Credit Protection and Animal Spirits: Product Market Competition with CDS *

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Abstract

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Abstract

Creditors are less stringent on borrowers when creditors can buy credit protection from the financial market, freeing borrowers for more aggressive strategies in the product market. We find that firms' sales and market share grow significantly faster if they have credit default swaps (CDS) traded. CDS firms achieve growth by reducing markups, developing products, and aggressively competing in rivals' product space. The growth effect is more pronounced for firms with financial constraints or technology uncertainties, consistent with CDS encouraging lenders' tolerance for failure. The effect is also stronger in industries with more growth opportunities and competition threats, where aggressive actions facilitated by CDS can potentially yield greater gains. This is the first study showing that credit protection through derivates markets can improve real outcomes in terms of growth and consumer welfare.

1. Introduction

How financial contracts affect product market competition is a central question in industrial organization. The seminal work of Bolton and Scharfstein (1990) points out that a lender's reign on a firm needs to be balanced such that the lender can be assured of the firm's ability to repay the loan while also allowing enough flexibility for the firm to thrive in the product market. Tolerance of the lender can encourage innovative and aggressive business strategies (Manso (2011)). These strategies are instrumental for growth when product markets keep changing (Hoberg and Phillips (2016)) and firms strive to stay dynamic and competitive (Hoberg and Maksimovic (2019)).[1]

While creditors in general are intolerant of risk due to agency concerns, a relatively recent innovation in credit derivatives, Credit Default Swaps (CDS), provides a contracting mechanism to increase lenders' tolerance. CDS are a means of insurance that indemnifies the lender in case of a borrower default. With this outside option, the lender is unlikely to renegotiate if the borrower reneges either strategically or unwillingly. As such, CDS strengthens the borrower's commitment to repay debt and make the lender less concerned of temporary setbacks, facilitating credit supply (Bolton and Oehmke (2011) and Saretto and Tookes (2013)). With lenders more tolerant, firms can pursue more aggressive strategies in product markets.[2] However, CDS protection, if excessive, can backfire. Over-insured lenders may be overly tough when refinancing or restructuring is needed, forcing firms into inefficient bankruptcy (Bolton and Oehmke (2011) and Subrahmanyam, Tang, and Wang (2014)).[3] The forward-looking firm may therefore act cautiously in product market competition, even if – or ironically because – they have more debt. To be sure, reputational

[1] While other sources of financing such as equity can be equally important, we focus on creditors, who are sensitive to agency problems and risks in product markets.

[2] Empirically firms with CDS also tend to receive more forgiveness after covenant violation (Chakraborty, Chava, and Ganduri (2015)), have less loan restrictions (Shan, Tang, and Winton (2019)), and invest and innovate more (Danis and Gamba (2018) and Chang et al. (20118)).

[3] Theoretically when investment decisions are made ex post in a dynamic setting, CDS can also discourage investment due to debt overhang (Wong and Yu (2019)).

concerns, business relationships, regulatory and cost disadvantages of CDS over-insurance, and CDS sellers' intervention can restrain the lender's moral hazard (Chakraborty, Chava, and Ganduri (2015) and Danis and Gamba (2019)). Therefore, the ultimate effect of CDS on firms' product market outcomes is best investigated empirically. Our key finding is that CDS prompt firm growth and competitiveness in product markets.

Our key variable, *CDS trading*, is an indicator that equals 1 if the firm has CDS traded in the quarter. OLS regressions show that CDS have positive and significant effects on sales and market share growth. This positive relation alleviates concerns of omitted variables causing industry downturns and CDS trading simultaneously. However, spurious relationship is still possible. For example, sales growth boosted by new products often occur after an initial spell of demand uncertainty, in which lenders are more likely to initiate CDS protection. To provide cleaner inferences, we use an instrumental variable (IV) approach based on the observation that a firm is more likely to have CDS if this firm's lenders and bond underwriters prefer borrowers with CDS traded in general.[4] We measure a lender's (underwriter's) CDS preference using its loan (bond underwriting) amount to CDS firms that are in different industries from the focal firm scaled by the lender's (underwriter's) total loan (bond underwriting) amount to client firms. Because lenders (underwriters) would care much less to hedge small clients' credit risk, we compute this ratio excluding clients whose loan (bond underwriting) amount with the lender (underwriter) is below the lender's (underwriter's) median client. Finally, for each sample firm, we average this ratio across the firm's lenders (underwriters) in the recent three year to get our IVs. There is no direct reason that unobserved firm and industry characteristics that may induce a particular firm's

[4] Lenders that actively hedge their loan positions using CDS are more likely to match with borrowers whose CDS are available or can be easily initiated with a counterparty. Bond underwriters often serve as market makers as well and hold substantial inventories of clients' bonds. Their hedging needs also favor clients with CDS readily available.

CDS trading would wind up influencing lenders and bond underwriters' preference for CDS firms in a broad range of industries unrelated to the focal firm.[5]

We use Hoberg and Phillips' (2010, 2016) Text-based Network Industry Classification (TNIC) to identify industries. TNIC has several advantages. First, rival classifications are based on firms' products and are firm-specific and time-varying. This dynamic network nature captures the constant shifts of rivalries in the product space. Second, Hoberg and Phillips (2016) show that TNIC is better at explaining differences in key characteristics such as profitability, sales growth, and market risk across industries. Therefore, when we use lenders' (underwriters') exposure to firms outside of the focal firm's industry, we are less likely to pick up lenders' (underwriters') unobserved preference for firms with similar characteristics. This helps to further improve the exogeneity of our IVs.

IV regressions find significantly positive effects of CDS trading on firms' product market outcomes. A one-standard-deviation increase in the instrumented *CDS trading* leads to a 1.3% (1.4%) increase in market share growth (sales growth), a 7% (6%) standard deviation increase. As shown in Figure 1, after netting out firm and quarter fixed effects, product market outcomes remarkably improve after CDS introduction. We further show that the results are not driven by a potential matching between large banks, which are more likely to trade CDS, and dominating product market players, which are more likely to outperform. We also find robust results using Li, Morgan and Zaslavsky's (2018) overlap weighting to orthogonalize the CDS treatment.

As argued above, although CDS can increase firms' credit supply (Saretto and Tookes (2013)), increased leverage does not necessarily boost product market outcomes if firms are subject to lenders' moral hazard or debt overhang. The observed positive effect of CDS indicates

[5] Balance tests also rule out significant correlations between important covariates and our IVs.

that the strengthening of lender tolerance overweighs the potential dark side of "empty creditors". Indeed, further analyses find that the CDS effects are more pronounced when firms face higher bankruptcy risk or greater financial constraints. These results are consistent with lenders remaining supportive in risky situations when CDS protection is available.

Product market success often calls for innovative and aggressive strategies. Lender tolerance is crucial in this regard because these strategies are also prone to agency problems such as asset substitution. In terms of technology strategies, we find that firms with unconventional technologies and high R&D expenses grow faster when they have CDS. In terms of competition agility, we find CDS firms grow faster in industries with more growth opportunities and more competitive threats, where aggressive actions are instrumental for growth. Overall, the evidence is consistent with CDS alleviating lenders' agency concerns and encouraging aggressive actions.

We dig deeper into CDS firms' product market strategies that support their growth over time. Using Hoberg, Phillips, and Prabhala's (2013) self-fluidity measure, we find firms making vigorous changes of their products after CDS trading. Over time, CDS firms pivot towards frontal competition in rivals' product space and reduce markups to stay competitive.[6] These aggressive turns of behavior are new to the literature and are consistent with CDS increasing lender tolerance and encouraging competitive actions. Perhaps more importantly, all these strategies, i.e., product development and competitive pricing, ultimately benefit the consumers. Our research thus reveals a direct welfare transfer to consumers from reduction of frictions in financial markets. In terms of investment policies, we find that CDS boost both R&D and capital expenditure (CAPX) but have no significant impact on acquisitions. Recent research by Hoberg and Maksimovic (2019) show

[6] Markups, i.e., the ratio of out price to marginal cost, are notoriously hard to measure. We rely on a structural estimation recently developed in the economics literature (see, e.g.., De Loecker and Warzynski (2012)) to estimate markups for most Compustat firms.

that more investment in R&D and CAPX (acquisition) is associated with youthful (mature) stages of the product life cycle. In this regard, CDS seem to help firms remain dynamic and competitive.

CDS's ability to alleviate the commitment problem in financial contracting (Bolton and Oehmke (2011)) has spurred research on various corporate policies such as capital structure (Saretto and Tookes (2013) and Subrahmanyam et al. (2017)), investment (Danis and Gamba (2018), Batta and Yu (2019), and Wong and Yu (2019)), innovation (Chang et al. (2018)), bankruptcy and restructuring (Subrahmanyam et al. (2014) and Danis (2017)), and supply chain effects (Li and Tang (2016)).[7] Their implication on product market outcomes, however, is not obvious. For example, high leverage can cause debt overhang and vulnerability to predation and business cycle risk (Phillips (1995) and Campello (2003)). Innovation can result in the first mover's curse and cannibalization. In fact, given the importance of financial contracting in the product market literature[8], it is surprising that there is little empirical investigation of CDS's product market effects. We are the first to fill this void.

Moreover, as our findings speak to a direct welfare effect of CDS on consumers, we make a novel contribution to the literature on the real effects of financial development (see, e.g., Jayaratne and Strahan (1996), Rajan and Zingales (1998), and Levine (2005)). Our work also adds to a growing literature on the effects of financial markets on real outcomes (Chen, Goldstein, and Jiang (2007) and Foucault and Fresard (2014)). While this literature mostly examines the informational role of asset prices in directing corporate decisions, we focus on the role of derivatives in reducing frictions in financial contracting. In a broad sense, our paper also contributes to the literature on how major corporate events impact product market competition

[7] For a survey of the CDS literature, see Augustin, Subrahmanyam, Tang, and Wang (2014, 2016).
[8] See, for example, Brander and Lewis (1986, 1988), Bolton and Scharfstein (1990), and Maksimovic and Zechner (1991), Chevalier (1995), Phillips (1995), Campello (2003))

(see, e.g., Spiegel and Tookes (2013, 2019), Aslan and Kumar (2016), Billet et al. (2017), Nain and Wang (2017), He and Huang (2017), and Grieser and Liu (2019)).

We develop the testable hypotheses in Section 2. Section 3 describes the data and our instrumental variables. Section 4 presents evidence of the CDS effect on product market outcomes. We analyze the mechanisms in Section 5. Section 6 concludes.

2. CDS protection, lender tolerance, and product market outcomes

Based on the theories on financial contracting and product market competition, we postulate that CDS trading has important effects on firms' product market outcomes. A borrower cannot credibly commit to repaying the lender because of moral hazard or uncontrollable business risk. This limited commitment problem in turn leads the lender to keep a rigid reign on the borrower to minimize credit risk. Without enough trust and consistent support from the lender, the borrower can be disadvantaged in product market competition. For example, the lender may perceive aggressive product market strategies as asset substitution attempts and refuse to finance. The firm can also become vulnerable to predation if rivals have less a commitment problem with their lenders. Because CDS provide insurance against default, they increase lenders' tolerance for failure. This tolerance encourages more aggressive product market strategies and can lead to better product market performance.

