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Credit Default Swaps and Firm Cyclicality

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Abstract

We find firm cyclicality decreases by 40% after the inception of credit default swap (CDS) trading. The effect stems from CDS firms' less aggressive asset growth in good times and is stronger for firms facing a more severe empty creditor problem. Important identification issues are addressed. The result cannot be explained with debt overhang, bank lending cyclicality or the cyclicality of firms' business fundamentals. It holds for the cyclicality of various corporate outcomes (inventories, cash and employment). Importantly, CDS trading impedes unhealthy growth and enhances profitability and firm value. Our finding indicates an important positive real effect of financial innovation.

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I. Introduction

Credit default swaps (CDSs) have been considered as the most important financial innovation during the past two decades. However, there has been debate about the real effects of CDSs. On the one hand, firms have better access to debt finance and can borrow at longer maturities after the onset of CDS trading (Saretto and Tookes (2013)). The average effect of CDS trading on investments tends to be positive, but there is large heterogeneity across firms (Danis and Gamba (2018)). On the other hand, CDS trading increases credit risk and may lower firm value (e.g., Subrahmanyam, Tang and Wang (2014), Narayan and Uzmanoglu (2018), Batta and Yu (2019), and Degryse, Gündüz, O'Flynn, and Ongena (2021)).

These divergent firm outcomes can be explained based on the ex-ante and ex-post effects of the empty creditor problem. CDSs allow for the separation of cash flow and control rights, creating empty creditors (Hu and Black (2008), and Bolton and Oehmke (2011)) and misaligning incentives between such creditors and the borrower (Campello and Matta (2012)). Bolton and Oehmke (2011) show that empty creditors have important ex-ante commitment benefits for firms (e.g., better access to credit) and ex-post costs of exacting creditors (e.g., higher credit risk). Both effects of CDSs have implications for firm growth and indicate that CDS firms are less cyclical than non-CDS firms. In this paper, we provide novel evidence that the inception of CDS trading lowers firm cyclicality. We further show that the CDS-induced reduction in cyclicality is beneficial to the firm.

The empty creditor problem has two effects. On the one hand, CDS-protected creditors adopt a tough stance during negotiations, particularly when engaged with borrowers facing financial distress. Anticipating a potential threat from exacting creditors, CDS firms may alter their behavior to cope with these creditors during economically tough times when credit events triggered by CDS become more likely. Consistent with this prediction, Subrahmanyam, Tang and Wang (2017) find that CDS firms increase their cash holdings. Wu, Fok, Chang and Chen (2022) document evidence that CDS firms smooth their performance. This strand of literature hints at smoother corporate growth over the business cycle, or lower cyclicality of CDS firms.

On the other hand, the ex-ante commitment benefits of CDS protection can discipline firms and improve their debt capacity even during economically difficult times (Bolton and Oehmke (2011) and Campello and Matta (2020)). The benefits of better access to credit have implications for firm cyclicality. The opportunity cost theory states that productivity-improving activities compete with production for resources so that firms concentrate such activities during economically difficult times when the returns to production are low (Aghion and Saint-Paul (1998)). However, empirical studies have shown that some productivity-improving activities, such as R&D, are pro-cyclical, accelerating firm (asset-growth) cyclicality (Barlevy (2004) and Comin and Gertler (2006)). A probable explanation is that higher financial constraints during difficult times induce a pro-cyclical bias in some productivity-improving activities (Aghion, Angeletos, Banerjee and Manova (2005) and Ouyang (2011)).[1] The ex-ante commitment benefits enable CDS firms to conduct productivity-improving investments during tough times, smoothing firm growth over the business cycle and reducing firm cyclicality.

Moreover, the cyclicality-reducing effect of CDS can benefit firms for several reasons. First, the benefits of a lower likelihood of inefficient liquidation in bad times may exceed the costs of reducing asset growth in good times. Second, by creating exacting creditors, CDS trading can discipline the underlying firms and reduce potentially unhealthy asset growth

[1] An alternative explanation is that dynamic externalities, which are inherent in some productivity-improving activities, make entrepreneurs short-sighted and concentrate their productivity-improving activities during economic booms (Barlevy (2007)).

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(overinvestment[2]) due to investments in negative net present value (NPV) projects. There is ample evidence of unhealthy corporate growth due to agency problems, mergers and acquisitions (M&A), inefficient internal capital markets, and behavioral biases (e.g., Jensen and Meckling, (1976), Titman, Wei and Xie (2004), Moeller, Schlingemann and Stulz (2004), Moeller, Schlingemann and Stulz (2005), and Malmendier and Tate (2008)). There is also evidence that corporate expansion is followed by abnormally low stock returns, implying that aggressive growth can destroy shareholder value (Cooper, Gulen and Schill (2008) and Mortal and Schill (2015)). Third, with better access to credit, CDS firms can use their resources more efficiently, concentrating productivity-improving activities during difficult times when the opportunity costs of forgone production output are low.

We base our study on data from publicly listed US firms during the period 2000-2018. Financial statement, employment and stock market data are gathered from Compustat and the Center for Research in Security Prices (CRSP). We collect macro-economic data (GDP growth and other variables) from the Federal Reserve Bank of St. Louis. We measure firm cyclicality as asset growth sensitivity to GDP growth. Based on CDS data from Markit, we identify firms that are traded in the CDS market and the time when their first CDS trading took place. To measure the influence of CDS trading on firm cyclicality, we employ an indicator variable that equals one after CDS trading was initiated on a firm's debt and interact this variable with GDP growth.

The analysis proceeds as follows. In the first part, we investigate the impact of the onset of CDS trading on firm cyclicality and its potential channels. We find that firm cyclicality

[2] Our reasoning does not necessarily contradict the model implication of Wong and Yu (2022) that CDS trading reduces firm equity value. Their model excludes overinvestment (i.e., unhealthy asset growth) and assumes that all firms invest only in positive net present value (NPV) projects. Another important model assumption in Wong and Yu (2022) is that all firms only rely on long-term debt financing. The debt overhang problem that drives key model predictions, for instance, underinvestment and lower firm asset growth for CDS firms, would disappear without this assumption.

decreases by approximately 40% after the inception of CDS trading on firms' debt. This result is based on panel regressions on the propensity-score matched sample of both CDS and non-CDS firms, using a large set of firm controls and firm (or industry) fixed effects. Our main result is not attributable to selection effects and robust in instrumental variable regressions where we address the potential endogeneity between CDS trading and firm characteristics. Our finding persists when we control for M&A activity. Furthermore, we find a qualitatively similar impact of CDS trading on the cyclicality of other corporate outcomes such as inventories, cash, accounts payable and employment.

