of this three-stage procedure is that it takes into account the binary nature of the endogenous variable. Moreover, the procedure does not require the binary model in the first stage to be correctly specified. Wooldridge (2002) shows that the procedure provides efficient estimations under fairly general conditions.

[29] The automatic stay restricts lenders' collection efforts related to collateral seizure. It is automatically imposed when a borrowing firm files for bankruptcy under Chapter 11.

[30] According to Mann (2016), the states that enacted the anti-recharacterization law include Texas and Louisiana in 1997, Alabama and Delaware in 2001, South Dakota in 2003, Virginia in 2004, and Nevada in 2005.

negative and significant, confirming that the beneficial effect of CDSs on innovation is reduced after a positive exogenous shock to creditor rights.

To summarize, while endogeneity is a perennial issue that no empirical test can entirely rule out, we conduct a battery of tests to alleviate the 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 running 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 probe the channels through which CDS trading enhances borrowing firms' innovation output. If the risk-taking channel plays an important role in shaping the positive CDS–innovation relation, the effect of CDS trading on innovation should be more pronounced for firms in which 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 toward more risky, novel, and impactful innovation projects. We also use several tests to examine the possibility that CDS trading promotes innovation by 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 the efficiency of corporate innovation to reconcile our findings that CDS trading improves innovation output but does not have a significant impact on innovation input in terms of R&D. We further investigate whether patents generated after CDS trading are of greater importance or have higher economic value, apart from having higher scientific value in terms of citations.

5.1. Cross-sectional heterogeneity in results

To investigate how our results vary across firms, we use variables one year prior to CDS trade initiation to partition our sample of CDS and non-CDS firm-years in several ways. We report the results in Table 5, where the regressions include all the control variables in Table 3. Again, to be concise, we only tabulate the coefficients of *CDS Trading* for different subsamples.

[Insert Table 5 Here]

We first examine how borrowing firms' dependence on debt financing affects our results. To the extent that CDSs alleviate compatibility issues between debt financing and innovation, we expect the CDS effect on innovation to be stronger for firms that are more dependent on debt financing for investment. We divide the sample into two groups according to the sample median level of debt dependence. Debt dependence is measured using the industry median fraction of investment financed with debt, i.e., the sum of net debt issued divided by the sum of capital expenditures and R&D expenses over the past decade (e.g., Rajan and Zingales, 1998). We then separately re-estimate Eq. (2) for the two subsamples with high and low debt dependence. The results presented in Panel A of Table 5 show that the CDS effect on innovation output is more pronounced for firms with higher debt dependence, confirming that the presence of CDSs alleviates compatibility issues between debt financing and innovation. Among firms with lower debt dependence, the *CDS Trading* coefficients are not significantly different from zero and are much smaller in magnitude.

Furthermore, the risk-taking channel suggests that CDS trading fosters corporate innovation by weakening lenders' incentives to engage in continuous monitoring. We thus expect that the effect of CDS trading is more prominent when the lender–borrower relationship is characterized by continuous monitoring prior to CDS trade initiation. To test this prediction, we partition the firms into two groups according to whether they have bank debt before the advent of CDS trading. To the extent that banks are likely to continuously monitor borrowing firms more than public debtholders (e.g., Atanassov, 2015), the CDS effect should be more evident for firms with bank debt. We then separately re-estimate Eq. (2) for the two groups and report the results in Panel B of Table 5.[31] Consistent with our

[31] For this analysis, we exclude 3,744 firm-years that do not exist in S&P Capital IQ. In an untabulated test, we treat these firm-years as having zero bank debt and find that our results are qualitatively the same.

expectations, the *CDS Trading* coefficients are positive and significant mainly for firms with bank debt, suggesting that CDSs are more effective in promoting innovation for firms financed with debt that is less compatible with innovation.

We also examine how the CDS–innovation relation is moderated by the number of bank lenders. Firms borrowing from fewer banks are more likely to be continuously monitored by banks because the borrower–lender relationship is strengthened as the number of lenders decreases (Carvalho, Ferreira, and Matos, 2015).[32] Hence, we expect the CDS effect on corporate innovation to be stronger for firms with fewer bank lenders. We split the subsample with bank debt into two groups based on the median number of unique bank lenders over the five years prior to CDS trade initiation.[33] The regression results tabulated in Panel C of Table 5 are consistent with our expectations.

As discussed in Section 1, the risk-taking channel also implies that CDSs foster corporate innovation by loosening debt covenants. Debt covenants are important vehicles through which lenders can exert control rights and monitor borrowing firms. In the presence of stringent covenants, borrowing firms may curb risk taking in innovation to avoid covenant violations. To the extent that firms' debt covenants are loosened after CDS trading starts (Shan, Tang, and Winton, 2015), their ability and flexibility to experiment with novel projects should increase (Atanassov, 2015). Against this backdrop, we expect the CDS effect on innovation to be stronger for firms with more debt covenants that are loosened after the introduction of CDSs. To test this prediction, we focus on the subsample with bank loans and collect covenant information from the Loan Pricing Corporation's DealScan database. Specifically, we are interested in two types of loan covenants, i.e., secured debt and net worth covenants, which have been shown by Shan, Tang, and Winton (2015) to loosen upon the inception of

[32] Additionally, Diamond (1984) argues that delegating monitoring to fewer lenders can enhance monitoring by mitigating the duplication of monitoring efforts, coordination failure, and free-rider problems associated with multiple lenders.

[33] Bank lenders are identified using the Loan Pricing Corporation's DealScan database. For each firm in a given year, we examine the prior five-year period for any syndicated loan facilities in place for this firm. Summing all such active facilities, we compute the number of unique banks that lend to the firm.

the CDS market.[34] Firms with bank debt are then divided into two groups according to whether their loan contracts contain at least one of the two types of covenants over the five years before CDS trading starts. We re-estimate Eq. (2) for the two groups and report the regression results in Panel D of Table 5, which show that the CDS effect on innovation is more positive and significant for firms with loan covenants that are loosened after CDS trade initiation, consistent with the risk-taking channel.