On the other hand, CDS's protection can induce the lender's moral hazard. If the lender is over-insured with CDS, it may have little incentive to support the firm in the long run or even favor bankruptcy over a more efficient restructuring. The firm therefore acts cautiously in the product market to avoid big setbacks. However, it is hard to boost growth with defensive strategies. The above arguments therefore lead to the following hypothesis (and its alternative).

Hypothesis 1: *CDS should have a positive effect on firms' product market outcomes.*

We expect the positive effect to be driven by lenders' tolerance for failure when CDS protection is available. This tolerance is important when the firm is under financial pressure. With a standard debt contract, the lender will be concerned about agency problems when the firm faces bankruptcy risk or financial constraints. However, it is often in these situations that the firm is vulnerable to predation and lenders' financial support is especially helpful. In an industry downturn, firms with more tolerant and supportive lenders may even grow stronger by consolidating rivals that lack financial support.

Lender tolerance is also instrumental when agency concerns threaten to undermine strategies that can ultimately boost growth. For example, some firms utilize unconventional technologies or invest in R&D for new growth opportunities. These strategies may be costly in the short term but can bear fruit given time. Unfortunately, it is often these innovative initiatives that are prone to agency concerns and discourage lenders from working closely with these firms. Lenders may also be hesitant when firms need to react to changing industry conditions. For example, growth opportunities or competition threats can appear unexpectedly. Firms often need aggressive actions to stay competitive. But due to information asymmetry and agency concerns, lenders can be slow or unwilling to support firms' reactions. In these situations, by easing lenders' agency concerns, CDS can free the firm for innovative or aggressive actions that eventually help growth. Thus, we also test the following hypothesis.

Hypothesis 2: *The positive effect of CDS on product market outcomes should be stronger when the firm is under financial pressure or in need of lender tolerance for risk taking and aggressive actions.*

We also investigate firms' product market strategies directly. We expect that with CDS available, firms' product market strategies become more aggressive as lenders are more tolerant. Firms can be more assertive and confrontational in both product and pricing policies. Specifically, we test the following hypothesis.

Hypothesis 3: *Firms with CDS available should appear more aggressive in their product market strategies. They should be more active in product development, more confrontational with rivals in product offerings, and more aggressive in price competition.*

3. Data and instruments

We compile a data set of CDS trading sourced from two major CDS interdealer brokers, CreditTrade and GFI, and supplemented by Markit. CreditTrade and GFI data are based on actual transaction information such as committed quotes and trades rather than non-tradable quotes. We identify the starting date of each firm's CDS trading from these records.[9] Similar data are used by Subrahmanyam, Tang, and Wang (2014) and Li and Tang (2016), among others. CreditTrade data cover the period from June 1997 to March 2006, and GFI data cover the period from January 2002 to April 2009. The overlapping period helps assure the data quality from each source. Data after 2009 are sourced from Markit. We focus on North American, single-name corporate CDS. We regard the underlying firm as a CDS-referenced firm (or simply CDS firm as we use throughout the paper) since the first transaction date. Because our data begin in 1997, which is regarded by

[9] CreditTrade merged with Creditex in 2007, and Creditex is now part of ICE (Intercontinental Exchange). CreditTrade was the biggest data source for CDS transactions during the earlier period of the CDS market. GFI Group is a major wholesale market brokerage in the derivatives markets, and it has also become a leading CDS data provider in recent years.

many market observers as the inception of the CDS market, there is minimal concern about the possible censoring of a firm's CDS trading status.[10]

Our base sample comes from WRDS's Compustat-CRSP merged database. We include firms that are incorporated in the U.S and are covered by Hoberg and Phillip's (2010, 2016) Text-based Network Industry Classification (TNIC), which we use to define industries. Compared with traditional industry classifications such as SIC and NAICS, TNIC construct time-varying and firm-specific networks of competitors directly based on their product descriptions in the 10-K. These dynamic networks better capture the ever-changing and multifrontal rivalries in product markets. TNIC also offers important advantages for constructing our IVs, which we discuss below. We then merge this sample with the above CDS firm sample to identify firms with CDS traded and the quarter when the trading starts. Our key independent variable, *CDS trading*, is a dummy variable that equals 1 if the firm has CDS traded in the quarter concerned. We use two measures of product market outcomes. *Sales growth* is the annual sales growth of a firm. *Market share growth* is computed as a firm's sales growth relative to the median of the firm's industry.

We follow the literature and control for the following potential determinants of product market performance.[11] *Market-to-book* is the ratio of market assets to book assets. *LnAssets* is the natural log of total assets. *Leverage* is the sum of long-term debt and debt in current liabilities divided by total assets. *Cash* is the firm's cash and short-term investments divided by total assets. *Stock return* is the firm's cumulative stock return in the last 12 months. *HHI* (the Herfindahl-Hirschman Index) is the sum of squared product market share of firms in an industry. Considering that institutional investors can influence firms' competition strategies while participating in CDS

[10] Nevertheless, it is possible that some less actively traded CDS contracts are not captured by our data set. Therefore, our estimated effect represents a lower bound of the actual effect because such a misclassification will bias the estimate toward zero.
[11] See, e.g., Fresard (2010), Hsu, Reed, and Rocholl (2010), and Aslan and Kumar (2016).

trading, we also control for *Institutional ownership*, the proportion of shares held by institutional investors, which we obtain from Thomson Reuters' 13F database.[12]

Our main identification strategy is instrumental variable (IV) regressions. We exploit cross-sectional variations in lenders and bond underwriters' preference to hedge their loan portfolio or bond inventory with CDS. We argue that lenders (underwriters) that prefer using CDS to hedge credit (inventory) risk are more likely to have lending (underwriting) business with firms that have CDS readily available. The challenging part is that we need to measure this preference by the lenders (underwriters) of a firm while not picking up the characteristics of the firm and its industry. We measure a lender's (underwriter's) CDS preference using the lender's (underwriter's) loan (bond underwriting) amount to CDS firms that are not in the focal firm's industry divided by the lender's (underwriter's) loan (bond underwriting) amount to all its client firms. When computing this ratio for a lender (underwriter), we exclude client firms whose loan (bond underwriting) amount is below the median client of the lender (underwriter), because these clients are inessential as far as credit (inventory) risk is concerned. There is no direct reason that unobserved firm and industry characteristics that may induce a firm's CDS trading would prompt lenders and bond underwriters' preference for CDS firms in a broad range of unrelated industries. TNIC offers further advantages to satisfy the exclusion restriction. First, TNICs are firm-specific, intransitive, product-based networks. Therefore, firms in different TNICs from the focal firm are clearly distinct as far as their products are concerned. A firm's suppliers and customers that could well be classified as in the same SIC or NAICS as the firm are much less likely to be in the firm's TNIC (unless they do produce similar products). Thus, when we use a lender's (underwriter's)

[12] Jiang and Zhu (2016) show that institutional investors such as mutual funds actively trade CDS for multiple purposes. Aslan and Kumar (2016) show that institutional ownership in the form of hedge funds activism affects both target firms' and their rivals' product market performance.

loan exposure to firms in TNICs different from the focal firm, it is less likely that these firms still have some connections, e.g., through the supply chain, with the focal firm. Therefore, our IVs mitigate the concern of omitted common shocks to the value chain. Second, Hoberg and Phillips (2016) show that text-based classifications offer economically large improvements in their ability to explain differences in key characteristics such as profitability, sales growth, market risk across industries. Therefore, when we use lenders' (underwriters') exposure to firms outside of the focal firm's industry, we are less likely to pick up lenders' (underwriters') unobserved preference for firms with similar characteristics. These advantages of TNIC make our IVs more likely to be exogenous to the focal firm's product market outcomes.

Finally, across the firm's lenders (underwriters) over the past 3 years, we compute the average of these lenders' (underwriters') CDS preference and use it as an IV for *CDS trading*. We label the IVs *Lender CDS preference* and *Underwriter CDS preference*. We obtain loan data from Thomson Reuters DealScan and merge with Compustat firms using the link file constructed by Chava and Roberts (2008). Bond underwriting data are from Mergent Fixed Income Securities Database (FISD) and are merged with Compustat firms using CUSIP.

Our final sample includes all firm-quarter observations from 1996-2015 with non-missing value in the above variables. Table 1 reports the summary statistics of the above variables. *Market share growth* (*Sales growth*) has a mean of 0.016 (0.039), a median of 0.000 (0.020), and a standard deviation of 0.197 (0.224). The relatively high volatility of product market outcomes suggests great uncertainty and dispersion across various product markets. 42.7% of the sample firm-quarters have CDS traded. *Lender* (*Underwriter*) *CDS preference* has a mean of 0.301 (0.598) and a standard deviation of 0.218 (0.337). These numbers indicate a reasonable average preference for

CDS firms in lenders' (underwriters') portfolios but also large variations across lenders (underwriters).

We also run balance tests to show that the IVs do not systematically correlate with firm characteristics. In Appendix Table A1, each row shows a regression of a firm characteristic variable on the two IVs, *Lender CDS preference* and *Underwriter CDS preference*, with firm and quarter fixed effects. The instruments are uncorrelated with all variables except for a significantly negative correlation between *Institutional ownership* and *Lender CDS preference*.

4. Results

We first run panel regressions with firm and quarter fixed effects to examine the effect of CDS on market share growth and sales growth, respectively. Table 2 reports the results. The coefficients on *CDS trading* are positive and statistically significant for both dependent variables. CDS firms' market share growth (sales growth) is 1.0% (1.1%) higher than non-CDS firms on average. We cannot take these results at the face value because the relationship can be endogenous. Nevertheless, the positive coefficients do alleviate a common endogeneity concern, namely, omitted variables causing industry downturns and CDS trading simultaneously, because this endogeneity would imply a negative relationship between CDS trading and product market outcomes. A spurious positive relationship is still possible. For example, new products often face demand uncertainty initially, before sales eventually take off. Lenders may seek CDS protection against initial demand risk, but CDS trading is not the cause of future sales growth.

4.1. Instrumental variable regressions

To tackle endogeneity, we use 2SLS with IVs discussed above. In the first stage, we use OLS to regress *CDS trading* on the two IVs as well as the covariates for *Market share growth* and *Sales growth*.[13] Panel A of Table 3 reports the results. Besides leverage and cash holdings, the two IVs, *Lender CDS preference* and *Underwriter CDS preference*, are the most significant determinants of a firm's CDS status. The F-test reports a solid 16.23; we consider the relevance assumption satisfied. Hansen's J statistic is 0.006, so we cannot reject the null that the IVs are independent of the error term.