The empty creditor problem is the main channel underlying the cyclicality-reducing effect of CDS trading. Our result is significantly stronger for firms facing a more severe empty creditor problem, i.e., those with powerful shareholders, high industry market-to-book ratios, high liquidation costs and low credit ratings. The evidence suggests that these firms reduce their asset growth strategically to strengthen their ex ante position vis-à-vis the exacting creditors.

We test and rule out three alternative explanations for our result. First, CDS firms may reduce cyclicality because of the debt overhang problem (Wong and Yu, 2022). Our main result is stronger for firms that rely more on short-term debt financing, suggesting that debt overhang is unlikely to serve as an explanation. Second, the lower cyclicality of CDS firms might be due to the lower cyclicality of their business fundamentals, as measured by their asset beta. We find that the cyclicality-reducing effect of CDS trading is similar and highly significant in the high and low asset beta subsamples. Third, we demonstrate that bank lending cyclicality does not drive our findings. We also perform several robustness tests. Our main result is robust to using the propensity-weighting approach of Bartram, Conrad, Lee and Subrahmanyam (2022) to address potential endogeneity biases, and holds before and after the global financial crisis. It is

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qualitatively similar when we use CDS net and gross positions instead of the CDS trading dummy.

In the second part of the analysis, we investigate if CDS firms benefit from lower cyclicality. First, we show that the reduction in firm cyclicality due to CDS trading occurs mainly during economically good times. Higher firm performance and the resulting pooling of high and low-quality firms in credit markets during good times facilitate access to finance but may also promote unhealthy growth (Dell'Ariccia and Marquez (2006) and Becker, Bos and Roszbach (2020)). Moreover, as shown by Campello and Matta (2020), CDS overinsurance is higher in good times, rendering the empty creditor problem more severe. Second, we find a stronger impact on firms that exhibit high asset growth and a low market-to-book ratio. High asset growth is likely to be unhealthy when the stock market is pessimistic about its investment opportunities, making it more vulnerable to exacting creditors. Third, we find an inversely U-shaped relationship between asset growth and firm profitability (ROA). CDS trading significantly increases the likelihood of a positive asset growth-profitability relationship. Fourth, we confirm the asset growth-stock return anomaly (Cooper, Gulen and Schill (2008)) and show that it is significantly reduced after the onset of CDS trading.

These novel results can be reconciled with the findings of Subrahmanyam et al. (2014) that CDS trading increases ex post default risk. We show that CDS firms partially mitigate the empty creditor problem ex ante by reducing their cyclicality. The increase in ex post credit risk would have been even higher if CDS firms had not responded precautiously by reducing growth during economically good times. Moreover, CDS trading can increase average profitability and stock returns and also increase default risk, as long as the benefits of CDS trading (healthier growth in non-default states) outweigh the costs (higher bankruptcy risk).

Our contribution to the literature is twofold. To the best of our knowledge, we are the first to empirically test and find a real effect of CDS that is theoretically supported by both the ex-ante and the ex-post implications of the empty creditor problem: CDS firms grow less aggressively during economically good times to better cope with exacting creditors. Such behavior impedes excessive growth and increases firm profitability and value. Our findings extend research on the costs and benefits of CDS trading for firms (e.g., Bartram et al. (2022), Wong and Yu (2022), Chang, Chen, Wang, Zhang and Zhang (2019), Chava, Ganduri and Ornthanalai (2019), Danis and Gamba (2018), and Subrahmanyam et al. (2014)). In particular, our results add to the evidence on how CDS firms and CDS sellers deal with empty creditors (Chakraborty, Chava and Ganduri (2023), Danis and Gamba (2023), Wu, Fok, Chang and Chen (2022), and Subrahmanyam et al. (2017)).

Moreover, this study provides a novel perspective on firm cyclicality. Understanding firm cyclicality is important as business cycles and growth are a unified phenomenon and the welfare cost of business cycles is huge (e.g., 33.6% as estimated in Bai and Zhang (2022)). The related literature has not investigated if financial innovation affects firm cyclicality, rather it has found mixed results on whether firms' productivity-improving activities are countercyclical or procyclical. The opportunity cost theory predicts that such activities are countercyclical (Aghion and Saint-Paul (1998)), while empirical evidence suggests that R&D is procyclical (Comin and Gertler (2006)). The latter may be overstated owing to time-varying corporate financial constraints (Aghion et al. (2005) and Ouyang (2011)). CDS firms that benefit from lower financial constraints in recessions (Saretto and Tookes (2013)) may be more able to invest in productivity-improving activities during economically tough times, which would lower their cyclicality. Our finding that CDS firms are less cyclical supports the financial constraint explanation of the procyclical pattern of productivity-improving activities, thereby advancing our understanding on firm cyclicality.

The remainder of the paper is organized as follows. In Section II, we describe the data. In Section III, we present our main empirical results on the impact of CDS trading on firm cyclicality as well as tests of alternative explanations and robustness tests. In Section IV, we show that CDS trading impedes unhealthy growth and enhances profitability and firm value. Section V concludes.

II. Data

We collect our data from two main sources. We extract CDS trading data from Markit, and merge them with the financial statement information from Compustat. We examine the most prevalent CDS contracts, written on bonds and loans ("borrowed money" from the ISDA term sheets). Recently, Loan CDS (LCDS) contracts, which are exclusively written on loans, have emerged (Choudhry (2011)). We are not able to obtain data on LCDS contracts and thus might consider LCDS firms as non-CDS firms. However, to the extent that LCDS contracts also induce the empty creditor problem, ignoring these contracts makes it harder to detect a potential effect. Moreover, the impact of LCDS contracts on our findings, if any, is likely to be limited. This is because the LCDS market is relatively illiquid; credit protection buyers typically use CDS contracts, rather than LCDS contracts, to hedge against credit risk. For more details, refer to Amiram, Beaver, Landsman and Zhao (2017).