Finally, we partition the sample according to the borrowing firms' probability of debt renegotiation with lenders. As discussed in Section 1, anticipating that CDS-insured lenders can be tough in debt renegotiation and force borrowing firms into inefficient bankruptcy, borrowing firms may take less risk in innovation to avoid corporate defaults that trigger debt renegotiation. We thus expect that the risk-taking effect of CDS trading on innovation is stronger for borrowing firms that are less likely to renegotiate their debt. We measure the probability of debt renegotiation using the average Altman's (1968) *Z*-score in the past two years and divide the sample into two groups according to its median value.[35] A higher *Z*-score indicates a lower probability of default, thereby implying a lower probability of debt renegotiation. We then separately re-estimate Eq. (2) for the two groups and present the results in Panel E of Table 5. We find that the *CDS Trading* coefficients are positive and significant for firms that are less likely to renegotiate their debt, whereas the coefficients are smaller and statistically insignificant for firms with high probabilities of debt renegotiation. These results are consistent with the view that the *ex post* threat of exacting CDS-protected creditors weakens borrowing firms' *ex ante* risk-taking incentives that arise from decreased creditor monitoring. Collectively, our cross-sectional analysis in Table 5 supports our arguments that CDS trading fosters corporate innovation by promoting borrowing firms' risk taking in innovation and enhancing the compatibility between debt financing and innovation.

[34] Specifically, the 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. The net worth covenant requires that the borrowing firm maintain a minimum (tangible) net worth value during the life of the loan.

[35] Altman's (1968) *Z*-score is defined as (3.3×*Pretax Income*+*Sales*+1.4×*Retained Earnings*+1.2×[*Current Assets*-*Current Liabilities*])/*Assets*. The results (untabulated) are similar if we alternatively use *Z*-score at *t*-1 or the average *Z*-score in the past three years to measure the probability of debt renegotiation.

5.2. CDS trading and innovation strategies

Corporate innovation strategies are highly heterogeneous across firms and vary drastically over time (e.g., Hall, 1993). The risk-taking channel suggests that CDS trading enables borrowing firms to achieve greater flexibility and tolerance to risky experimentation. We thus expect borrowing firms to shift the trajectory of innovation from low-risk and incremental innovations to high-risk and radical innovations after CDS trade initiation. To test this, we define several measures of innovation strategies.

First, we follow prior studies (e.g., Balsmeier, Fleming, and Manso, 2017) and categorize innovation strategies as exploitative or exploratory strategies. Exploitative innovations refine and extend existing knowledge and have less risky payoffs and shorter gestation periods. By contrast, exploratory innovations require new knowledge or a departure from existing knowledge, and their payoffs are riskier and take a longer time to realize. We construct proxies for exploitative and exploratory innovations using the extent to which a firm's patents rely on existing versus new knowledge. Specifically, a firm's existing knowledge includes its existing patents and the patents that its existing patents cite. We categorize a patent as exploitative if at least 60% of its citations are based on the firm's existing knowledge and as exploratory if at least 60% of its citations are based on new knowledge (i.e., patents not in the firm's existing knowledge). We then define *%Exploitative* (*%Exploratory*) as the number of exploitative (exploratory) patents divided by the total number of patents that each firm applies for each year.

Second, we separate innovations into product and process innovations. According to Chava et al. (2013), product innovations result in the creation of new products and are thus more radical and risky than process innovations, which mainly involve enhancing the efficiency of existing production processes. We follow Chava et al. (2013) and classify patents as process patents if they fall into the International Patent Classification (IPC) category B01, which primarily focuses on Physical and Chemical Processes, and define all other patents as product patents. We then define *Process* (*Product*) as the natural logarithm of one plus the number of process (product) patents that each firm applies for each year.

Third, we construct a measure of originality of the patents filed by firms. Patent originality reflects how far a patent is away from the extant technology class, thus indicating the impact of innovation. Hall, Jaffee, and Trajtenberg (2001) argue that original patents cite previous patents that belong to a wide range of technological fields. We use their definition and compute the originality score of a patent as one minus the Herfindahl index of the three-digit technology class distribution of all the patents that the patent cites. A higher score corresponds to a higher level of originality for patents. We then define *Originality* as the mean originality score of a firm's new patents in each year.

[Insert Table 6 Here]

Table 6 reports the results obtained by re-estimating Eq. (2) with the dependent variables *%Exploitative*, *%Exploratory*, *Process*, *Product*, and *Originality*. The *CDS Trading* coefficients suggest that after CDS trade initiation, CDS firms, compared with non-CDS firms, significantly decrease the fraction of exploitative patents but increase the fraction of exploratory patents (columns (1) and (2)), create more product patents rather than process patents (columns (3) and (4)), and enhance the patent originality (column (5)). To the extent that exploratory and product patents are more risky and radical than exploitative and process patents and that patents with higher originality scores represent more impactful inventions, our findings indicate that after CDS trade initiation, firms shift away from low-risk and incremental innovations to high-risk and path-breaking innovations.

5.3. Tests of the financing channel

Prior studies suggest that the presence of CDS trading increases borrowing firms' debt capacities (Bolton and Oehmke, 2011) and relaxes their credit constraints (Saretto and Tookes, 2013). Firms with traded CDSs possibly issue more debt and use the proceeds to increase innovation input (i.e., R&D investments), giving rise to greater innovation output. In other words, CDSs may promote corporate innovation through a financing channel. This financing channel has at least three implications. First, the CDS effect on innovation should be stronger for more financially constrained firms than for less constrained firms because more constrained firms should benefit more from the relaxation of credit constraints after CDS trade initiation. Second, the CDS effect on innovation should be more pronounced for firms where debtholders are less willing to finance innovation investments because of their conflicts with shareholders. Third, compared with non-CDS firms, CDS firms should increase R&D investments more after the inception of CDS trading. We use several tests to examine whether any of these implications of the financing channel are supported empirically. The results are reported in Table 7.

[Insert Table 7 Here]

In Panel A of Table 7, we partition our sample using financial constraints measures and separately estimate the CDS effect on innovation for more and less financially constrained firms. Specifically, our classification schemes are based on firm size (*Ln*(*Assets*)), the dividend payer indicator, and Whited and Wu's (2006) financial constraints index (the *WW* index).[36] A firm is defined as more (less) financially constrained if its size is smaller (larger) than the sample median, if it pays zero (non-zero) dividends, or if its *WW* index is above (below) the sample median. The regression results reveal that the *CDS Trading* coefficients are larger and more significant for less financially constrained firms than for more constrained firms. This finding runs counter to the first implication of the financing channel, indicating that our main results are not driven by CDSs relaxing borrowing firms' financial constraints and increasing their debt financing. Similar inferences can be drawn if we partition the sample using alternative financial constraints classifications, such as credit ratings (e.g., Almeida,

[36] The *WW* index is equal to -0.091×*Cash Flow/Assets*-0.062×*Dividend Payer Indicator*+0.021×*Long-term Debt/Assets*-0.044×*Ln*(*Assets*)+0.102×*Industry Median Sales Growth*-0.035×*Sales Growth.* By construction, higher scores of the *WW* index indicate that firms are more financially constrained. Similar to the tests in Section 5.1, we partition the sample using financial constraints variables one year prior to CDS trade initiation.