In the second stage, we regress *Market share growth* and *Sales growth*, respectively, on the covariates, firm and quarter fixed effects, and the fitted values of *CDS trading* from the first stage. Panel B of Table 3 reports the second stage results. *CDS trading* (instrumented) is positive and highly significant for both product market performance measures. It is also economically significant. A one standard deviation increase in the instrumented *CDS trading* leads to a 1.3% (1.4%) increase in *Market share growth* (*Sales growth*), a 7% (6%) standard deviation increase.[14] Because the instrumented *CDS trading* is not a dummy variable, it is only an extrapolation that a change from 0 (a non-CDS firm) to 1 (a CDS firm) leads to 13.1% (13.7%) increase in *Market share growth* (*Sales growth*), a 0.66 (0.61) standard deviation increase.

Although our IVs pass standard tests for both the relevance and exclusion restrictions, there is no way to rule out endogeneity entirely. One potential concern is that large banks tend to be more specialized in lending and underwriting businesses with bigger players in an industry. While

[13] An alternative approach is a 3SLS in which we start with a Probit or Logit regression of *CDS trading* on the two IVs and covariates in the first stage and then use the fitted value of *CDS trading* as an instrument in a conventional 2SLS procedure. The 3SLS can be more efficient than the 2SLS if the Probit or Logit model is a better approximation of the first stage conditional expectation function than OLS. However, the nonlinearity introduced by the Probit or Logit model provides an additional source of identifying information that may not be justified for identification purposes; see Angrist and Pischke (2009). We follow Angrist and Pischke (2009) and use the garden-variety 2SLS, which is always consistent and safe.

[14] The standard deviation of the instrumented *CDS trading* is 0.10.

bigger players tend to outgrow their rivals, they are also more likely to have CDS traded because of their size and their businesses with large banks. This potential matching between large banks and big firms could make our IVs not strictly exogenous. To address this concern, we reconstruct our IVs excluding either (1) firms that are the largest players in any TNIC industries in which they participate or (2) the top 10 largest lenders and underwriters. These restrictions aim to break the potential match originated from either the bank or the firm side. Our results turn out to be highly robust. As reported in Table 4, the coefficients on *CDS trading* when our IVs exclude either large firms (columns 1 and 2) or large lenders and underwriters (columns 3 and 4) are very similar to our baseline 2SLS. This finding indicates that the potential matching between large firms and big banks is not driving the results.

The firm-specific, intransitive TNIC does not have a "packaged" financial or utility industry as we traditionally have with SIC or NAICS. In our next robustness check, we exclude firms whose SIC is between 4900 and 4999 (the traditional utility industry) and between 6000 and 6999 (the traditional financial industry). The results, as shown in columns 5 and 6 of Table 4, are highly robust. The positive CDS effect on product market outcomes are largely unchanged after we exclude financial and utility firms.

4.2. Overlap weighting

We apply a relatively new econometric technique, overlap weighting (Li Morgan, and Zaslavsky (2018)), as an alternative approach to addressing potential endogeneity. Bartram, Conrad, Lee, and Subrahmanyam (2019) first introduces this method to the finance literature when they examine the interaction of CDS with legal environment in determining firm investment and financing policies, where endogeneity is a major issue.

We first use a logit model to estimate the propensity of a firm-quarter to have CDS traded. Then to a firm-quarter that does not have (does have) CDS traded, we assign its estimated propensity score (one minus its estimated propensity score) as a weight. Finally, using the weighted sample, we regress *Market share growth* and *Sales growth*, respectively, on *CDS trading* as well as control variables to estimate the CDS effect on product market outcomes. With this overlap weighting scheme, firm-quarters that have a low (high) propensity of having CDS but have (do not have) CDS in reality effectively receive larger weights in the regression sample, while firm-quarters that have a high (low) propensity of having CDS and have (do not have) CDS in reality receive smaller weights in the regression sample. That is, firm-quarters whose estimated CDS propensity betrays its actual CDS status get upweighted and firm-quarters whose estimated CDS propensity aligns with its actual CDS status get downweighted. Importantly, the reweighting leads to exact balance in the means of any included covariate between treatment and control groups (Li Morgan, and Zaslavsky (2018)). In essence, at least for the means of observed firm characteristics, CDS firms and non-CDS firms look the same after the reweighting, making CDS treatment independent of observed characteristics. This reweighting scheme is appealing also because oftentimes it is the units whose combination of characteristics could appear with substantial probability in either the treated or the control group that are of substantive interest to the researcher.

Appendix Table A2 reports the logit regression for estimating the propensity of having CDS. In addition to an extensive list of firm characteristics, we include the two IVs, *Lender CDS preference* and *Underwriter CDS preference*, to control for the credit hedging preference of the firm's lenders and bond underwriters. It turns out large firms, firms with credit ratings, and firms with high profitability, high cash flow volatility, large proportions of fixed assets, high asset turnover, low capital expenditures, and large institutional ownership are more likely to have CDS. This is largely consistent with prior research on the characteristics of CDS firms.

Table 5 reports the CDS effects on product market outcomes after applying the overlap weighting. The results are statistically significant and economically meaningful. CDS firms' market share growth (sales growth) is 1.4% (2.1%) higher than non-CDS firms, a 7% (9%) standard deviation increase. Although it is not straightforward to compare the coefficient estimates from the overlap weighting approach with those from the IV approach due to their respective variations from a traditional OLS, it is reassuring to see robust evidence of a positive and substantial effect of CDS on product market outcomes from both approaches.

5. Mechanisms

The positive effects of CDS on product market outcomes are consistent with CDS alleviating the commitment problem between the firm and the lender. As agency concerns abated and lenders more tolerant, the firm are more likely to weather stressful situations and implement aggressive strategies. We test these mechanisms in the following.

5.1. Financial support

Saretto and Tookes (2013) document that CDS firms tend to have higher leverage, which is consistent with CDS alleviating the commitment problem. However, high leverage does not necessarily help firms' product market performance. Lenders' moral hazard, debt overhang, and vulnerability to predation and business cycle risk can undermine high-leverage firms' product market outcomes. Given the multiperiod dynamic game played between product market rivals as well as unpredictable demand conditions, a firm needs lenders' continuous support to keep competitive over time. We examine whether CDS induce lenders' continuous commitment by focusing on firms that are under financial pressure. Lenders' tolerance and support in stressful situations are key to these firms' success in the product market. If CDS alleviate agency concerns and encourage lenders' support in difficult times, then we expect these firms to benefit more from the availability of CDS. If the dark side of CDS such as lenders' moral hazard dominates, then these firms are more likely to suffer.

We interact *CDS trading* with two measures of financial stress, respectively. *High bankruptcy risk* is a dummy variable that equals 1 if the firm's Altman's Z-score (Altman (1968)) is below the median. *Financially constrained* is a dummy variable that equals 1 if the Whited-Wu index (Whited and Wu (2006)) is above the median. In addition to instrumenting *CDS trading* with *Lender CDS preference* and *Underwriter CDS preference*, we also instrument the interaction term *CDS trading* × *X*, where *X* is either *High bankruptcy risk* or *Financially constrained*, with *Lender CDS preference* × *X* and *Underwriter CDS preference* × *X*. Table 6 report the results. In panel A, both *CDS trading* and *CDS trading* × *High bankruptcy risk* are positive and significant, indicating that while CDS firms perform better in the product market in general, firms with high bankruptcy risk benefit even more from the availability of CDS. In terms of economic magnitude, the market share growth (sales growth) of firms with high bankruptcy risk is 2.6% (2.4%) greater if the firm has CDS traded. In panel B, firms facing financial constraints also achieve better product market outcomes when CDS are available. The market share growth (sales growth) of financially constrained firms is 6.3% (6.7%) greater if they have CDS traded. These results are consistent with lenders' sustained support when CDS firms are in need. As CDS protection makes lenders more supportive in stressful situations, firms become more competitive in the product market.

5.2. Tolerance for aggressive strategies

Product market competition is a multi-player, dynamic game. It often requires taking risks and bearing losses in the short-run to stay competitive in the long-run. It also calls for innovative and aggressive actions in response to changing circumstances and rival actions. As Manso's (2011) theory suggests, to implement this type of strategies requires investors' tolerance for early or even repeated failure. Because of lenders' natural concern of agency problems, traditional debt contracts cannot accommodate these challenges, preventing lenders from working closely with firms to fulfill their product market ambitions. The invention of CDS provides a flexible way for lenders to tackle agency problems. With CDS protection available, lenders can be more accommodating to innovative and aggressive strategies, freeing firms' "animal spirits" in the product market. Therefore, we expect firms that pursue growth with risky strategies and aggressive actions are more likely to benefit from CDS trading.

5.2.1 Technology

Technology is one of those areas where risk and information asymmetry abound, and so do agency concerns. However, development of new technologies and adoption of unconventional operation methods are often key to growth in the product market. We focus on firms' production technologies as well as research and development (R&D). To capture mavericks in production technologies and operation methods, we follow MacKay and Phillips (2005) and construct *Fringe technology*, an indicator that equals 1 if the absolute value of the deviation of a firm's capital-labor ratio from its industry-year median is above the overall sample median, where capital-labor ratio is defined as net property, plant, and equipment divided by the number of employees. MacKay and Phillips (2005) use this measure to capture technologies that deviate from the industry core. These fringe technologies can be associated with competitive firms improving extant technologies in their industries or open-minded entrants challenging an industry's operational tradition with new ideas. To measure investment in R&D, we use *High R&D*, an indicator that equals 1 if the firm's R&D expense as a fraction of lagged total assets is above the median. We interact *CDS trading* with these two measures of aggressive technology strategies, respectively. Same as before, we instrument the interaction term *CDS trading* × *X* with *Lender CDS preference* × *X* and *Underwriter CDS preference* × *X*.

Table 7 reports the results. In Panel A, in addition to the significant, positive effects of CDS on sales growth and market share growth in general, firms that utilize unconventional technologies enjoy significantly better product market outcomes when they have CDS available. In Panel B, for firms that are active in R&D, having CDS significantly boost their sales growth, though the effect on market shares growth is statistically insignificant. Depending on the specific measure of technology development, the market share growth (sales growth) of these innovative firms is 1.5-2.0% (2.7-3.1%) greater if they have CDS traded. These results are consistent with CDS increasing lenders' tolerance for innovative and aggressive strategies.

5.2.2. Industry conditions

Growth opportunities and rival challenges can hit a firm unexpectedly, and the firm often needs swift and aggressive responses to stay competitive. But lenders, concerned of conflicts of interest and underinformed, may be hesitant to provide close support. In these situations, the availability of CDS can be a boon because protected lenders will be more accommodating to changing industry conditions and aggressive firm actions. Thus, we expect CDS firms to perform better than non-CDS firms when industry conditions call for aggressive strategies, e.g., when growth opportunities show up or when competition threats heighten.

In panel A of Table 8, we examine the effect of CDS on a firm's product market outcomes when good vs. poor growth opportunities appear in the firm's industry, respectively. Column *High (Low) Q industry* denotes firm-quarters where the industry average market-to-book assets ratio is above (below) the median, indicating good (poor) growth opportunities in the industry. As expected, CDS firms perform significantly better than non-CDS firms when their industries have good growth opportunities. When growth opportunities are poor in the industry, the CDS effect is still positive but statistically insignificant, and the magnitude is much weaker.