Excluding firms in the financial industry (standard industry classification code 6000-6999), our final sample comprises 8,449 firms with 266,065 firm quarter observations, spanning the period from the last quarter of 2000 to the last quarter of 2018. For additional variables, we use data from other sources, including GDP data from the Federal Reserve Bank of St. Louis website, institutional ownership data from Thomson Reuters 13F holdings, mergers and acquisitions data from SDC, and stock price data from CRSP.

Our main variable is $CDSTrading$, an indicator variable that equals one for a firm in the quarter in which CDS trading for the firm started and for all subsequent quarters, and zero otherwise. Overall, we identify 849 CDS firms and 33,832 CDS firm-quarter observations. *Asset growth* (AG), our main dependent variable, is defined as the percentage quarterly change in the book value of a firm's total assets. To address the effect of confounding factors that drive both CDS trading and asset growth, we follow related studies such as Saretto and Tookes (2013) and Chang et al. (2019) and consider a comprehensive set of control variables. These include firm size, net PPE, leverage, working capital, cash, asset turnover, retained earnings, stock return volatility, excess stock return, investment grade dummy, credit rating dummy, and market to book ratio. Appendix A provides detailed definitions of all the variables used in the study.

The Internet Appendix (Table IA.1) compares the characteristics of CDS firms with those of non-CDS firms. Importantly, the average quarterly asset growth rate of CDS firms (1.4%) is lower than that of non-CDS firms (1.9%), suggesting that CDS trading reduces asset growth. However, there are several differences between CDS firms and non-CDS firms. For example, CDS firms are on average larger, more levered, more profitable, and less risky. These findings suggest that CDS firms are not randomly assigned. Therefore, it is important to control for potential selection biases. Consistent with prior studies (e.g., Ashcraft and Santos (2019) and Chang et al. (2019)), we use the propensity score matching (PSM) method to conduct matched-sample analysis. Specifically, we match each CDS (treated) firm with a non-CDS (control) firm and include both the treated and control firms in the matched sample throughout all our regression analyses.

The matching approach is based on the propensity score, defined as the conditional probability of receiving treatment (e.g., CDS trading). For each treated firm (CDS firm), we find one matching non-CDS firm with the closest propensity score for CDS trading, calculated using the following probit model:

$$(1)\ \ \text{Prob}(\text{CDS initiation}_{i,t} = 1) = \Phi(\alpha + \boldsymbol{\beta_1 X_{i,t-1}} + \beta_2 \text{Industry}_j + \beta_3 Quarter_t)$$

where Φ is the cumulative distribution function of the standard normal distribution. $\text{CDS initiation}_{i,t}$ equals one for CDS firms in the first CDS transaction quarter and zero for non-CDS firms in all quarters. $X_{i,t-1}$ includes a variety of firm characteristics that determine the initiation of CDS trading on a firm as documented in previous studies (e.g., Saretto and Tookes, (2013), Subrahmanyam et al. (2014), and Batta and Yu (2019)): AG, $CAPX$, ROA, Size, Net PPE, Leverage, Working Capital, Cash, Asset Turnover, Retained Earnings, Volatility, Excess Return, Investment − grade, and Rated. All independent variables are lagged by one quarter. Industry and Quarter represent two-digit SIC industry and quarter fixed effects, respectively. Following Subrahmanyam et al. (2014), we estimate Equation (2) using all the sampled firms (both CDS and non-CDS firms) during the entire sample period 2000-2018 and exclude the post-CDS initiation quarters of CDS firms. We use matching with replacement (multiple matching) because it allows for better matches.[3]

Table 1 presents the matching results. As shown in Panel A, the model predicts the onset of CDS trading reasonably well with a pseudo R-squared of 0.278. The coefficients of the

[3] The advantage of multiple matching may be at the expense of precision if a few control firms dominate the control group, as they are best matches for several treated firms. To address this concern, we construct an alternative control sample, in which multiple matching is not allowed, e.g., a non-CDS firm can only be matched to one CDS firm. Our results are robust to using this alternative matching method.

explanatory variables are generally consistent with those reported in previous studies. For instance, larger firms, firms with higher leverage and less volatile stock returns, and rated firms are more likely to experience CDS trading. Panel B provides summary statistics for CDS firms and PSM-matched non-CDS firms prior to the quarter of the CDS trading initiation. The results confirm effective matching and show that before the onset of CDS trading the treated and control firms are not significantly different for all firm characteristics, with the single exception of $\mathrm{Investment-grade}$. The insignificant difference in the propensity scores shown in the last row further suggests that the two groups are equally likely to have CDS trading initiated. In an unreported test, we estimate Equation (2) using the propensity score-matched sample and find that the pseudo R^2 drops substantially to 0.171, confirming that the matching is successful.

(Insert Table 1 here)

Figure 1 displays the dynamics of quarterly asset growth for CDS firms and matched non-CDS firms during the entire sample period 2000-2018.

(Insert Figure 1 here)

Interestingly, the figure shows that CDS firms show lower asset growth than non-CDS firms mainly in economically good times, i.e., when the GDP growth rate is relatively high. We investigate these descriptive results in formal econometric analysis in the remainder of this study.

III. CDS Trading and Firm Cyclicality

In this section, we first investigate the impact of the onset of CDS trading on firm cyclicality using panel-data regression analysis with the matched sample. Second, we address the potential selection bias and endogeneity issues in our matched-sample analysis. Third, we analyze the role of M&A activities. Fourth, we conduct additional tests to examine the impact of

CDS trading on the cyclicality of additional corporate outcomes. Subsequently, we examine the presence of empty creditors as a potential channel through which CDS trading affects firm growth. Finally, we test three alternative explanations for the impact of CDS trading on firm cyclicality.