Campello, and Weisbach, 2004) and the financial constraints indices suggested by Kaplan and Zingales (1997), Cleary (1999), and Hadlock and Pierce (2010).[37]

In Panel B, we partition the sample according to the median value of institutional ownership defined as the fraction of shares outstanding held by institutional investors from Thomson 13f. Colonnello, Efing, and Zucchi (2016) argue that institutional investors have stronger bargaining power than retail investors in debt renegotiation, thereby exacerbating the conflicts between shareholders and debtholders. They show that debtholders of firms with higher institutional ownership are more likely to buy CDS protections. Thus, if CDSs enhance corporate innovation through encouraging debtholders to finance more innovation investments, the CDS effect on innovation should be stronger for firms with higher institutional ownership. We then estimate Eq. (2) separately for firms with high and low institutional ownership, which reflect strong and weak debtholder-shareholder conflicts, respectively. However, we do not find a stronger CDS effect on innovation for firms with higher institutional ownership.[38]

In Panel C, we examine the effect of CDS trading on firms' R&D investments by re-estimating Eq. (2) with the dependent variable $(R\&D/Assets)_t$. The results show that regardless of whether we control for lagged R&D in the regression, the *CDS Trading* coefficients are not significantly different from zero, indicating that compared with non-CDS firms, CDS firms experience no significant increases in R&D expenditures after the advent of CDS trading. This finding suggests that our main results are not driven by an increase in innovation input financed with new debt issuances after the

[37] Specifically, in untabulated tests, we find that the coefficients of *CDS Trading* are significantly positive only for less financially constrained firms when the sample is bifurcated using credit ratings or the financial constraints indices of Kaplan and Zingales (1997) and Cleary (1999). When we partition the sample using Hadlock and Pierce's (2010) index, which is defined as $-0.737\times Ln(Assets)+0.043\times Ln(Assets)^2-0.04\times Firm\ Age$, we find that the *CDS Trading* coefficients for both more and less constrained firms are significantly positive.

[38] Apart from institutional ownership, Colonnello, Efing, and Zucchi (2016) use three additional measures of shareholder bargaining power, i.e., ownership concentration among the top five institutional investors, active ownership defined as the fraction of shares held by investors that each allocate at least 2% of their portfolio wealth to the firm, and the ratio of bank debt to total assets, a lower value of which indicates a stronger shareholder bargaining power. Our results reported in Panel B of Table 5 suggest that the CDS effect is not stronger for firms with no bank debt. Further analysis (untabulated) using top five institutional ownership and active ownership generates qualitatively similar findings.

inception of CDS trading. However, if CDS firms borrow more (Saretto and Tookes, 2013) but do not allocate the proceeds of new debt issues to R&D investment, where do the proceeds go? To address this question, in untabulated tests, we investigate whether CDS firms allocate new debt proceeds for alternative uses, which include capital expenditures, acquisitions, dividends, and cash holdings, by using each alternative use (deflated by total assets) as the dependent variable in Eq. (2). We find that the *CDS Trading* coefficient is positive and statistically significant in the cash holdings regression, consistent with Subrahmanyam, Tang, and Wang's (2017) finding that CDS-referenced firms hold more cash after CDS trading begins on their debt. However, we detect no significant CDS effects on capital expenditures, acquisitions, and dividends after CDS trade initiation. In sum, although CDS trading increases the credit supply for borrowing firms, the additional funding seems to be used to build up cash reserves rather than to finance R&D spending or other investments. Overall, the evidence in Table 7 does not support the alternative explanation that the CDS effect on innovation output works through the financing channel.

5.4. CDS trading, innovation efficiency, and the economic value of patents

Our analysis has shown thus far that CDS trading leads to greater innovation output (i.e., patents and citations) but does not significantly increase innovation input (i.e., R&D spending). This implies that CDS trading engenders greater innovation output by enhancing innovation efficiency, which captures a firm's ability to generate patents and patent citations per dollar of R&D investment. To confirm the implication, 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 (*Ln*(1+*Patent/R&D*) and *Ln*(1+*Citation/R&D*)). We then re-estimate Eq. (2) using the two innovation efficiency measures as dependent variables.[39] The results reported in columns (1) and (2) of Table 8 show that the *CDS Trading* coefficients are positive and

[39] For these regressions, the number of observations is reduced to 9,507 because the innovation efficiency measures cannot be defined for firms with missing or zero R&D investments.

significant at the 5% level. This finding suggests that CDS trading enhances innovation output by more efficiently deploying R&D investments toward more innovative projects rather than increasing R&D investments *per se*.

[Insert Table 8 Here]

Finally, we examine the effect of CDS trading on three additional quality measures of corporate innovation. Firms face a trade-off between patenting their innovation and keeping it secret. While patenting innovation can protect innovators' intellectual property, the information disclosure through patenting may enable competitors to obtain certain technological knowledge (Saidi and Zaldokas, 2017). It is possible that after CDS trade initiation, firms become more willing to patent their innovation, instead of becoming more innovative. To wit, CDS trading may increase firms' propensity to patent without increasing the amount and quality of innovation.

To alleviate this concern, we first use the number of citations per patent ($\overline{Citation}$) to measure the average importance or quality of patents. The second measure is the number of citation-weighted patents (*CW_Patent*) used by Chava et al. (2013). Hall, Jaffe, and Trajtenberg (2005) show that citation-weighted patents are much more correlated with firm value than simple patent counts. The third measure is Kogan et al.'s (2017) *economic* value of patents (*Patent Value*), which is defined as the present value of the monopoly rents associated with patents. Forward citations, which have been used as one of our primary innovation output measures, mainly capture the *scientific* value of patents. Kogan et al. (2017) note that, while the economic and scientific values of patents are strongly and positively correlated, the two values do not necessarily coincide with one another. For example, a patent that makes a scientific breakthrough may not be very effective in stifling competition and thus may only generate small monopoly rents. Kogan et al.'s (2017) measure is computed based on stock market reactions to the announcement of patents that the USPTO grants to public firms.[40] Specifically, they separate the component of a firm's stock return that is related to patent values from those that are

[40] We download data on the economic value of patents from Dimitris Papanikolaou's website.

unrelated to patent values and then compute a patent's economic value as the increase in the firm's market valuation in the three-day period of patent grant announcements after adjusting for the market return, the success rate of the patent application, and the component of the idiosyncratic return unrelated to the patent. For firms with more than one patent in a fiscal year, we compute the total economic value of all patents filed that year.