In panel B of Table 8, we use Hoberg, Phillips, and Prabhala's (2013) product market fluidity (PMF) to measure competition threats. PMF captures changes in rival firms' products relative to the firm's products, and higher values of PMF indicates that rival firms' products become more similar to the firm's products, therefore greater competition threats. We find that the effects of CDS on product market outcomes are positive and significant when a firm faces heightened competition threats. The effects are statistically insignificant and much smaller when competition threats are low. These results corroborate the notion that CDS strengthen lenders' tolerance when industry circumstances call for aggressive competition strategies.

5.3. Product market strategies

In this section, we dig deeper into CDS firms' product market strategies to understand how they support growth over time. To examine the dynamics, we introduce three indicators of time since a firm's CDS introduction: *Q0-3* (*Q4-15*, *Q16&later*) is a dummy variable that equals 1 if the current quarter is 0-3 quarters (4-15 quarters, 16 quarters or more) after the firm's CDS introduction and 0 otherwise. We interact *CDS trading* with these indicators to track how the CDS effects evolve in the short-term, intermediate term, and long-term, respectively. Provided that a firm's CDS trading status is controlled for, these indicators are determined only by the passage of time and therefore can be considered as exogenous. And we instrument *CDS trading* × *Q0-3* with *Lender CDS preference* × *Q0-3* and *Underwriter CDS preference* × *Q0-3*, *CDS trading*× *Q4-15* with *Lender CDS preference* × *Q4-15* and *Underwriter CDS preference* × *Q4-15*, and *CDS trading* × *Q16&later* with *Lender CDS preference* × *Q16&later* and *Underwriter CDS preference* × *Q16&later*.

We first examine how the effects of CDS on product market outcomes evolve over time. Table 9 reports the results. The positive effects on market share growth and sales growth are marginal in the first year after CDS introduction but get stronger in the intermediate term and keep strong in the long run. So CDS availability can spur a sustained growth for underlying firms. This is perhaps not surprising. The positive effects on lender tolerance and eventually sales growth need a short time to kick in, but the effects last because the trading of CDS provides a continued market for credit protection.

We then use a similar dynamic specification to examine how CDS firms' product market strategies evolve over time. We focus on three major aspects of product market strategies: product development, product differentiation, and price competition.

5.3.1. Product development and differentiation

To measure how a firm changes its products over time, we use *Self-fluidity*, the logarithm of one minus the cosine similarity between the firm's current and previous years' product descriptions (Hoberg, Phillips, and Prabhala (2013)). *Self-fluidity* should be higher when the firm actively develops new products or makes significant improvements of existing products. To measure how a firm differentiate its products from its rivals', we use *Product similarity*, the logarithm of the average cosine similarity between the firm and its rival's products (Hoberg and

Phillip's (2016)). *Product similarity* should be higher when the firm pivots towards a frontal competition in rivals' product space.

Table 10, column 1 shows the effect of CDS on firms' product development. Firms start to actively update their products shortly after CDS introduction, make more significant improvements in the intermediate term, and stay dynamic in product offerings in the long run. *Self-fluidity* is approximately 10% greater than the mean in the first year after CDS introduction, 18% greater in the next three years, and 14% greater later on. CDS firms seem to engage in active product development, which is often an effective approach to growth.

Table 10, column 2 shows how the availability of CDS affects firms' product differentiation. In the first year after CDS introduction, a firm's product similarity to rivals does not change significantly. From the second year, *Product similarity* starts to increase significantly. Relative to an average firm, CDS firms' product similarity to rivals are approximately 27% of a standard deviation greater. In the long-term, CDS firms' product similarity to rivals increase even further. This pattern shows that firms gradually engage rivals in a frontal competition after CDS introduction. [15] Pivoting towards rivals' product space is consistent with CDS encouraging aggressive business strategies.

5.3.2. Price competition

To measure a firm's pricing strategy, we use *Markup*, the ratio of output price to marginal cost of production. It is notoriously hard to measure markups because data on prices and marginal costs are not readily available. We rely on a structural estimation recently developed in the economics literature (De Loecker and Warzynski (2012)). The method uses information from the firm's financial statements and does not require any assumptions on demand and how firms

[15] The effects are virtually the same if we also control for peer characteristics in this regression.

compete. Instead, markups are obtained by exploiting cost minimization of a variable input of production, which can be proxied by cost of goods sold. This approach does need an explicit treatment of the production function. We use the Cobb-Douglas production function, a standard choice in the literature. The empirical implementation relies on a two-stage approach. In the first stage, the measurement error and unanticipated shocks to sales are purged, and their estimated values will be used to correct the revenue share of the variable input. The second stage provides estimates for all product function coefficients, which are used to measure output elasticity of the variable input. Markups are then computed as the ratio of the output elasticity of the variable input to the revenue share of the variable input. Appendix provides details about this estimation.

We use either OLS or GMM in the second stage estimation of markups. Columns 1 and 2 of Table 11 report results based on these two approaches, respectively. Firms start to cut prices (relative to marginal costs of production) shortly after CDS introduction and get more aggressive in price competition over time. *CDS trading* has a negative effect on *Markup* in the first year after CDS introduction. The effect is marginally significant in column 1 and shy of statistical significance in column 2. In the next three years, markups of CDS firms are 2.3% lower than an average firm and get even more competitive (3.5-3.8% lower) in the long term. The capability for sustained price competition shows CDS firms' aggressiveness in the product market. This aggressive strategy is consistent with CDS strengthening lenders' tolerance and is a clear driver of CDS firms' growth in the product market.

Taken together, firms seem to adopt more aggressive product market strategies after CDS introduction. Active product development, frontal competition in rivals' product space, and aggressive pricing policies all point to the narrative that CDS help release firms' animal spirits

While we cannot completely rule out other forces, with the availability of CDS protection, lenders' increased tolerance for innovative and aggressive strategies is likely a major driver.

Interestingly and more importantly, we note that these product market strategies will eventually benefit consumers, as they can enjoy newer product offerings and lower prices. In unreported results, we find CDS have an insignificant, positive effect on firms' return on equity. This suggests that although CDS firms cut markups to boost growth, shareholders are not hurt, if not faring better. To the extent that creditors are unlikely to be hurt by CDS, the value passed on to consumers through lower prices must come from savings in agency costs of debt as CDS alleviate the agency conflicts. This is a direct welfare transfer to consumers from reduction in financial frictions. In this regard, our research is the first, to our best knowledge, to document a direct welfare effect of financial markets on consumers. This contributes to the literature on the real effects of financial markets (see, e.g., Jayaratne and Strahan (1996), Levine and Zervos (1998), Rajan and Zingales (1998), Fisman and Love (2005), and Edmans, Goldstein, and Jiang (2012)).

Lastly, we examine CDS firms' spending policies in Table A3. R&D expenses experience some growth in the short- and intermediate term after CDS introduction and rise more significantly in the long run. CAPX starts to grow significantly shortly after CDS introduction and keeps at a higher level going forward. Acquisition spending, however, does not experience statistically significant increase after CDS trading, neither do sales and general expenses. It seems that CDS firms' expansion in the product market are mainly supported by spending increase in R&D and CAPX. Recent research by Hoberg and Maksimovic (2019) shows that firms that are youthful in their product life cycle spend more on R&D and CAPX while firms in a mature stage of life tend to resort to acquisitions for growth. In this regard, our evidence suggests that CDS firms strive to maintain a more dynamic and youthful product life cycle. This is again in line with the narrative that CDS help release firms' animal spirits by aligning lenders risk appetite with firms' ambition.

6. Conclusion

Motivated by seminal theories that link frictions in financial contracting with product market competition, we provide the first evidence that credit derivatives that alleviate financial frictions can improve real outcomes, in terms of both firm growth and consumer welfare. This evidence contributes to the literature on the real effects of financial development.

Given their ability to commit the borrower as well as the potential to spoil the lender, CDS have been a controversial instrument for practitioners, academics, and policy makers alike ever since their birth. Our work sheds new light on the debate and paints an overall benign view of CDS as far as real outcomes are concerned.

Appendix Estimation of markups

This section is largely based on De Loeck and Warzynski (2012) and De Loecker and Eeckhout (2017). A firm *i* at time *t* produces output using the following production technology:

$$Q_{it} = Q_{it}(\Omega_{it}, V_{it}, K_{it}) \tag{1}$$

where V_{it} is a bundle of variable inputs of production (including labor, intermediate inputs, materials, etc.), K_{it} is the capital stock and Ω_{it} is a firm-specific productivity term. We consider the Lagrangian objective function associated with the firm's cost minimization:

$$\mathcal{L}(V_{it}, K_{it}, \lambda_{it}) = P_{it}^{V} V_{it} + r_{it} K_{it} + F_{it} - \lambda_{it}(Q(\cdot) - \bar{Q}_{it}) \tag{2}$$

where P_{it}^{V} is the price of the variable input, r_{it} is the user cost of capital, F_{it} is the fixed cost, $Q(\cdot)$ is the technology specified in equation (1), $\bar{Q}_{it}$ is a scalar, and λ_{it} is the Lagrangian multiplier. The first order condition with respect to the variable input V_{it} is given by:

$$\frac{\partial \mathcal{L}_{it}}{\partial V_{it}} = P_{it}^{V} - \lambda_{it} \frac{\partial Q(\cdot)}{\partial V_{it}} = 0 \tag{3}$$

Multiplying all terms by $\frac{V_{it}}{Q_{it}}$ and rearranging terms yields an expression for the output elasticity of input V_{it}:

$$\theta_{it}^{V} \equiv \frac{\partial Q(\cdot)}{\partial V_{it}} \frac{V_{it}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^{V} V_{it}}{Q_{it}} \tag{4}$$

The Lagrangian multiplier λ_{it} is a direct measure of marginal cost, i.e., it is the value of the objective function as we relax the output constraints. We define the markup as $\mu_{it} = \frac{P_{it}}{\lambda_{it}}$, where P_{it} is the price for output goods. Substituting marginal cost for the markup to price ratio, we obtain a simple expression for the markup:

$$\mu_{it} = \theta_{it}^{V} \frac{P_{it}\, Q_{it}}{P_{it}^{V} V_{it}} \tag{5}$$

So there are two key ingredients needed in order to measure the markup: the revenue share of the variable input, $\frac{P_{it}\,Q_{it}}{P_{it}^{V}V_{it}}$, and the output elasticity of the variable input θ_{it}^{V}.

We directly observe sales, $S_{it} = P_{it}\,Q_{it}$ and total variable cost of production, $C_{it} = P_{it}^{V}V_{it}Q_{it}$, measured by cost of goods sold. We use sector-specific Cobb-Douglas production functions with variable inputs and capital. For a given sector we consider the production function:

$$q_{it} = \beta_v v_{it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it} \tag{6}$$

where lower cases denote logs and all inputs and outputs are deflated real values.