A. Baseline Results

Table 2 presents the results of the following model and some modified specifications.

$$(2) \quad AG_{i,t} = \alpha + \beta_1 \Delta GDP_t \times CDSTrading_{i,t-1} + \beta_2 CDSTrading_{i,t-1} + \beta_3 \Delta GDP_t + \boldsymbol{\gamma X_{i,t-1}} + \varepsilon_{i,t}$$

where $AG_{i,t}$ is the asset growth rate of firm i in quarter t. $CDSTrading_{i,t}$ is a dummy variable that is equal to one for firm i starting from the first quarter in which the firm has its CDS trading in the market and all subsequent quarters, and zero otherwise. ΔGDP_t is quarterly nominal gross domestic product growth rate.[4] [5] $\boldsymbol{X_t}$ is a vector of control variables and it incorporates the determinants of CDS introduction as specified in Subrahmanyam et al. (2014) and the determinants of firm asset growth (corporate investment) as in Chen and Chen (2012). $\varepsilon_{i,t}$ is the i.i.d. residual term. Appendix A presents the definitions of all the variables. We are interested in coefficient β_1, which indicates the moderating effect of CDS trading on firms' cyclicality, measured as firm asset growth-GDP growth sensitivity.

(Insert Table 2 here)

[4] The quarterly nominal gross domestic product (GDP) growth rate is calculated as one fourth of the seasonally adjusted annual nominal growth rate. Our results are robust for real GDP growth and GDP growth that is not adjusted for seasonality.

[5] We obtain qualitatively similar results when using quarterly industrial production growth rate (ΔIP), instead of ΔGDP, as a measure of economic growth.

First, the positive and significant coefficient of ΔGDP (1.410) as shown in column (1) of Table 2 confirms firm asset growth cyclicality, suggesting that the total assets of a typical (matched) non-CDS firm in our sample grow by 1.410% when GDP increases by 1%. Second, the negative coefficient of the interaction term in the same column shows that the average cyclicality of CDS firms is significantly lower than that of non-CDS firms. Importantly, firm cyclicality decreases by 29% $(= -\frac{0.413}{1.410})$ after the onset of CDS trading. The coefficient of the interaction term remains negative and statistically highly significant when we progressively add controls and fixed effects, as shown in columns (2) through (4). Column (4) reports our baseline results, estimated by augmenting the regression specification (Equation 1) with firm fixed effects. Strikingly, the results show that CDS trading reduces firm cyclicality by 40% $(= -\frac{0.367}{0.910})$, controlling for a comprehensive set of time-varying firm characteristics, and firm fixed effects. These results are consistent with our hypothesis that CDS trading reduces firm cyclicality.

B. Selection Effects and Endogeneity

One challenge for any study on the real effects of CDS trading on corporate decisions is that CDS firms may differ from non-CDS firms in ways that are related to how firms make various decisions. Specifically, CDS firms may be less cyclical even if there was no CDS trading on their debt. Our baseline analysis addresses this problem using a propensity-score-matched sample and by controlling for CDS introduction determinants and firm fixed effects. However, the selected CDS introduction determinants may not be exhaustive and there may be omitted variables that drive both CDS introduction and firm growth. To address this concern, we account for the time invariant differences between CDS firms and matched non-CDS firms by including

$CDSTraded$ as an additional control variable, following Saretto and Tookes (2013) and other related studies. $CDSTraded$ is an indicator variable that equals one for a firm in all the quarters if it has a traded CDS contract on its debt at any time during the sample period, and zero otherwise. This variable captures a potential selection effect as it absorbs any time-invariant differences between CDS and non-CDS firms. Including both $CDSTrading$ and $CDSTraded$ in a single regression specification enables us to leverage the differences in the timing of CDS introduction across *CDSTraded* firms to estimate the impact of CDS trading on asset growth cyclicality. In Table 3, Panel A presents the results.

(Insert Table 3 here)

We find that compared to firms that have never had CDS contracts on their debt, *CDSTraded* firms make different asset growth decisions, as indicated by the significant coefficient estimates of $CDSTraded$. Importantly, the coefficient of the interaction term β_1 remains negative and highly significant in all model specifications, confirming our baseline result from Table 2.[6]

The previous analysis with $CDSTraded$ assumes that the timing of CDS introduction is exogenous to firms' asset growth decisions. A legitimate concern is that the inception of CDS trading could be the result of creditors' reaction to firms' asset growth decisions that significantly increase credit risk, for example, via increased hedging demand. To address this issue, we need to identify variables that explain the hedging needs of firms' creditors but are not directly related to firm growth. We follow the related literature (e.g., Saretto and Tookes (2013), Subrahmanyam et al. (2014), Subrahmanyam et al. (2017), and Chang et al. (2019)) and use

[6] CDSTraded and firm fixed effects cannot be included in the same regression specification. Therefore, we control for industry fixed effects instead in column 3 of Panel A in Table 3.

$Lender\ FX\ Usage$ as the instrument to address this issue.[7] $Lender\ FX\ Usage$ is defined as the average of foreign exchange derivatives that are 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 past five years. As the variable of interest is an interaction term, we adopt the control function (CF) approach instead of the usual two-stage least squares (2SLS) estimator method (Wooldridge, 2015). Specifically, we first regress $CDSTrading$ on the instrument and control variables. Next, we use the predicted values of $CDSTrading$ to compute the fitted residuals $\hat{\theta} = \mathrm{CDSTrading} - \widehat{\mathrm{CDSTrading}}$ and subsequently include $\hat{\theta}$ as an additional regressor in the baseline regression specification. In Table 3, Panel B presents the results of the instrumental variable (IV) regressions.