We log-transform the three measures and use them as the dependent variables in Eq. (2). The regression results reported in columns (3)-(5) of Table 8 show that the *CDS Trading* coefficients are positive and significant at the 5% level. In terms of economic significance, the annual increases in the number of citations per patent, the number of citation-weighted patents, and the economic value of patents for CDS firms are, 13.3%, 14.8%, and 8.1% higher than those for non-CDS firms after CDS trade initiation, respectively. Collectively, these results imply that CDSs enable borrowing firms to generate both scientifically and economically more valuable patents. While our tests in Table 8 can mitigate the concern that CDS introduction increases firms' propensity to patent without enhancing their innovation, they cannot completely address the issue.[41] In particular, they cannot rule out the possibility that while the overall amount of innovation remains the same, firms shift their patenting strategy from patenting less important innovations to more important ones because, for example, firms may have fewer secrecy concerns after CDS trade initiation. This challenge is difficult to overcome because empirical researchers can only observe a firm's patents, rather than its total innovation that includes both patents and unpatented innovations. Thus, we highlight the issue as an important topic for future research, particularly if unpatented innovations become measurable.

6. Conclusion

[41] Specifically, our tests can rule out the possibility that after CDS introduction, firms, instead of increasing the overall amount of innovation, just patent more economically unimportant innovations, or patent more innovations of the same importance (e.g., the same number of citations per patent) as before.

We study the link between CDSs and companies' technological innovation. On the one hand, as an important innovation in global financial markets in recent decades, CDSs have come under harsh criticism since the financial crisis of 2007–2009. While some have debated whether CDSs contributed to the crisis and how CDS markets should be regulated, little is known about whether CDSs have any real effects on the economy. On the other hand, technological innovation has become a core strategy to enhance firms' competitiveness and long-term growth in the new millennium. Despite the abundant literature on various factors that spur or impede corporate innovation, few studies examine the role of CDS trading in affecting technological innovation. Our paper fills these gaps.

Using a large sample of U.S. listed firms, we show that CDS trade initiation significantly increases reference firms' innovation output measured by patents and citations. These results are robust to a variety of tests on model specifications, variable definitions, and selection and endogeneity issues. We also find that CDSs shift borrowing firms away from low-risk and incremental innovations to high-risk, radical, and economically more valuable innovations. Additional analysis reveals that CDSs mainly spur corporate innovation by enhancing lenders' risk tolerance and encouraging borrowing firms' risk taking in innovation rather than by increasing borrowing firms' R&D investments.

Finally, we stress two limitations of our study. First, since most CDS firms in our sample are large and mature firms, our results should be generalized with caution, especially to small and start-up firms. Second, although our findings suggest a "bright" side of CDSs in terms of stimulating corporate innovation, we do not conclude that CDSs have a positive aggregate welfare effect. Similar to other financial innovations, CDSs are a double-edged sword capable of producing both positive and negative outcomes. Prior research has documented various effects of CDSs on risk sharing, market completeness, credit supply, financing costs, accounting conservatism, corporate cash holdings, bankruptcy risk, and corporate governance, among others (Augustin et al., 2016). We add to the literature by showing that CDSs promote borrowing firms' risk taking, leading to greater innovation output. However, the risk-taking effect may induce moral hazard problems in borrowing firms and encourage them to take excessive risks in value-decreasing investment projects. Meanwhile, the discipline imposed by the threat of tough lenders in debt renegotiations may curb moral hazard and excessive risk taking. Thus, to better understand the aggregate welfare effect of CDSs, one needs to conduct a thorough investigation into these possible scenarios and consider various financial and real effects of CDSs, which we leave to future research.[42] At a minimum, our findings highlight that regulators need to determine how CDS markets should be regulated based on the trade-off between the various benefits and costs of CDSs.

[42] Danis and Gamba (2016) take an important step toward addressing this issue by documenting the positive effect of CDSs on reference firms' value. In particular, they find that, on average, the reference firms' value increases by 2.9% with the introduction of a CDS market.

Appendix A. Distribution of CDS firms over time and across industries

The sample consists of firms jointly covered in the CreditTrade, the GFI Group and Markit CDS databases, 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 CDSs traded 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

SIC code	Included industries	(1) Number of CDS firms	(2) Percentage of all CDS firms
1	Mining and construction	82	10.5%
2	Food, tobacco, textile mill, apparel, and lumber and wood products, furniture and fixtures, paper, printing, publishing, and chemical products, petroleum refining, etc.	208	26.6%
3	Rubber and plastic products, leather, stone, clay, glass, concrete, and metal products, machinery, electronic and electrical equipment, transportation equipment, measuring, analyzing, and controlling instruments, etc.	213	27.2%
4	Transportation, communications, electric, gas, and sanitary services	99	12.7%
5	Retail and wholesale trade	78	10.0%
7	Hotels, personal and business services, automotive repair services, motion pictures, amusement and recreation services, etc.	80	10.2%
8	Health, legal, educational, and social services, museums, art galleries, botanical and zoological gardens, membership organizations, engineering, accounting, research, and management services, private households, etc.	22	2.8%

Appendix B. Robustness checks

The sample consists of CDS firms that initiated CDS trading between 1997 and 2008 and the matched non-CDS firms. *CDS Trading* is equal to one in and after the first year of CDS trading on a reference firm and zero prior to it. 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	0.139***	0.166**
	(2.6)	(2.3)

Panel B: Including additional variables identified by Oehmke and Zawadowski (2017) and Bank Size in Eq. (1) to construct the matched sample (N = 5,045)

	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
CDS Trading	0.201***	0.298***
	(2.8)	(2.8)

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

	$Patent_t$	$Citation_t$
CDS Trading	0.176**	0.535***
	(2.5)	(3.0)

Panel D: Using corporate innovation output measured at t+2 (N = 13,543)