We follow the literature and control for the simultaneity and selection bias that are inherently present in the estimation of the above equation. We rely on a control function approach paired with an AR(1) process for productivity to estimate the output elasticity of the variable input, here β_v. The unobserved productivity term, ω_{it}, is given by a function of the firm's inputs such that $\omega_{it} = h(v_{it}, k_{it})$.

This approach relies on a two-stage procedure. In the first stage, the measurement error and unanticipated shocks to sales are purged using

$$q_{it} = \phi(v_{it}, k_{it}) + \epsilon_{it} \tag{7}$$

where $\phi = \beta_v v_{it} + \beta_k k_{it} + h(v_{it}, k_{it})$. The second stage provides estimates for all production function coefficients by relying on the law of motion for productivity

$$\omega_{it} = \rho\omega_{it-1} + \xi_{it} \tag{8}$$

This gives rise to the following moment conditions:

$$E(\xi_{it}(\beta)\binom{v_{it-1}}{k_{it}}) = 0 \tag{9}$$

where $\beta = (\beta_v, \beta_k)$, to estimate the production function parameters. The moments above exploit the fact that capital is assumed to be decided a period ahead and should not be correlated with the innovation in productivity. We rely on lagged variable input to identify the coefficient on variable input since current variable input is expected to react to shocks to productivity. In order for lagged variable input to be a valid instrument for current variable input, we require input prices to be correlated over time, which is a reasonable assumption. We use standard GMM technique to obtain the estimates of the production function. In an alternative specification, we use OLS with time fixed effects to control for time-specific productivity and estimate the product function directly from equation (6). Finally, we correct the markup estimates for the presence of measurement error in sales, ϵ_{it}, which we obtain in the first stage (equation (7)).

References

Altman, Edward I., 1968, Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, Journal of Finance 23, 589-609.

Aslan, Hadiye, and Praveen Kumar, 2016, The product market effects of hedge fund activism, *Journal of Financial Economics* 119, 226-248.

Augustin, Patrick, Marti Subrahmanyam, Dragon Yongjun Tang, and Sarah Qian Wang, 2014, Credit default swaps: A survey, *Foundations and Trends in Finance* 9, 1-196.

Augustin, Patrick, Marti Subrahmanyam, Dragon Yongjun Tang, and Sarah Qian Wang, 2016, Credit default swaps: Past, present, and future, *Annual Review of Financial Economics* 8, 175-196.

Batta, George, and Fan Yu, 2019, Credit derivatives and firm investment, Working paper.

Bartram, Sohnke M., Jennifer Conrad, Jongsub Lee, and Marti G. Subrahmanyam, 2019, Credit default swaps around the world: investment and financing effects, Working paper.

Billet, Mattew T., Jon A. Garfinkel, and Miaomiao Yu, 2017, The effect of asymmetric information on product market outcomes, *Journal of Financial Economics* 123, 357-376.

Bolton, Patrick, and Martin Oehmke, 2011, Credit default swaps and the empty creditor problem, *Review of Financial Studies* 24, 2617-2655.

Bolton, Patrick, and David S. Scharfstein, 1990, A theory of predation based on agency problems in financial contracting, *American Economic Review* 80, 93-106.

Brander, James, and Tracy R. Lewis, 1986, Oligopoly and financial structure: The limited liability effect, *American Economic Review* 76, 956-970.

Brander, James and Tracy R. Lewis, 1988, Bankruptcy costs and the theory of oligopoly, *Canadian Journal of Economics* 21, 221-243.

Campello, Murillo, 2003, Capital structure and product market interactions: Evidence from business cycles, *Journal of Financial Economics* 68, 353-378.

Chakraborty, Indraneel, Sudheer Chava, and Rohan Ganduri, 2015, Credit default swaps and moral hazard in bank lending, Working paper, Georgia Institute of Technology.

Chang, Xin, Yangyang Chen, Sarah Qian Wang, Kuo Zhang, and Wenrui Zhang, 2018, Credit default swaps and corporate innovation, *Journal of Financial Economics* Forthcoming

Chava, Sudheer and Michael R. Roberts, 2008, How does financing impact investment? The role of debt covenants, *Journal of Finance* 63, 2085-2121.

Chen, Qi, Itay Goldstein, and Wei Jiang, 2007, Price informativeness and investment sensitivity to stock prices, *Review of Financial Studies* 20, 619-650.

Chevalier, Judith A., 1995, Capital structure and product-market competition: Empirical evidence from the supermarket industry, *American Economic Review* 85, 415-435.

Danis, Andras, 2017, Do empty creditors matter? evidence from distressed exchange offers, *Management Science* 63, 1271-1656.

Danis, Andras, and Andrea Gamba, 2018, The real effects of credit default swaps, *Journal of Financial Economics* 127, 51-76.

Danis, Andras, and Andrea Gamba, 2019, Dark knights: the rise in firm intervention by CDS investors, Working paper, Georgia Institute of Technology and Warwick University.

De Loecker, Jan and Jan Eeckhout, 2017, The rise of market power and the macroeconomic implications, Working paper, KU Leuven and Princeton University.

De Loecker, Jan, and Frederic Warzynski, 2012, Markups and firm-level export status, *American Economic Review* 102, 2437-2471.

Edmans, Alex, Itay Goldstein, and Wei Jiang, 2012, The real effects of financial markets: the impact of prices on takeovers, *Journal of Finance* 67, 933-971.

Fisman, Raymond, and Inessa Love, 2005, Financial development and intersectoral allocation: a new approach, *Journal of Finance* 59, 2785-2807.

Foucault, Thierry, and Laurent Fresard, 2014, Learning from peers' stock prices and corporate investment, *Journal of Financial Economics* 111, 554-577.

Fresard, Laurent, 2010, Financial strength and product market behavior: The real effects of corporate cash holdings, *Journal of Finance* 65, 1097-1122.

Grieser, William and Zack Liu, 2019, Corporate investment and innovation in the presence of competitor constraints, *Review of Financial Studies* forthcoming.

He, Jie (Jack), and Jiekun Huang, 2017, Product market competition in a world of cross-ownership: Evidence from institutional blockholdings, *Review of Financial Studies* 30, 2674-2718.

Hoberg, Gerard and Vojislav Maksimovic, 2019, Product life cycles in corporate finance, Working paper.

Hoberg, Gerard and Gordon Phillips, 2010, Product market synergies and competition in mergers and acquisitions: a text-based analysis, *Review of Financial Studies* 23, 3773-3811.

Hoberg, Gerard and Gordon Phillips, 2016, Text-based network industries and endogenous product differentiation, *Journal of Political Economy* 124, 1423-1465.

Hoberg, Gerard, Gordon Phillips, and Nagpurnanand Prabhala, 2014, Product market threats, payouts, and financial flexibility, *Journal of Finance* 69, 293-324.

Hsu, Hung-chia, Adam V. Reed, and Jorg Rocholl, 2010, The new game in town: Competitive effects of IPOs, *Journal of Finance* 65, 495-528.

Jayaratne, Jith, and Philip E. Strahan, 1996, The finance-growth nexus: evidence from bank branch deregulation, *Quarterly Journal of Economics* 111, 639-670.

Jiang, Wei, and Zhongyan Zhu, 2016, Mutual fund holdings of credit default swaps: Liquidity management and risk taking, Working Paper.

Levine, Ross, 2005, Finance and growth: theory and evidence. In: Handbook of economic growth. Elsevier, pp.865-934.

Levine, Ross and Sara Zervos, 1998, Stock markets, banks, and economic growth, *American Economic Review* 88, 537-558

Li, Fan, Kari L. Morgan, and Alan M. Zaslavsky, 2018, Balancing covariates via propensity score weighting, *Journal of the American Statistical Association* 113, 390-400.

Li, Jay Y. and Dragon Y. Tang, 2016, The leverage externalities of credit default swaps, *Journal of Financial Economics* 120, 491-513.

MacKay, Peter, and Gordon Phillips, 2005, How does industry affect firm financial structure, *Review of Financial Studies* 18, 1433-1466.

Maksimovic, Vojislav, 1986, Optimal capital structure in oligopolies, Unpublished doctoral dissertation, Harvard University.

Maksimovic, Vojislav and Sheridan Titman, 1991, Financial policy and reputation for product quality, *Review of Financial Studies* 4, 175-200.

Maksimovic, Vojislav and Josef Zechner, 1991, Debt, agency costs, and industry equilibrium, *Journal of Finance* 46, 1619-1643.

Manso, Gustavo, 2011, Motivating innovation, *Journal of Finance* 66, 1823-1860.

Nain, Amrita, and Yan Wang, 2017, The product market impact of minority stake acquisitions, *Management Science*, forthcoming.

Phillips, Gordon, 1995, Increased debt and industry product markets: An empirical analysis, *Journal of Financial Economics* 37, 189-238.

Rajan, Raghuram, and Luigi Zingales, 1998, Financial dependence and growth, *American Economic Review* 88, 559-586.

Saretto, Alessio. and Heather Tookes, 2013, Corporate leverage, debt maturity, and credit supply: The role of credit derivatives, *Review of Financial Studies* 26, 1190 – 1247.

Schumpeter, Joseph, 1969, The theory of economic development, Oxford University Press.

Shan, Chenyu, Dragon Y. Tang, and Andrew Winton, 2019, Do banks still monitor when there is a market for credit protection? *Journal of Accounting and Economics*, forthcoming .

Spiegel, Matthew, and Heather Tookes, 2013, Dynamic competition, valuation, and merger activity, *Journal of Finance* 68, 125-172.

Spiegel, Matthew, and Heather Tookes, 2019, Why does an IPO affect rival firms, *Review of Financial Studies* forthcoming.

Subrahmanyam, Marti G., Dragon Y. Tang, and Sarah Q. Wang, 2014, Does the tail wag the dog? Credit default swaps and credit risk, *Review of Financial Studies* 27, 2927 – 2960.