Column (1) shows that econometrically the relevance condition is met, as $CDSTrading$ is significantly associated with $Lender\ FX\ Usage$ and, as expected, the coefficient is positive. In column (2), after controlling for $\hat{\theta}$, we still find a strong effect of CDS trading in determining the cyclicality of firm asset growth, e.g., the coefficient of the interaction term remains negative and significant. To better deal with the binary nature of the (potentially) endogenous variable $CDSTrading$, we follow Chang et al. (2019) and perform the 3-stage procedure proposed by Wooldridge (2002). In the first stage, we estimate a probit model with $Lender\ FX\ Usage$ and controls as the explanatory variables and compute the fitted probability of $CDSTrading$ being equal to 1. In the second stage, we regress $CDSTrading$ on the fitted probability computed from the first stage and the controls. We next use the predicted values of $CDSTrading$ obtained from the second-stage regression to calculate the fitted residuals $\hat{\theta}$. In the third stage, we regress AG on $\mathrm{CDSTrading} \times \Delta GDP$, $\hat{\theta}$ and the control variables from the baseline regression specification.

[7] The authors thank Sarah Wang for providing data on the instrumental variable.

The last column reports the third-stage regression results. Clearly, the interaction term $\text{CDSTrading} \times \Delta GDP$ enters the regression with a coefficient of -0.300, which is statistically significant at the 1% level. Notably, the economic magnitude of the coefficient on the interaction term is similar to that in our baseline analysis (see Table 2, column 4).

We next conduct a placebo test for further identification. In this falsification exercise, instead of mapping the first CDS transaction dates to the corresponding CDS firms, we assign these first dates to a randomly selected sample of firms. These selected firms are considered as "CDS firms". Specifically, we define a new dummy variable, $CDSTrading^{Placebo}$, which equals one for these counterfactual "CDS firms" after the CDS trading inception dates, and 0 otherwise. Employing the randomization of CDS trading status, we create a placebo treatment and re-estimate our baseline regression (specification 4 in Table 2) using the new variable $CDSTrading^{Placebo}$. We repeat this exercise 1,000 times and obtain 1,000 coefficient estimates for the interaction term $CDSTrading^{Placebo} \times \Delta GDP$, each time with a randomly designated sample of "CDS firms". Next, we plot a histogram of the estimated placebo coefficients. As shown in Figure 2, the actual interaction effect (-0.367), reported in column 4 of Table 2 and represented by the dashed vertical line in the graph, is highly significantly different from the placebo effect at any traditional significance levels. Importantly, most of the placebo estimates are around zero, with an average of 0.04 and a standard deviation of 0.19. If anything, the placebo results suggest that the cyclicality-reducing effect that we document is attributable to the presence of CDS trading and not to a treatment misidentification.

(Insert Figure 2 here)

In summary, the results obtained from the set of identification strategies are consistent, indicating that the onset of CDS trading lowers firm cyclicality. In the Internet Appendix, we show that our results are robust to using a propensity-weighted approach, over different sample periods, and when using the CDS net and gross positions instead of the CDS trading dummy (Table IA.2).

C. M&A Activity

Firm cyclicality varies with corporate growth strategy. Firms grow because of regular investments in projects and/or M&A activities. Evidence shows that firms tend to reduce their M&A activities after the onset of CDS trading (Batta and Yu (2019)). Hence, it is important to investigate whether the cyclicality-reducing effect of CDS trading is driven mainly by firms adjusting their M&A activities as a precautionary response to the potential exacting creditor problem. To address this, we consider two M&A variables in our analysis. First, we define a dummy variable *MADummy*, which is equal to one if a firm announces an M&A event in a quarter, and zero otherwise. *MADummy* is a relatively coarse measure of M&A activities as it does not distinguish between large and small M&A deals. Therefore, we consider a second measure of M&A activities, namely the change in goodwill (*ΔGoodwill*). An advantage of this measure is that it captures the magnitude of the M&A deal. First, we add *MADummy* or/and *ΔGoodwill* as the control variables to our baseline regression model and re-estimate the augmented model. Next, we exclude firm-quarter observations, for which *MADummy* equals one and conduct a subsample analysis. Table 4 presents the corresponding regressions results.

(Insert Table 4 here)

In columns (1) and (2), we control for *MADummy* and *ΔGoodwill*, respectively. In column (3), we include both M&A controls simultaneously. We obtain consistent results across the different model specifications. We find that M&A activities, as shown in the literature, are significantly and positively associated with firm asset growth. Importantly, the cyclicality-reducing effect of CDS trading remains statistically and economically significant after controlling for M&A activities. In column (4), we exclude firm-quarter observations, for which *MADummy* equals one, and re-estimate model (4) from Table 2 based on this slightly smaller sample, which is free of any impact of M&A activity. The coefficient of *CDSTrading* × *ΔGDP* is negative and highly significant, confirming the baseline findings in Table 2. Overall, the analysis suggests that the cyclicality-reducing effect is not driven by firms reducing their M&A transactions following the inception of CDS trading. Instead, CDS trading is likely to have implications across several firm investment decisions.

D. Additional Analysis

In this section, we perform a number of additional tests with the propensity-score-matched sample to examine the impact of CDS trading on the cyclicality of several growth-related firm characteristics, such as the likelihood of M&A, inventory expansion, and growth in cash holdings, payables, receivables, and employment.

(Insert Table 5 here)

Several interesting findings emerge from these analyses. First, as shown in column 2 of Table 5, CDS trading has a negative effect on the cyclicality of inventory growth. This finding is consistent with our hypothesis that CDS firms behave precautionarily, by not producing and holding excessive inventory during economically good times, to avoid negotiations with CDS-protected creditors during economically difficult times. Interestingly, the interaction term CDSTrading × ΔGDP enters the cash holdings growth regression (column 3) with a negative and significant coefficient. This finding, together with the result in Subrahmanyam et al. (2017) that

CDS firms generally hold more cash, suggests that CDS firms hold more cash during economically difficult times, but not during economically good times.

In column 4, the regression results show that CDS firms reduce the cyclicality of trade credit, as measured by accounts payable. These results, combined with those in column 3, indicate that CDS firms may shift to cash from trade credit in paying their suppliers during economically good times. This finding is in line with the precautionary response hypothesis, e.g., CDS firms reduce borrowing from suppliers (through trade credit) during good times. Finally, we do not find a significant CDS trading effect on the cyclicality of M&A (column 1), consistent with the results shown in Table 4, or accounts receivable (column 5). These analyses suggest that CDS firms reduce asset-growth cyclicality by cutting back production and reducing trade credit during economically good times, e.g., they reduce inventory and borrowing from suppliers.