	$Ln(1+Patent)_{t+2}$	$Ln(1+Citation)_{t+2}$
CDS Trading	0.233***	0.204**
	(2.8)	(2.1)

Panel E: 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***
	(3.3)	(3.6)

Panel F: Excluding self-citations (N = 16,636)

	$Ln(1+Citation)_t$
CDS Trading	0.174***
	(2.6)

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***
	(2.7)	(3.2)

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***
	(2.9)	(3.2)

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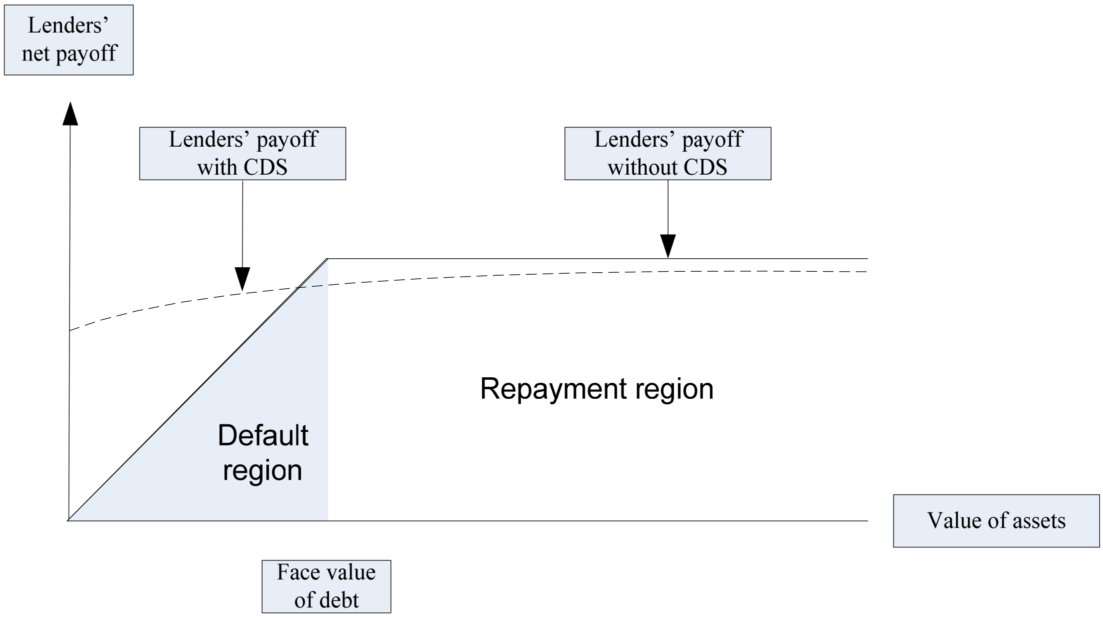
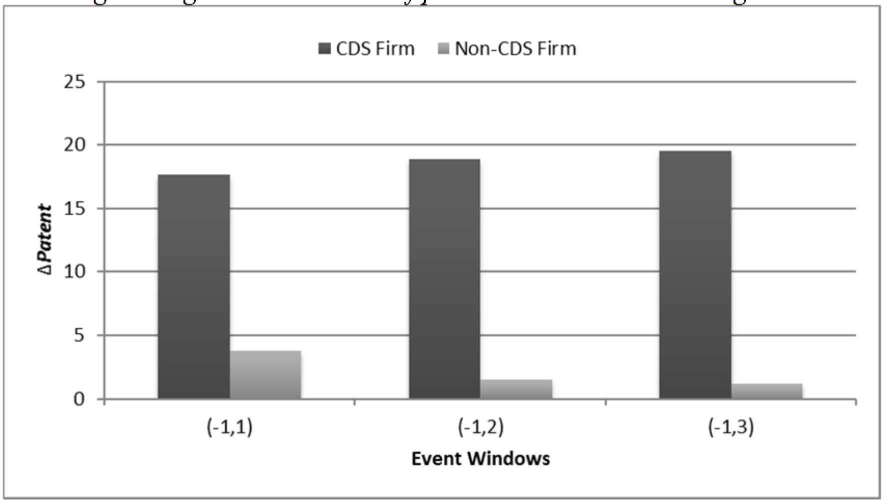


Fig. 1. Lenders' net payoff with and without CDS protection. The figure shows lenders' net payoffs with and without CDS protection. The horizontal axis denotes the value of borrowing firms' assets and the vertical axis denotes lenders' net payoff. The dashed (solid) line indicates lenders' net payoffs with (without) the CDS protection. With CDS protection, lenders' net payoff is the face value of debt minus CDS premiums, which increases with borrowing firms' default risk.

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



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

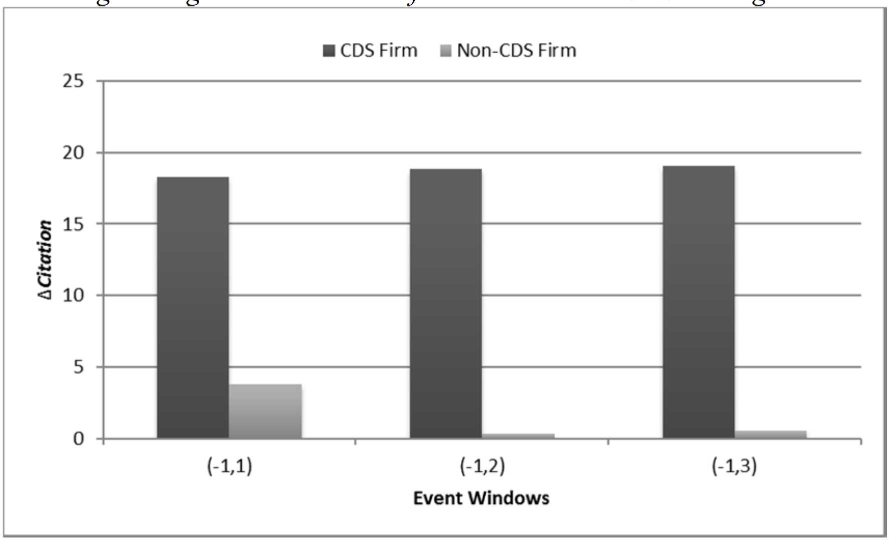


Fig. 2. Changes in innovation output around CDS trade initiation. The sample consists of CDS firms that initiated CDS trading between 1997 and 2008 and the matched non-CDS firms jointly. The matched non-CDS firms is selected based on the nearest one propensity score matching method, which is estimated 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 effects. Panel A (B) plots the average changes 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.