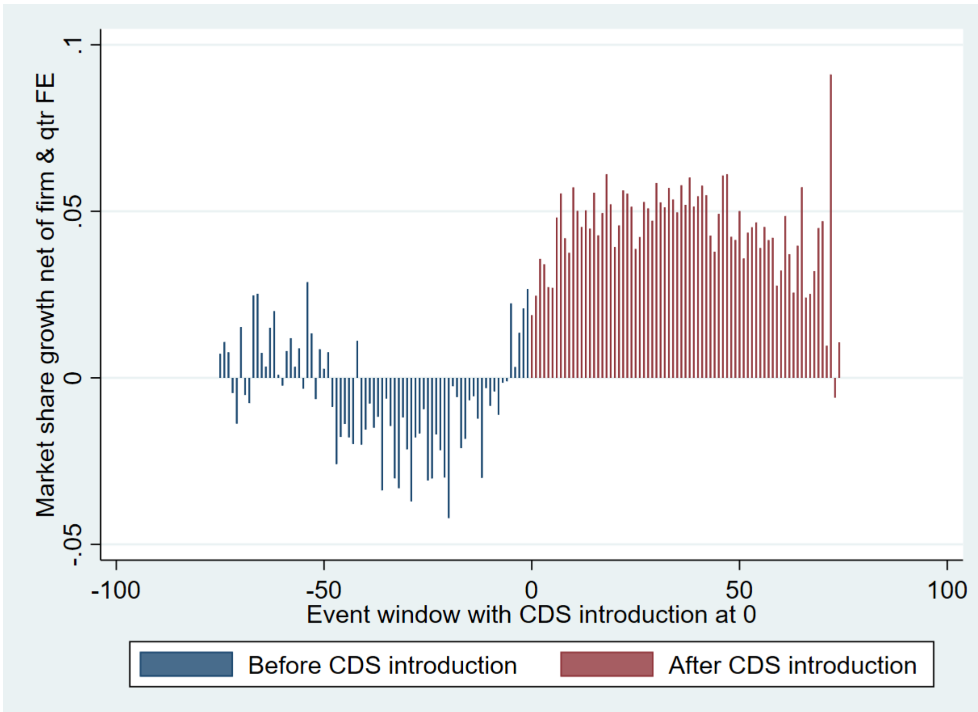
Subrahmanyam, Marti G., Dragon Y. Tang, and Sarah Q. Wang, 2017, Credit default swaps, exacting creditors, and corporate liquidity management, *Journal of Financial Economics* 124, 395-414.

Sundaram, Anant K., Teresa A. John, and Kose John, 1996, An empirical analysis of strategic competition and firm values: the case of R&D competition, *Journal of Financial Economics* 40, 459-486.

Whited, Toni M., and Guojun Wu, 2006, Financial constraints risk, *Review of Financial Studies* 19, 531-559

Wong, Tak-Yuen, and Jin Yu, 2019, Credit default swaps and debt overhang, Working paper

Figure 1 Market growth before and after CDS introduction
The top (bottom) graph depicts how the average *Market share growth* (*Sales growth*) net of firm and quarter fixed effects evolves over time, based on estimates from Table 3, Panel B, column 1 (2). Event time 0 is the quarter in which CDS starts trading on a firm. For firms never had CDS trading in the sample period 1996-2015, event time 0 is assumed to be December 31, 2020.



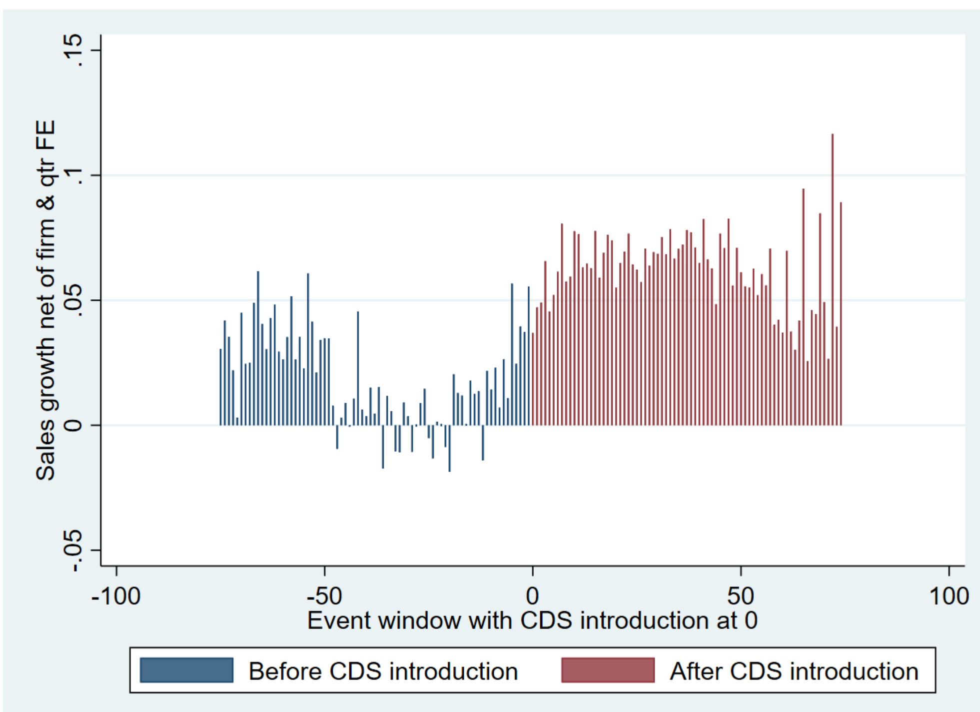


Table 1 Summary statistics

The sample consists of Compustat firms between 1996 and 2015 that are incorporated in the U.S., have common stocks covered by CRSP, and are covered by Hoberg and Phillip's (2010, 2016) Text-based Network Industry Classification (TNIC). *Market share growth* is the firm's sales growth, i.e., $sale_t/sale_{t-1}$-1, minus the median sales growth of the firm's TNIC. *Sales growth* is the firm's sales growth, i.e., $sale_t/sale_{t-1}$-1. *CDS trading* is a dummy variable that equals 1 if the firm has CDS traded in the quarter concerned. *Market-to-book* is the ratio of market assets to book assets, i.e., (prcc_f*csho+at-ceq-txdb)/at. *LnAssets* is the natural log of total assets, i.e., ln(at). *Leverage* is the sum of long-term debt and debt in current liabilities divided by total assets, i.e., (dltt+dlc)/at. *Cash* is the firm's cash and short-term investments divided by total assets, i.e., che/at. *Stock return* is the firm's cumulative stock return in the last 12 months. *HHI* is the sum of squared product market shares of firms in the TNIC. *Institutional ownership* is the proportion of shares held by institutional investors. *Lender CDS preference* is the average, across the firm's lenders over the past 3 years, of each lender's fraction of loan amount to "unrelated CDS borrowers" over the lender's total loan amount. *Underwriter CDS preference* is the average, across the firm's bond underwriters over the past 3 years, of each underwriter's fraction of underwriting amount for "unrelated CDS borrowers" over the underwriter's total underwriting amount. Unrelated CDS borrowers are defined as borrowers with CDS traded that are in different TNIC than the firm concerned.

Variable	N	Mean	Std. dev.	Min	25th pctl.	50th pctl.	75th pctl.	Max
Market share growth	49,919	0.016	0.197	-0.660	-0.049	0.000	0.052	1.798
Sales growth	49,969	0.039	0.224	-0.667	-0.041	0.020	0.091	1.966
CDS trading	49,969	0.427	0.495	0.000	0.000	0.000	1.000	1.000
Market-to-book	49,969	1.620	0.928	0.437	1.087	1.351	1.817	12.075
LnAssets	49,969	8.257	1.552	2.895	7.161	8.150	9.272	11.802
Leverage	49,969	0.350	0.194	0.000	0.212	0.324	0.457	0.939
Cash	49,969	0.088	0.112	0.000	0.018	0.048	0.114	0.912
Stock return	49,969	0.154	0.511	-0.865	-0.135	0.105	0.347	2.813
HHI	49,969	0.210	0.187	0.024	0.085	0.148	0.268	1.000
Institutional ownership	49,969	0.708	0.248	0.000	0.575	0.754	0.883	1.000
Lender CDS preference	49,969	0.301	0.218	0.000	0.093	0.305	0.468	0.793
Underwriter CDS preference	49,969	0.598	0.337	0.000	0.289	0.754	0.870	0.993

Table 2 CDS and product market outcomes: OLS

The sample consists of Compustat firms between 1996 and 2015 that are incorporated in the U.S., have common stocks covered by CRSP, and are covered by Hoberg and Phillip's (2010, 2016) Text-based Network Industry Classification (TNIC). Dependent variables are shown at the head of each column. In parentheses are *t*-statistics. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Market share growth	(2) Sales growth
CDS trading	0.0102***	0.0111***
	(2.703)	(2.732)
Market-to-book	0.00750***	0.0117***
	(2.972)	(4.198)
LnAssets	-0.0266***	-0.0328***
	(-8.679)	(-9.237)
Leverage	0.0401***	0.0632***
	(2.618)	(3.357)
Cash	-0.00864	-0.0603*
	(-0.298)	(-1.822)
Stock return	0.00979***	0.0188***
	(4.786)	(8.191)
HHI	-0.00275	0.0106
	(-0.387)	(1.392)
Inst. Ownership	0.0217***	0.0238***
	(3.370)	(3.266)
Firm fixed effects	Yes	Yes
Quarter fixed effects	Yes	Yes
Clustered std. err.	Yes	Yes
N	49,917	49,969
Adj. R-sqr.	0.193	0.216

Table 3 CDS and product market outcomes: 2SLS

The sample consists of Compustat firms between 1996 and 2015 that are incorporated in the U.S., have common stocks covered by CRSP, and are covered by Hoberg and Phillip's (2010, 2016) Text-based Network Industry Classification (TNIC). We use 2SLS to instrument *CDS trading* with *Lender CDS preference* and *Underwriter CDS preference*. Panel A reports the first stage. Panel B reports the second stage. In parentheses are *t*-statistics. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A	CDS trading
Lender CDS preference	0.0972***
	(3.700)
Underwriter CDS preference	0.120***
	(4.200)
Market-to-book	-0.00755
	(-1.060)
LnAssets	0.0491***
	(3.960)
Leverage	0.121***
	(3.220)
Cash	0.121***
	(2.750)
Stock return	-0.00853**
	(-2.080)
HHI	-0.0151
	(-0.640)
Inst. Ownership	-0.0102
	(-0.540)
Firm fixed effects	Yes
Quarter fixed effects	Yes
Clustered std. err.	Yes
N	49,969
Adj. R-sqr	0.84
1st stage F test	16.23
Hansen's J test	0.006

Panel B	(1)	(2)
	Market share growth	Sales growth
CDS trading	0.131***	0.137***
	(3.023)	(2.966)
Market-to-book	0.00844***	0.0127***
	(3.246)	(4.535)
LnAssets	-0.0325***	-0.0391***
	(-8.470)	(-8.973)
Leverage	0.0256	0.0479**
	(1.584)	(2.459)
Cash	-0.0237	-0.0761**
	(-0.794)	(-2.236)
Stock return	0.0108***	0.0198***
	(5.107)	(8.426)
HHI	-0.000937	0.0125
	(-0.122)	(1.545)
Inst. Ownership	0.0234***	0.0257***
	(3.453)	(3.401)
Firm fixed effects	Yes	Yes
Quarter fixed effects	Yes	Yes
Clustered std. err.	Yes	Yes
N	49,917	49,969
Adj. R-sqr	0.191	0.213

Table 4 Robustness

The sample consists of Compustat firms between 1996 and 2015 that are incorporated in the U.S., have common stocks covered by CRSP, and are covered by Hoberg and Phillip's (2010, 2016) Text-based Network Industry Classification (TNIC). Reported are the second stage of 2SLS with *CDS trading* instrumented by *Lender CDS preference* and *Underwriter CDS preference*. Dependent variables are shown at the head of each column. Columns 1 and 2 construct the instrumental variables in the same way as in Table 3 except that borrowers that are the largest players in terms of sales in a TNIC industry are excluded. Columns 3 and 4 construct the instrument variables in the same way as in Table 3 except that the top ten lenders or underwriters in terms of loan or underwriting amount are excluded. Column 5 and 6 exclude financial and utility firms (with SIC between 4900 and 4999 and between 6000 and 6999) from the sample. In parentheses are t-statistics. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 4 — Continued