We also consider the cyclicality of employment growth (EG) as it directly reflects firms' labor market decisions, and capital and labor intensities vary across firms and over time. Although both asset and employment growth are positively correlated in the long term, it is not necessarily the case where CDS trading affects both in a similar way. For example, when facing exacting creditors, firms may decide to temporarily reduce asset growth but maintain their current employment level, as it can be costly to fire now and hire later employees. To understand the implications of CDS trading on employment growth cyclicality, we perform additional analysis by replacing *Asset growth* (*AG*), the dependent variable in the baseline model, with *Employment growth* (*EG*).[8] In Table 5, column 6 presents the regression results. We find a negative effect of CDS trading on employment growth cyclicality, extending our main result on firm asset growth cyclicality to employment growth cyclicality.

[8] We use yearly data for this analysis as data on employment growth rates is available only at the yearly frequency.

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E. Anticipating Empty Creditors

Our main result indicates that firms reduce their cyclicality following the inception of CDS trading. Theoretically, CDS can change creditors' incentives in multiple ways. Our findings are consistent with the effect of empty creditors documented in the literature. As modeled by Bolton and Oehmke (2011), ex post, when a firm is in distress empty creditors, protected by CDS contracts, tend to be tougher and are motivated to push the firm into bankruptcy. Anticipating this incentive of empty creditors, CDS firms strategically adjust their asset growth behavior, e.g., they grow less aggressively when the economy is booming to avoid potential bankruptcy during subsequent economic downturns. This theory immediately leads to two empirical predictions. First, we expect that the CDS trading effect is more prominent for firms facing a more severe empty creditor problem. Second, the cyclicality-reducing effect of CDS trading should materialize during economically good times, allowing firms to cope better with empty creditors during economically tough times. In this section, we focus on testing the first prediction. We test the second prediction in Section IV.

We identify firms that experience greater pressure from empty creditors and expect a greater impact of CDS trading on cyclicality for these firms, as they are more likely to adopt precautionary measures. Specifically, we split the matched sample into two sub-samples based on various partitioning variables. The related literature shows that firms with powerful shareholders, greater industry Q, higher liquidation costs, and higher credit risk are more likely to experience the empty creditor problem (e.g., Kim (2016) and Colonnello, Efing and Zucchi (2018)). Accordingly, we use total active institutional ownership, industry Q, liquidation costs, and investment-grade, respectively, as the partitioning variables to split the sample.[9] Next, we re-estimate the baseline regression model (column 4 of Table 2) for the sub-samples and present the results in Table 6.

(Insert Table 6 here)

Comparing columns (1) and (2), we find that, as expected, the coefficient of the interaction term β_1 is statistically significant only for firms with a larger total active institutional ownership ($TAIO$). Consistent with our expectation, the results in columns (3) through (8) confirm that the cyclicality-reducing effect of CDS trading is more prominent for (only exists in) firms experiencing a more severe empty creditor problem, e.g., firms with higher industry Q ($INDQ$), higher liquidation costs (LC), and higher credit risk (non-IG or not-rated).

These findings are highly significant and consistent across several split variables, suggesting that our main result – the lower asset growth cyclicality of CDS firms – can be considered as a precautionary strategy that CDS firms adopt to mitigate the empty creditor problem.

F. Alternative Explanations

1. Debt Overhang

Wong and Yu (2022) show in a two-stage model, in which firms exclusively rely on long-term debt financing, that CDS trading causes debt overhang, which leads to underinvestment and lower asset growth. Although both our hypothesis and the theoretical model

[9] We assign each firm-quarter observation to a sub-sample based on the median of the partitioning variable for all partitioning variables, except investment-grade (IG). When we use IG as the partitioning variable, a firm-quarter observation is assigned to the IG group if the dummy variable investment-grade is equal to 1, and to the non-IG or not-rated group otherwise. We assign not-rated firms to the same group as non-IG firms because not-rated firms are almost twice risky as IG firms when we measure default risk based on the 5-year CDS spreads.

of Wong and Yu (2022) indicate a reduction in firm asset growth after the inception of CDS trading, the driving forces and implications are distinct. If the reduction in asset growth (and the resulting lower cyclicality) is the outcome of firms giving up positive NPV projects as modeled by Wong and Yu (2022), it is detrimental and value-destroying. By contrast, if CDS firms proactively reduce unhealthy asset growth as a precautionary response to the potential threat of empty creditors, growth reduction is beneficial and value-enhancing.

Therefore, we examine the extent to which debt overhang drives the cyclicality-reducing effect documented in Section III.A. To investigate this question, we explore the key model assumption of Wong and Yu (2022), which is crucial for their prediction that CDS trading causes debt overhang: firms are financed only by long-term debt (and equity). Specifically, we divide our (propensity-score-matched) sample into four sub-groups: firms that rely more on long-term debt (LTD CDS firms and LTD non-CDS firms) and those that rely more on short-term debt (STD CDS firms and STD non-CDS firms), and estimate asset growth cyclicality for the four sub-samples, respectively. If debt overhang is the driving force, we expect that the cyclicality-reducing effect of CDS trading only exists or is stronger for LTD firms. However, the results in columns (1) through (4) of Table 7 show that during our sample period both LTD firms and STD firms reduce cyclicality (measured by the coefficient of *ΔGDP)* after the inception of CDS trading on their debt.

(Insert Table 7 here)

Interestingly, the reductions are 14% (from 0.793 to 0.683) and 41% (from 0.916 to 0.537) for the two types of firms, respectively. The higher cyclicality reduction in STD firms is not consistent with the debt overhang explanation. Instead, it aligns with our precautionary response explanation. Furthermore, the results of the interaction term analysis (see column (5) of

Table 7) confirm this conclusion, showing that the cyclicality-reducing effect is economically and statistically stronger for firms that rely more on short-term debt. Considered together, it is unlikely that debt overhang can explain our main findings.