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 first 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 a binary variable that equals one if a borrowing firm has a debt rating assigned by Standard & Poor's and zero otherwise. *Investment Grade* is a binary 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. 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 * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Probit model 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)
Industry and year fixed effects	Yes
N/Pseudo R-squared	50,018/0.465

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

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 effects. *Ln*(1+*Patent*) is the log of one plus *Patent*. *Ln*(1+*Citation*) is the log of one plus *Citation*. *CDS Trading* is a binary 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/Assets* 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/Assets* 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
Innovation measures						
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
CDS variables						
CDS Trading	16,636	0.268	0.443	0.000	0.000	1.000
Daily Quotes	4,579	236	59	146	261	262
Distinct Dealers	4,330	6.719	4.573	3.030	5.191	9.767
Distinct Maturities	4,433	7.474	3.453	5.115	8.605	10.487
Control variables in innovation regressions						
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 effects. *CDS Trading* is a binary variable that 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 is 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.

Dependent variables	(1) $Ln(1+Patent)_t$	(2) $Ln(1+Citation)_t$
CDS Trading	0.147***	0.199***
	(2.8)	(3.0)
Ln(*Assets*)	0.247***	0.243***
	(6.2)	(4.9)
Ln(*Firm Age*)	0.153	0.297**
	(1.5)	(2.2)
Ln(*PPE/Employees*)	0.286***	0.341***
	(4.7)	(4.4)
R&D/Assets	0.339	0.507
	(0.6)	(0.6)
ROA	0.117	-0.078
	(0.6)	(-0.3)
MB	0.105***	0.156***
	(9.1)	(10.3)
Sales Growth	-0.074**	-0.112**
	(-2.4)	(-2.4)
Leverage	-0.262**	-0.512**
	(-2.1)	(-2.6)
Cash/Assets	0.723***	0.357
	(3.9)	(1.4)
Stock Volatility	4.823***	8.357***
	(3.2)	(3.6)
Herfindahl	-0.461	0.485
	(-0.6)	(0.5)
$Herfindahl^2$	0.609	-0.247
	(1.0)	(-0.3)
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. Panel A presents the regressions results on the effects of CDS liquidity measures on innovation output. Panel B presents the regression results with state-by-year and industry-by-year fixed effects. Panel C 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 D presents the regression results related to *cov-lite* loans. Panel D.1 presents the regression results controlling for the *Cov-Lite* indicator that equals one in and after the first year when the firm starts borrowing in the cov-lite loan market, and zero prior to it. Panel D.2 presents the regression results controlling for net fund inflows to collateralized loan obligations (CLOs) and loan mutual funds. Panel D.3 presents the regression results excluding firms with CDS introduction dates after the first quarter of 2005, and their corresponding control firms. Panel E presents the regression results controlling for other corporate governance measures. Panel F presents the regression results on the dynamics of innovation differentials between CDS and non-CDS firms over the years surrounding CDS trade initiation. $Year^{-2}$ ($Year^{-1}$) is a binary variable that takes the value of one if CDS trading initiates in two (one) years and zero otherwise. $Year^{0}$ is a binary variable that equals one if CDS trading initiates this year and zero otherwise. $Year^{+1}$ is a binary variable that equals one if CDS trading initiates one year ago and zero otherwise. $Year^{\geq+2}$ is a binary variable that equals one if CDS trading initiates two or more years ago and zero otherwise. Panel G presents the regression results controlling for bank size defined as the log of average total assets of firms' bank lenders. Panel H presents the regression results controlling for past innovation investments, innovation success, and implied volatility. Panel I presents the third-stage estimation of the instrumental variable regression results. In the first-stage regression, we use *Lender FX Hedging* as the instrument to predict the probability of CDS trading. *Lender FX Hedging* is defined as the average of foreign exchange 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. Panel J presents the regression results using the Anti-Recharacterization Law as an exogenous shock. *Post AR* is a binary variable that equals one after the enactment of anti-recharacterization laws in the state of a firm's headquarter or incorporation, and zero otherwise. 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: Effects of CDS liquidity measures on innovation output using CDS firm-years only.

	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
Panel A.1: Number of daily quotes (N = 4,579)		
Daily Quotes	0.001***	0.002***
	(4.2)	(4.1)
Panel A.2: Number of distinct dealers (N = 4,330)		
Distinct Dealers	0.014*	0.031***
	(1.8)	(2.6)
Panel A.3: Number of distinct maturities (N = 4,433)		
Distinct Maturities	0.042***	0.055***
	(3.1)	(2.9)

Panel B: Controlling for state-by-year and industry-by-year fixed effects (N = 16,458)

	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
CDS Trading	0.111**	0.086*
	(2.5)	(1.7)

Panel C: Distribution of the coefficient of CDS Trading constructed using randomized CDS initiation dates (1,000 replications)

	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
Mean	0.003	0.002
	(0.173)	(0.196)
Median	0.007	0.008
	(0.155)	(0.116)
1st percentile	-0.121	-0.278
	(-1.579)	(-1.621)
10th percentile	-0.065	-0.084
	(-0.872)	(-1.252)
90th percentile	0.064	0.093
	(1.197)	(1.367)
99th percentile	0.115	0.153

	(2.253)	(2.293)

Panel D: Testing the Cov-lite loan as an alternative explanation

	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
Panel D.1: Controlling for the Cov-Lite indicator (N = 16,636)		
CDS Trading	0.144***	0.195***
	(2.7)	(2.9)
Cov-Lite	0.526***	0.588**
	(3.0)	(2.3)
Panel D.2: Controlling for net fund inflows to CLOs and loan mutual funds (N = 10,231)		
CDS Trading	0.261***	0.310***
	(4.4)	(3.9)
Inflow_CLO	0.001	-0.001
	(1.3)	(-0.3)
Inflow_MF	0.070***	0.096***
	(12.6)	(7.2)
Panel D.3: Excluding firms with CDS trading initiated after 2005: Q1 (N = 14,600)		
CDS Trading	0.130**	0.189***
	(2.2)	(2.6)

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

	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
CDS Trading	0.104**	0.083*
	(2.1)	(1.9)
G-index	0.018	0.020
	(0.7)	(1.0)
Board Size	0.026	0.100
	(0.2)	(0.8)
Institutional Ownership	0.323**	0.614***
	(2.1)	(3.8)