	(1) Market share growth	(2) Sales growth	(3) Market share growth	(4) Sales growth	(5) Market share growth	(6) Sales growth
	IV excluding big borrowers	IV excluding big borrowers	IV excluding big lenders	IV excluding big lenders	Excluding utility & financial firms	Excluding utility & financial firms
CDS trading	0.123**	0.157***	0.127**	0.131**	0.124***	0.127***
	(2.460)	(2.854)	(2.145)	(2.087)	(3.194)	(3.036)
Market-to-book	0.00847***	0.0129***	0.00793***	0.0125***	0.00762***	0.0119***
	(3.249)	(4.532)	(2.640)	(3.843)	(2.941)	(4.296)
LnAssets	-0.0320***	-0.0399***	-0.0372***	-0.0440***	-0.0313***	-0.0379***
	(-7.762)	(-8.310)	(-7.268)	(-7.873)	(-7.840)	(-8.269)
Leverage	0.0264	0.0453**	0.0321*	0.0494**	0.0212	0.0445**
	(1.596)	(2.267)	(1.721)	(2.289)	(1.300)	(2.229)
Cash	-0.0221	-0.0784**	-0.0210	-0.0724*	-0.0173	-0.0735*
	(-0.737)	(-2.277)	(-0.573)	(-1.779)	(-0.520)	(-1.938)
Stock return	0.0107***	0.0200***	0.0126***	0.0211***	0.0122***	0.0215***
	(5.058)	(8.466)	(4.838)	(7.434)	(5.596)	(8.859)
HHI	-0.000599	0.0128	-0.00433	0.0141	-0.00256	0.00911
	(-0.0791)	(1.564)	(-0.514)	(1.514)	(-0.321)	(1.100)
Inst. Ownership	0.0236***	0.0263***	0.0205***	0.0215***	0.0280***	0.0299***
	(3.506)	(3.448)	(2.798)	(2.692)	(3.913)	(3.724)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Qtr fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered std. err.	Yes	Yes	Yes	Yes	Yes	Yes
N	49,805	49,857	40,440	40,479	41,160	41,201
Adj. R-sqr	0.190	0.213	0.191	0.213	0.185	0.207

Table 5 CDS and product market outcomes: overlap weighting

The sample consists of Compustat firms between 1996 and 2015 that are incorporated in the U.S., have common stocks covered by CRSP, and are covered by Hoberg and Phillip's (2010, 2016) Text-based Network Industry Classification (TNIC). We run OLS with overlap weighting (Li, Morgan, and Zaslavsky (2017)), which reweights the original sample such that the distribution of covariates is balanced across treated firms (*CDS trading* = 1) and control firms (*CDS trading* = 0). Dependent variables are shown at the head of each column. In parentheses are t-statistics. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Market share growth	(2) Sales growth
CDS trading	0.0138***	0.0207***
	(2.642)	(3.350)
Market-to-book	0.00564*	0.0112***
	(1.685)	(2.808)
LnAssets	-0.0236***	-0.0326***
	(-5.800)	(-6.479)
Leverage	0.0633***	0.0995***
	(3.673)	(3.841)
Cash	-0.0915***	-0.162***
	(-2.919)	(-4.050)
Stock return	0.00592**	0.0139***
	(1.990)	(4.088)
HHI	0.0152	0.0203**
	(1.630)	(2.058)
Inst. Ownership	0.0142	0.0161
	(1.482)	(1.527)
Firm fixed effects	Yes	Yes
Quarter fixed effects	Yes	Yes
Clustered std. err.	Yes	Yes
N	43,799	43,844
Adj. R-sqr	0.166	0.190

Table 6 CDS and product market outcomes: lender financial support

The sample consists of Compustat firms between 1996 and 2015 that are incorporated in the U.S., have common stocks covered by CRSP, and are covered by Hoberg and Phillip's (2010, 2016) Text-based Network Industry Classification (TNIC). Reported are the second stage of 2SLS with *CDS trading* instrumented by *Lender CDS preference* and *Underwriter CDS preference*, and *CDS trading* × *X* instrumented by *Lender CDS preference* × *X* and *Underwriter CDS preference*× *X*, where *X* is a different indicator in each panel and is defined as follows. *High bankruptcy risk* is a dummy variable that equals 1 if the Altman's Z-score (Altman (1968)) is below the median. *Financially constrained* is a dummy variable that equals 1 if the Whited-Wu index (Whited and Wu (2006)) is above the median. All regressions include the same control variables and firm and quarter fixed effects as in Table 3, Panel B. Dependent variables are shown at the head of each column. In parentheses are *t*-statistics. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A	Market share growth	Sales growth
CDS trading	0.113***	0.120***
	(2.885)	(2.841)
CDS trading × High bankruptcy risk	0.0263**	0.0242**
	(2.324)	(1.965)
High bankruptcy risk	-0.0326***	-0.0304***
	(-4.531)	(-3.879)
N	49,913	49,913
Adj. R-sqr	0.190	0.213
Panel B	**Market share growth**	**Sales growth**
CDS trading	0.100**	0.126**
	(2.104)	(2.051)
CDS trading × Financially constrained	0.0634**	0.0668**
	(2.260)	(2.094)
Financially constrained	-0.0908***	-0.0956***
	(-5.551)	(-5.033)
N	46,938	46,987
Adj. R-sqr	0.186	0.209

Table 7 CDS and product market outcomes: lender failure tolerance

The sample consists of Compustat firms between 1996 and 2015 that are incorporated in the U.S., have common stocks covered by CRSP, and are covered by Hoberg and Phillip's (2010, 2016) Text-based Network Industry Classification (TNIC). Reported are the second stage of 2SLS with *CDS trading* instrumented by *Lender CDS preference* and *Underwriter CDS preference*, and *CDS trading* × *X* instrumented by *Lender CDS preference* × *X* and *Underwriter CDS preference*× *X*, where *X* is a different indicator in each panel and is defined as follows. *Fringe technology* is a dummy variable that equals 1 if the absolute value of the deviation of a firm's capital-labor ratio from its industry-year median is above the sample median, where capital-labor ratio is defined as net property, plant, and equipment divided by the number of employees. *High R&D* is a dummy variable that equals 1 if the firm's R&D expense as a fraction of lagged total assets is above the median. All regressions include the same control variables and firm and quarter fixed effects as in Table 3, Panel B. Dependent variables are shown at the head of each column. In parentheses are *t*-statistics. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A	Market share growth	Sales growth
CDS trading	0.106***	0.110***
	(2.760)	(2.642)
CDS trading × Fringe technology	0.0195**	0.0266***
	(2.346)	(2.988)
Fringe technology	-0.0128**	-0.0106*
	(-2.422)	(-1.889)
N	47,996	47,996
Adj. R-sqr	0.191	0.209
Panel B	**Market share growth**	**Sales growth**
CDS trading	0.114**	0.100**
	(2.499)	(2.057)
CDS trading × High R&D	0.0152	0.0306**
	(1.330)	(2.432)
High R&D	-0.00409	-0.0207
	(-0.397)	(-1.582)
N	46,938	46,987
Adj. R-sqr	0.187	0.209

Table 8 CDS and product market outcomes: industry conditions

The sample consists of Compustat firms between 1996 and 2015 that are incorporated in the U.S., have common stocks covered by CRSP, and are covered by Hoberg and Phillip's (2010, 2016) Text-based Network Industry Classification (TNIC). Reported are the second stage of 2SLS with *CDS trading* instrumented by *Lender CDS preference* and *Underwriter CDS preference*. We use an indicator in each panel to split the sample into two subsamples. *High* (*Low*) *Q industry* is a dummy variable that equals 1 if the firm's industry average market-to-book assets ratio is above (below or equal to) the median. *High* (*Low*) *fluidity* is a dummy variable that equals 1 if the firm's Product Market Fluidity (Hoberg, Phillips, and Prabhala (2013)) is above (below or equal to) the median. All regressions include the same control variables and firm and quarter fixed effects as in Table 3, Panel B. Dependent variables are shown at the head of each column. In parentheses are *t*-statistics. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Market share growth		Sales growth	
Panel A	High Q industry	Low Q industry	High Q industry	Low Q industry
	(1)	(2)	(3)	(4)
CDS trading	0.141**	0.0895	0.140**	0.0552
	(2.273)	(1.142)	(2.121)	(0.646)
N	23,350	23,419	23,370	23,448
Adj. R-sqr	0.188	0.182	0.205	0.208
Panel B	High fluidity	Low fluidity	High fluidity	Low fluidity
	(1)	(2)	(3)	(4)
CDS trading	0.227**	0.0840	0.222**	0.0826
	(2.224)	(1.203)	(2.116)	(1.116)
N	21,081	26,266	21,103	26,289
Adj. R-sqr	0.204	0.175	0.219	0.203

Table 9 CDS and product market outcomes: effects over time

The sample consists of Compustat firms between 1996 and 2015 that are incorporated in the U.S., have common stocks covered by CRSP, and are covered by Hoberg and Phillip's (2010, 2016) Text-based Network Industry Classification (TNIC). Reported are the second stage of 2SLS with *CDS trading* × *Q0-3* instrumented by *Lender CDS preference* × *Q0-3* and *Underwriter CDS preference* × *Q0-3*, *CDS trading*× *Q4-15* instrumented by *Lender CDS preference* × *Q4-15* and *Underwriter CDS preference* × *Q4-15*, and *CDS trading* × *Q16&later* instrumented by *Lender CDS preference* × *Q16&later* and *Underwriter CDS preference* × *Q16&later*. *Q0-3* (*Q4-15*, *Q16&later*) is a dummy variable that equals 1 if the current quarter is 0-3 quarters (4-15 quarters, 16 quarters or more) after the firm's CDS introduction and 0 otherwise. Dependent variables are shown at the head of each column. In parentheses are t-statistics. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
	Market share growth	Sales growth
CDS trading × Q0-3	0.00664	0.00763*
	(1.616)	(1.739)
CDS trading × Q4-15	0.0115***	0.0121***
	(2.822)	(2.752)
CDS trading × Q16&later	0.0128***	0.0143***
	(2.584)	(2.667)
Market-to-book	0.00758***	0.0118***
	(2.993)	(4.222)
LnAssets	-0.0265***	-0.0327***
	(-8.646)	(-9.210)
Leverage	0.0399***	0.0629***
	(2.603)	(3.343)
Cash	-0.00905	-0.0608*
	(-0.312)	(-1.837)
Stock return	0.00975***	0.0187***
	(4.765)	(8.166)
HHI	-0.00264	0.0107
	(-0.370)	(1.411)
Inst. Ownership	0.0219***	0.0240***
	(3.405)	(3.299)
Firm fixed effects	Yes	Yes
Quarter fixed effects	Yes	Yes
Clustered std. err.	Yes	Yes
N	49,917	49,969
Adj. R-sqr	0.189	0.211