2. Asset Beta

In Table 1, the probit regression results show that firms with low stock return volatility are more likely to induce CDS trading on their debt. To the extent that a firm's return volatility is positively correlated with the cyclicality of its business fundamentals (measured by the firm's asset beta), $CDSTrading$ may simply pick up low-asset-beta firms. In other words, the cyclicality-reducing effect of CDS trading may be an asset-beta effect in disguise, e.g., low - asset-beta firms are less cyclical. Hence, a possible explanation of our findings based on asset beta deserves a further analysis. Specifically, at each quarter we define our sample firms as high-asset-beta firms and low-asset-beta firms, based on a split using the median asset beta of all firms. Asset beta is calculated as equity beta times 1 minus net market leverage as in Baker, Hoeyer, and Wurgler (2020). The equity beta is calculated from the Capital Asset Pricing Model (CAPM), using the previous 5-year monthly returns of individual stocks and returns of the market portfolio. As shown in the last row of Table 8, on average, high-beta firms have an asset beta approximately three times that of low-beta firms (1.679 vs. 0.590). Next, we re-estimate the baseline regression on two subsamples: high-beta subsample and low-beta subsample, respectively. If the CDS trading effect is indeed a low beta effect, one would expect an insignificant or much smaller effect for the two subsamples. However, the results in Table 8 show that the interaction term coefficient estimates for the two subsamples are not only significant but also similar in magnitude to that from the baseline regression reported in column

(4) of Table 2. A formal statistical test confirms that the differences are not significantly different from zero. The results of this analysis contradict the view that firm asset beta can explain the cyclicality-reducing effect of CDS trading.

(Insert Table 8 here)

3. Bank Lending Cyclicality

Previous research has documented that bank lending is procyclical, e.g., banks tend to loosen lending standards, reduce loan rates and increase credit supply during economic upturns (e.g., Dell'Ariccia and Marquez (2006), Mian and Sufi (2009), and Becker and Ivashina (2014)). Such lending cyclicality makes it easier for firms to grow during economically good times, thereby inducing firm growth cyclicality. However, if the existence of a CDS market either forces or helps banks to place a correct (and higher) price tag on their loans when they are reluctant or unable to do so otherwise, then CDS firms may exhibit lower cyclicality versus non-CDS firms. Specifically, if banks charge higher loan spreads for CDS firms during economic upturns but not for non-CDS firms, then it would be more difficult for CDS firms to grow with the economy, thus resulting in their lower cyclicality. Does bank lending cyclicality explain our main findings? In other words, compared to non-CDS firms, is it costlier for CDS firms to borrow from banks during good times? We attempt to address this question in the remainder of this section.

In Figure 3, we plot the quarterly average borrowing costs for CDS firms (solid black line), and propensity score-matched (PSM matched) non-CDS firms (dashed gray line) over time, together with the average 5-year CDS spreads for CDS firms (dotted gray line). Firm borrowing costs are measured by the average *All-in Spread Drawn* (*AISD*), obtained from

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Thomson Reuters Dealscan. *AISD* is the spread that the borrower pays in basis points over LIBOR for each dollar drawn down, including the loan spread and annual fees paid to the bank.

(Insert Figure 3 here)

Two interesting observations emerge from Figure 3. First, during economically good times, when the average CDS spreads are relatively low, the average loan spreads of CDS firms are similar to their average 5-year CDS spreads. This observation confirms that banks have used CDS spreads as benchmarks for pricing corporate loans (e.g., Norden and Wagner (2008)). Second, the loan spreads of CDS firms are constantly lower than those of the PSM matched non-CDS firms during the entire sample period, including economic upturns. These findings suggest that bank lending cyclicality does not explain our main results. In an untabulated test, we control for changes in leverage ($\Delta Leverage$) in our baseline regression and find that the CDS trading effect remains highly significant, confirming that debt market cyclicality fails to explain our results.

IV. CDS trading, firm cyclicality and healthy vs. unhealthy growth

In this section, we investigate if the cyclicality-reducing effect of CDS trading is beneficial for CDS firms. If CDS trading reduces cyclicality because it impedes unhealthy corporate growth during economically good times or conducts productivity-improving activities more efficiently during economically difficult times, then the effect should enhance profitability and firm value. We conduct several empirical tests to examine these predictions.

A. Impact of CDS Trading on Cyclicality during Good and Bad times

We have rationalized our empirical findings with the role of exacting creditors. As discussed previously, the same model predicts that CDS firms have incentives to grow at a relatively lower rate during economically good times. Figure 1 provides the first evidence supporting this prediction. We formally test it by estimating the following regression model:

$$(3)\quad AG_{i,t} = \alpha + \beta_1^{high} \Delta GDP^{high}{}_t \times CDSTrading_{i,t-1} + \beta_1^{low} \Delta GDP^{low}{}_t \times CDSTrading_{i,t-1} + \beta_2 \Delta GDP^{high}{}_t + \beta_3 \Delta GDP^{low}{}_t + \beta_4 CDSTrading_{i,t-1} + \boldsymbol{\gamma X_{i,t-1}} + \varepsilon_{i,t}$$

where $\Delta GDP^{high}{}_t$ takes the value of the quarterly GDP growth rate when the growth rate is above the sample median. It is equal to zero when the GDP growth rate is below or equal to the median. Similarly, $\Delta GDP^{low}{}_t$ takes the value of the quarterly GDP growth rate when the growth rate is below the sample median. It is equal to zero when the GDP growth rate is above or equal to the median. The difference between coefficients β_1^{high} and β_1^{low}, if any, captures the asymmetric effects of CDS trading on firm cyclicality, as predicted by the exacting creditor theory. Table 9 presents the regression results.

(Insert Table 9 here)

The negative and highly significant coefficient β_1^{high} in all the specifications, and the insignificant coefficient β_1^{low} in the last column (regression specification 4) indicate that CDS firms adjust their cyclicality only in the high growth regime of the economy, confirming the mechanism of the exacting creditor problem. Importantly, this empirical finding also signals that firms could benefit from a reduction in cyclicality because CDS firms grow less aggressively exactly at times when unhealthy growth is more likely (e.g., some firms tend to grow beyond the optimal rate during good times).