Panel F: Dynamics of the CDS effect on innovation over the years surrounding CDS trade initiation (N = 16,636)

	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
$Year^{-2}$	0.012	0.019
	(0.5)	(0.6)
$Year^{-1}$	0.006	0.000
	(0.2)	(0.0)
$Year^{0}$	0.035	0.073**
	(1.1)	(2.0)
$Year^{+1}$	0.087***	0.134***
	(2.6)	(3.1)
$Year^{\geqslant +2}$	0.225***	0.230**
	(2.7)	(2.3)

Panel G: Controlling for the size of bank lenders (N = 4,377)

	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
CDS Trading	0.225**	0.279**
	(2.6)	(2.2)
Bank Size	0.039	0.001
	(1.1)	(0.0)

Panel H: Controlling for past innovation investments, innovation success and implied volatility (N = 11,002)

	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
CDS Trading	0.165***	0.191***
	(3.0)	(2.6)
Past Innovation Investments	0.804	0.820
	(0.7)	(0.6)
Past Innovation Success	0.613***	0.503***
	(15.4)	(8.7)
Implied Volatility	0.101	-0.093
	(0.5)	(-0.4)

Panel I: Using Lender FX Hedging as an instrument (N = 16,636)

	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
Instrumented CDS Trading	0.362**	0.514**
	(2.0)	(2.5)

Panel J: Using Anti-Recharacterization Law as a natural experiment (N = 16,458)

	$Ln(1+Patent)_t$	$Ln(1+Citation)_t$
CDS Trading	0.183***	0.282***
	(3.3)	(4.0)
CDS Trading×Post AR	-0.112*	-0.229***
	(-1.9)	(-2.9)
Post AR	0.284***	0.377***
	(4.8)	(5.1)

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

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. In Panel A, the sample is split according to the sample median level of debt dependence. Debt dependence is measured using the industry median fraction of investment financed by debt, i.e., the sum of net debt issued divided by the sum of capital expenditures and R&D expenses over the past decade. In Panel B, we partition the firms into two groups according to whether they have bank debt or not before the advent of CDS trading. In Panel C, we split the subsample with bank debt into two groups based on the median number of unique bank lenders over the five years prior to CDS trade initiation. In Panel D, firms with bank debt are divided into two groups according to whether or not their loan contracts contain secured debt or net worth covenants over the five years before CDS trading starts. In Panel E, the sample is split using the median probability of debt renegotiation measured by the average Altman's *Z*-score in the past two years prior to CDS trade initiation. 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.

	(1)	(2)	(3)	(4)
Dependent variables		*Ln*(1+*Patent*)$_t$		*Ln*(1+*Citation*)$_t$
Panel A: Partitioning the sample according to industry median debt dependence (N_{high} = 8,311; N_{low} = 8,325)				
	High	Low	High	Low
CDS Trading	0.205***	0.080	0.229***	0.146
	(2.9)	(1.1)	(2.6)	(1.6)
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
	(2.1)	(-0.1)	(4.0)	(0.4)
Panel C: Partitioning firms with bank debt according to the number of bank lenders (N_{low} = 2,658; N_{high} = 2,633)				
	Low	High	Low	High
CDS Trading	0.214*	0.073	0.299*	0.032
	(1.8)	(1.0)	(1.7)	(0.3)
Panel D: Partitioning firms with bank debt according to loan covenants (N_{yes} = 3,136; N_{no} = 2,215)				
	Yes	No	Yes	No
CDS Trading	0.165*	0.075	0.162***	0.090
	(1.7)	(0.6)	(3.2)	(0.5)
Panel E: Partitioning the sample according to firms' probability of debt renegotiation (N_{low} = 6,683; N_{high} = 6,756)				
	Low	High	Low	High
CDS Trading	0.188***	0.088	0.227**	0.077
	(2.8)	(0.9)	(2.5)	(0.8)

Table 6
Effects of CDS trading on innovation strategies.

The sample consists of CDS firms that initiated CDS trading between 1997 and 2008 and the matched non-CDS firms. *%Exploitative* (*%Exploratory*) is the proportion of exploitative (exploratory) patents. A firm's existing knowledge comprises its existing patents and the patents that its existing patents cite. A patent is categorized as exploitative if at least 60% of its citations are based on the firm's existing knowledge, and as exploratory if at least 60% of its citations are based on new knowledge (i.e., patents not in the firm's existing knowledge). Patents falling into the International Patent Classification (IPC) category B01 are defined as process patents, and all other patents are defined as product patents. *Process* (*Product*) is the natural logarithm of one plus the number of process (product) patents applied for by each firm each year. The originality score of a patent as one minus the Herfindahl index of the three-digit technology class distribution of all the patents that the patent cites. *Originality* is the mean originality score of a firm's patents in each year. Detailed definitions of control variables are 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)	(5)
Dependent variables	*% Exploitative*	*%Exploratory*	*Process*	*Product*	*Originality*
CDS Trading	-0.027***	0.025**	0.027	0.149***	0.029***
	(-2.7)	(2.2)	(1.3)	(2.8)	(3.2)
Ln(*Assets*)	0.001	0.012	0.020*	0.246***	0.005
	(0.1)	(1.1)	(1.7)	(6.2)	(0.5)
Ln(*Firm Age*)	0.143***	-0.182***	0.129***	0.152	-0.023
	(8.0)	(-8.9)	(3.1)	(1.5)	(-1.1)
Ln(*PPE/Employees*)	-0.055***	0.046***	0.013	0.285***	0.010
	(-4.8)	(3.4)	(1.1)	(4.7)	(0.8)
R&D/Assets	0.092	-0.008	-0.002	0.320	0.118
	(0.8)	(-0.1)	(-0.0)	(0.5)	(1.4)
ROA	0.070	-0.030	0.137**	0.118	-0.011
	(1.4)	(-0.6)	(2.3)	(0.6)	(-0.2)
MB	-0.008***	0.009***	0.004	0.105***	-0.002
	(-3.7)	(3.7)	(0.8)	(9.1)	(-1.3)
Sales Growth	0.047***	-0.066***	-0.004	-0.072**	0.013
	(3.7)	(-4.6)	(-0.3)	(-2.4)	(1.3)
Leverage	0.062*	-0.066*	0.096***	-0.274**	0.029
	(1.9)	(-1.8)	(3.0)	(-2.2)	(1.0)
Cash/Assets	0.185***	-0.162***	0.222*	0.722***	0.039
	(4.8)	(-3.9)	(1.8)	(3.9)	(1.1)
Stock Volatility	-0.289	0.513	0.966	4.871***	-0.682*
	(-0.7)	(1.2)	(1.5)	(3.3)	(-1.7)
Herfindahl	-0.145	0.149	-0.071	-0.486	-0.162
	(-0.8)	(0.7)	(-0.3)	(-0.7)	(-0.7)
Herfindahl^2	0.184	-0.204	0.126	0.628	0.276
	(1.1)	(-1.1)	(0.7)	(1.0)	(1.5)
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes
N/Adjusted R-squared	7,775/0.575	7,775/0.580	16,632/0.707	16,632/0.895	6,982/0.381

Table 7
Testing the financing channel as an alternative explanation.