Table 10 CDS and product market outcomes: product strategies over time

The sample consists of Compustat firms between 1996 and 2015 that are incorporated in the U.S., have common stocks covered by CRSP, and are covered by Hoberg and Phillip's (2010, 2016) Text-based Network Industry Classification (TNIC). Reported are the second stage of 2SLS with *CDS trading* × *Q0-3* instrumented by *Lender CDS preference* × *Q0-3* and *Underwriter CDS preference* × *Q0-3*, *CDS trading*× *Q4-15* instrumented by *Lender CDS preference* × *Q4-15* and *Underwriter CDS preference* × *Q4-15*, and *CDS trading* × *Q16&later* instrumented by *Lender CDS preference* × *Q16&later* and *Underwriter CDS preference* × *Q16&later*. *Q0-3* (*Q4-15*, *Q16&later*) is a dummy variable that equals 1 if the current quarter is 0-3 quarters (4-15 quarters, 16 quarters or more) after the firm's CDS introduction and 0 otherwise. Dependent variables are shown at the head of each column. *Self-fluidity* is the logarithm of the firm's self-fluidity by Hoberg, Phillips, and Prabhala (2013), which equals one minus the cosine similarity between the firm's current and previous years' business descriptions. *Product similarity* is the logarithm of the average product similarity score between the firm and its rivals. The product similarity score is the cosine similarity between the firm and its rival's products (Hoberg and Phillip's (2010, 2016)). In parentheses are t-statistics. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 10 — continued

	(1) Self-fluidity	(2) Product similarity
CDS trading Q0-3	0.0664*	-0.00431
	(1.847)	(-0.254)
CDS trading Q4-15	0.120***	0.0385*
	(3.164)	(1.696)
CDS trading Q16&later	0.0920**	0.0619**
	(2.215)	(2.094)
Market-to-book	-0.0112	0.00769
	(-1.005)	(0.885)
LnAssets	0.0174	-0.00824
	(0.863)	(-0.628)
Leverage	-0.0382	0.00827
	(-0.556)	(0.195)
Cash	0.338***	0.0497
	(4.027)	(0.956)
Stock return	-0.00245	-0.00231
	(-0.233)	(-0.406)
HHI	0.285***	-0.353***
	(5.105)	(-7.296)
Inst. Ownership	-0.0581	0.0344
	(-1.232)	(1.385)
Firm fixed effects	Yes	Yes
Quarter fixed effects	Yes	Yes
Clustered std. err.	Yes	Yes
N	47,538	49,634
Adj. R-sqr	0.572	0.271

Table 11 CDS and product market outcomes: price strategy over time

The sample consists of Compustat firms between 1996 and 2015 that are incorporated in the U.S., have common stocks covered by CRSP, and are covered by Hoberg and Phillip's (2010, 2016) Text-based Network Industry Classification (TNIC). Reported are the second stage of 2SLS with *CDS trading* × *Q0-3* instrumented by *Lender CDS preference* × *Q0-3* and *Underwriter CDS preference* × *Q0-3*, *CDS trading*× *Q4-15* instrumented by *Lender CDS preference* × *Q4-15* and *Underwriter CDS preference* × *Q4-15*, and *CDS trading* × *Q16&later* instrumented by *Lender CDS preference* × *Q16&later* and *Underwriter CDS preference* × *Q16&later*. *Q0-3* (*Q4-15*, *Q16&later*) is a dummy variable that equals 1 if the current quarter is 0-3 quarters (4-15 quarters, 16 quarters or more) after the firm's CDS introduction and 0 otherwise. We obtain *Markup*, the ratio of output price to marginal cost, through a structural two-stage estimation following De Loecker and Warzynski (2012). In column 1 (2), we use OLS (GMM) in the second stage of the estimation procedure. Please see Appendix for details about the markup estimation. In parentheses are t-statistics. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) OLS	(2) GMM
CDS trading Q0-3	-0.0210*	-0.0203
	(-1.788)	(-1.605)
CDS trading Q4-15	-0.0324**	-0.0338**
	(-2.117)	(-2.021)
CDS trading Q16&later	-0.0483**	-0.0547**
	(-2.345)	(-2.447)
Market-to-book	-0.0225***	-0.0259***
	(-3.401)	(-3.565)
LnAssets	-0.0219*	-0.0226*
	(-1.768)	(-1.694)
Leverage	-0.0757*	-0.0747*
	(-1.880)	(-1.709)
Cash	-0.00288	0.00113
	(-0.0409)	(0.0149)
Stock return	0.0230***	0.0237***
	(4.674)	(4.565)
HHI	0.0175	0.0148
	(0.954)	(0.750)
Inst. Ownership	0.0582***	0.0641***
	(2.781)	(2.715)
Firm fixed effects	Yes	Yes
Quarter fixed effects	Yes	Yes
Clustered std. err.	Yes	Yes
N	46,348	46,348
Adj. R-sqr	0.232	0.248

Table A1 Balance tests of the instrumental variables

The sample consists of Compustat firms between 1996 and 2015 that are incorporated in the U.S., have common stocks covered by CRSP, and are covered by Hoberg and Phillip's (2010, 2016) Text-based Network Industry Classification (TNIC). Each of the firm characteristic variables shown in each row of the table is regressed on the instrumental variables, *Lender CDS preference* and *Underwriter CDS preference* with firm and quarter fixed effects. Reported are regression coefficients and associated t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Lender CDS preference	t-stat	Underwriter CDS preference	t-stat
Market-to-book	-0.0290	-0.42	-0.0464	-0.73
LnAssets	-0.02374	-0.48	0.0799	1.48
Leverage	0.00303	0.28	0.00689	0.62
Cash	0.00298	0.45	0.00273	0.47
Stock return	0.0184	0.63	-0.0263	-0.83
HHI	0.0101	0.89	-0.00888	-0.67
Inst. Ownership	-0.0365**	-2.13	-0.0149	-0.81

Table A2 Propensity of CDS trading

The sample consists of Compustat firms between 1996 and 2015 that are incorporated in the U.S., have common stocks covered by CRSP, and are covered by Hoberg and Phillip's (2010, 2016) Text-based Network Industry Classification (TNIC). We run a logit model of *CDS trading*. *ROA* is operating income after depreciation scaled by total assets, i.e., oiadpq/atq. *Cash flow volatility* is the standard deviation of the firm's operating income before depreciation scaled by total assets, i.e., oibdpq/atq, in the past five years. *Return volatility* is the firm's daily stock return volatility in the past five years. *Fixed Assets* is fixed assets as a fraction of total assets, i.e., ppentq/atq. *Asset* t*urnover* is sales divided by total assets, i.e., saleq/atq. *CAPX* equals capital expenditure divided by total assets, i.e., capxq/atq. *Rated* is a dummy variable that equals 1 if the firm has a Standard & Poor long-term issuer credit rating. Other variables are defined in Table 1. In parentheses are *t*-statistics. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A2 — continued

	CDS trading
Market-to-book	-0.0697
	(-1.116)
LnAssets	1.277***
	(19.02)
Leverage	0.554
	(1.358)
ROA	4.499***
	(2.589)
Cash flow volatility	6.988*
	(1.664)
Stock return	-0.0734
	(-1.551)
Return volatility	-0.910
	(-0.167)
Fixed assets	0.866***
	(2.584)
Asset turnover	1.455***
	(3.658)
Cash	-0.432
	(-0.704)
CAPX	-16.65***
	(-4.234)
Rated	2.116***
	(6.017)
HHI	0.388
	(1.261)
Inst. Ownership	0.587**
	(2.375)
Lender CDS preference	1.860***
	(5.879)
Underwriter CDS preference	2.468***
	(11.42)
N	45,828
Pseudo R-sqr.	0.452

Table A3 CDS and product market outcomes: spending policies over time

The sample consists of Compustat firms between 1996 and 2015 that are incorporated in the U.S., have common stocks covered by CRSP, and are covered by Hoberg and Phillip's (2010, 2016) Text-based Network Industry Classification (TNIC). Reported are the second stage of 2SLS with *CDS trading* × *Q0-3* instrumented by *Lender CDS preference* × *Q0-3* and *Underwriter CDS preference* × *Q0-3*, *CDS trading*× *Q4-15* instrumented by *Lender CDS preference* × *Q4-15* and *Underwriter CDS preference* × *Q4-15*, and *CDS trading* × *Q16&later* instrumented by *Lender CDS preference* × *Q16&later* and *Underwriter CDS preference* × *Q16&later*. *Q0-3* (*Q4-15*, *Q16&later*) is a dummy variable that equals 1 if the current quarter is 0-3 quarters (4-15 quarters, 16 quarters or more) after the firm's CDS introduction and 0 otherwise. Dependent variables are shown at the head of each column. *R&D* is R&D expense divided by lagged sales, i.e., $xrd_t/sale_{t-1}$, where missing xrd_t is replaced by 0. *CAPX* is capital expenditure divided by lagged sales, i.e., $capx_t/sale_{t-1}$. *Acquisition* is acquisitions cash flow divided by lagged sales, i.e., $acq_t/sale_{t-1}$. *Sales expense* is sales, general, and administrative expenses divided by lagged sales, i.e., $xsga_t/sale_{t-1}$. In parentheses are t-statistics. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) R&D	(2) CAPX	(3) Acquisition	(4) Sales expense
CDS trading Q0-3	0.00418*	0.0322***	0.00787	-0.00124
	(1.828)	(2.918)	(1.266)	(-0.101)
CDS trading Q4-15	0.00461*	0.0350***	0.00462	0.00584
	(1.825)	(3.172)	(0.676)	(0.598)
CDS trading Q16&later	0.0114**	0.0496***	0.00969	0.0219
	(2.076)	(3.767)	(1.215)	(1.515)
Market-to-book	0.0152	0.0169***	0.00235	-0.00243
	(1.427)	(2.774)	(0.733)	(-0.486)
LnAssets	0.00126	0.00419	-0.0348***	-0.0206**
	(0.231)	(0.471)	(-7.643)	(-2.215)
Leverage	-0.0169	-0.247***	-0.149***	-0.0670*
	(-0.641)	(-6.433)	(-8.389)	(-1.795)
Cash	0.127***	0.338***	0.316***	0.302***
	(2.877)	(3.594)	(11.47)	(3.339)
Stock return	-0.00562**	0.000221	0.00362*	-0.00393
	(-2.244)	(0.0506)	(1.665)	(-1.035)
HHI	-0.0131	-0.0156	0.000943	0.0208
	(-0.839)	(-1.097)	(0.0953)	(0.963)
Inst. Ownership	-0.000589	0.0164	0.0109	0.000406
	(-0.0765)	(0.862)	(1.262)	(0.0299)
Firm fixed effects	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
Clustered std. err.	Yes	Yes	Yes	Yes
N	50,061	48,713	46,256	40,724
Adj. R-sqr	0.124	0.179	0.152	0.146