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. In Panel A, the sample is divided into more financially constrained (MFC) and less financially constrained (LFC) using classification schemes based on firm size (*Ln*(*Assets*)), the dividend payer indicator, and Whited and Wu's (2006) financial constraints index (the *WW* index). A firm is defined as MFC (LFC) if its size is below (above) the sample median, if it pays zero (non-zero) dividends, or if its *WW* index is above (below) the sample median. In Panel B, the sample is divided into high institutional ownership and low institutional ownership according to the sample median. Institutional ownership is defined as the fraction of shares outstanding held by institutional investors from Thomson 13f. Panel C presents the regression results on the effect of CDS trading on *R&D/Assets*. Detailed definitions of dependent variables and control variables can be found in the legend of Table 2. Both firm and year fixed effects are included in all regressions. 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: Partitioning the sample using financial constraints measures

	(1)	(2)	(3)	(4)
Dependent variables	*Ln*(1+*Patent*)$_t$		*Ln*(1+*Citation*)$_t$	
	LFC	MFC	LFC	MFC
A.1. Partitioning the sample according to firm size (N_{LFC} = 8,295; N_{MFC} = 8,341)				
CDS Trading	0.203**	0.069	0.316***	0.026
	(2.2)	(1.5)	(3.0)	(0.4)
A.2. Partitioning the sample according to dividend payer indicator (N_{LFC} = 10,274; N_{MFC} = 6,362)				
CDS Trading	0.155**	0.031	0.224***	0.053
	(2.4)	(0.5)	(2.7)	(0.6)
A.3. Partitioning the sample according to Whited and Wu's (2006) financial constraints index (N_{LFC} = 8,222; N_{MFC} = 8,213)				
CDS Trading	0.215**	0.029	0.331***	-0.030
	(2.4)	(0.6)	(3.2)	(-0.5)

Panel B: Partitioning the sample according to institutional ownership (N_{high} = 8,315; N_{low} = 8,321)

	(1)	(2)	(3)	(4)
Dependent variables	*Ln*(1+*Patent*)$_t$		*Ln*(1+*Citation*)$_t$	
	High	Low	High	Low
CDS Trading	0.071	0.193**	0.076	0.339***
	(1.5)	(2.2)	(1.0)	(3.3)

Panel C: Effect of CDS trading on R&D

	(1)	(2)
Dependent variables	*R&D*$_t$	*R&D*$_t$
CDS Trading	-0.002	-0.002
	(-1.6)	(-1.4)
R&D$_{t-1}$	0.166***	
	(3.0)	
N/R-squared	16,636/0.927	16,636/0.920

Table 8
CDS trading, innovation efficiency, and the economic value of patents.

The sample consists of CDS firms that initiated CDS trading between 1997 and 2008 and the matched non-CDS firms. *Patent/R&D* is the number of patents over the average R&D expenditures in the past five years. *Citation/R&D* is the number of citations over the average R&D expenditures in the past five years. $\overline{Citation}$ is the average citation count per patent. *CW_Patent* is the number of citation-weighted patents. *Patent Value* is the sum of estimated patent value from Kogan et al. (2017). 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)	(5)
Dependent variables	$Ln(1+Patent/R\&D)_t$	$Ln(1+Citation/R\&D)_t$	$Ln(1+\overline{Citation})_t$	$Ln(1+CW\_Patent)_t$	$Ln(1+Patent\ Value)_t$
CDS Trading	0.020**	0.026**	0.036**	0.147**	0.081**
	(2.3)	(2.3)	(2.2)	(2.4)	(2.4)
Ln(*Assets*)	-0.013***	-0.019***	-0.005	0.267***	0.299***
	(-3.2)	(-3.7)	(-0.4)	(5.8)	(10.1)
Ln(*Firm Age*)	-0.001	0.007	0.120***	0.179	0.271***
	(-0.2)	(0.9)	(3.5)	(1.5)	(3.9)
Ln(*PPE/Employees*)	0.018*	0.011	0.055***	0.328***	0.364***
	(1.9)	(0.8)	(3.1)	(4.8)	(9.6)
R&D/Assets	-0.510***	-0.534***	0.162	0.641	1.414**
	(-3.5)	(-3.1)	(0.4)	(1.0)	(2.5)
ROA	-0.097	-0.073	-0.261***	0.040	0.301*
	(-1.5)	(-0.8)	(-2.9)	(0.2)	(1.8)
MB	0.013***	0.016***	0.055***	0.120***	0.183***
	(3.1)	(2.9)	(8.8)	(9.4)	(15.5)
Sales Growth	0.117***	0.133***	-0.045***	-0.071**	-0.086***
	(4.3)	(4.1)	(-2.6)	(-2.1)	(-2.7)
Leverage	-0.121***	-0.124***	-0.248***	-0.348**	-0.255***
	(-3.7)	(-3.1)	(-5.0)	(-2.3)	(-2.6)
Cash/Assets	0.073*	0.068	-0.441***	0.678***	0.126
	(1.7)	(0.9)	(-5.1)	(3.4)	(0.8)
Stock Volatility	-0.093	0.485	2.494***	5.703***	8.007***
	(-0.2)	(0.8)	(6.1)	(3.3)	(6.5)
Herfindahl	0.084	-0.035	1.063***	0.011	2.022***
	(0.7)	(-0.3)	(4.2)	(0.0)	(3.7)
$Herfindahl^2$	-0.080	0.026	-0.906***	0.206	-1.440**
	(-0.6)	(0.2)	(-3.6)	(0.3)	(-2.5)
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes
N/R-squared	9,057/0.558	9,057/0.543	16,636/0.310	16,636/0.884	16,018/0.864