B. High Growth and Low Tobin's Q Firms

Firms with high asset growth, despite poor investment opportunities, are more exposed to the exacting creditor problem and would benefit from reducing unhealthy growth. Thus, we expect a stronger CDS trading effect on asset growth for these vulnerable (to exacting creditors) firms following the inception of CDS trading on their debt. To identify such vulnerable firms, we consider jointly firms' asset growth and investment opportunities. A firm is vulnerable if its asset growth (AG_{t-1}) is high (e.g., higher than the sample median) and its Tobin's Q ($Market\ to\ Book_{t-1}$) is low (e.g., lower than the sample median). On the other hand, one would expect that firms with justified asset growth (neutral firms), e.g., firms with high AG_{t-1} and high $Market\ to\ Book_{t-1}$, are less likely to amend their asset growth as better investment opportunities mitigate the potential threats from exacting creditors. We perform regression analysis for the two sub-samples (vulnerable and neutral firms), respectively, using the following model:[10]

(4) $AG_{i,t} = \alpha + \beta_1 CDSTrading_{i,t-1} + \boldsymbol{\gamma X_{i,t-1}} + \varepsilon_{i,t}$

As shown in columns (1) and (2) of Table 10, we detect a significant CDS trading effect on asset growth only for vulnerable firms, supporting the view that the onset of CDS trading reduces cyclicality by impeding unhealthy growth.

(Insert Table 10 here)

Furthermore, a firm's high growth may be justified as healthy, provided it has a comparative advantage over its industry peers (even if its absolute Q is low). To address this concern, we calculate the difference between a firm's Q and its industry median Q, denoted as Q^{Dev}. We use $Q^{Dev.}$, instead of Q, to differentiate between vulnerable and neutral firms and

[10] In this analysis and the following ones, we investigate if CDS trading (and its induced reduction in asset growth) is value-enhancing or value-destroying, focusing on $CDSTrading$ as the variable of interest, rather than the interaction term between $CDSTrading$ and ΔGDP.

repeat the regression analysis. We obtain similar results, as shown in columns (3) and (4) of Table 10.

C. Firm Profitability

Next, we examine if and how the cyclicality-reducing effect of CDS trading relates to firm profitability. If lower cyclicality is associated with CDS trading impeding unhealthy asset growth, then CDS firms will be healthier. We define firms as healthy based on the asset growth-profitability (*AG-ROA*) relationship. Specifically, a firm is healthy if the *AG-ROA* relationship is positive, e.g., additional asset growth increases firm profitability.[11] We postulate that for a typical firm in our sample the *AG-ROA* relationship is positive when *AG* is low to moderate, but it turns negative when *AG* surpasses a certain threshold (e.g., when the firm reaches an extremely high growth rate). To identify the turning point, we conduct regression analysis with a quadratic term using the following model:

$$(5) \quad ROA_{i,t} = \alpha + \beta_1 AG_{i,t} + \beta_2 AG_{i,t}^2 + \boldsymbol{\gamma X_{i,t-1}} + \varepsilon_{i,t}$$

Table 11 presents the regression results.

(Insert Table 11 here)

Consistent with our expectation, we detect an inversely U-shaped *AG-ROA* relationship from the positive (and significant) β_1 and the negative (and significant) β_2 in column (1) of Table 11. Combining the coefficients of *AG* and its squared term, we can derive the turning point: $AG^* = \frac{0.064}{2\times 0.099} = 0.32$. When a firm's quarterly asset growth is lower than 0.32, any further increase in asset growth raises profitability (e.g., the firm is healthy). However, when a

[11] Note that a firm with a negative AG-ROA relation can still be healthy. The firm is just more likely to be unhealthy, e.g., it is more likely that some asset growth of the firm is associated with negative NPV projects.

firm's quarterly asset growth is higher than 0.32, any further increase in asset growth decreases profitability, i.e., the firm is more likely to be unhealthy. To examine if CDS firms are more likely to be on the left side of the inversely U-shaped AG-ROA relationship, we first define a dummy variable $Healthy$, which equals one when a firm's asset growth is lower than AG^*, and 0 otherwise. We then regress $Healthy$ on $CDSTrading$ and control variables. The positive coefficient of $CDSTrading$ reported in column (2) of Table 11 indicates that CDS firms are more likely to be healthy firms, which is consistent with our prediction. In the Internet Appendix, we show in Table IA.3 that the cyclicality-reducing effect of CDS trading is value enhancing, as it reduces the asset growth-stock return anomaly documented in Cooper et al. (2008).

V. Conclusion

In this paper, we investigate whether CDS trading affects the cyclicality of U.S. firms during 2000-2018. CDS trading results in better access to credit but also higher credit risk due to the empty credit problem. Both effects likely influence firm cyclicality.

We find two key results. First, firm cyclicality decreases by 40% after the inception of CDS trading on firms' debt. The cyclicality-reducing effect is significantly stronger for firms facing a more severe empty creditor problem. Our main finding cannot be explained with debt overhang, asset beta or bank lending cyclicality. Second, we provide consistent evidence that the lower cyclicality is beneficial to CDS firms. The cyclicality-reducing effect of CDS trading is due to lower growth in good times and mainly found for firms exhibiting high asset growth and low market-to-book ratio. Furthermore, CDS trading enhances profitability and firm value.

We contribute to the literature by documenting a novel disciplining effect of CDS trading. CDS firms reduce their growth to better cope with exacting creditors and such strategy increases firm profitability and market value. More broadly, our work is the first to uncover a beneficial effect of financial innovation on firm cyclicality. CDS trading makes it possible to separate the allocation of capital and risk in the economy and therefore can create feedback effects on financing, investment, and other corporate decisions. We highlight such feedback effect on the cyclicality of individual firms. Future research can investigate this effect at the macro-economic level. Macroeconomists have long recognized that cycles and growth are a unified phenomenon and the welfare cost of business cycles, at the economy-wide level, is significant (Bai and Zhang (2022)). To the extent that the reduction in the cyclicality of individual firms smooths business cycles, our finding implies benefits also at the economy-wide level.

Finally, financial regulators and policymakers should consider our findings when designing, evaluating, or changing rules and regulations related to CDS. For instance, the previous literature suggests imposing limits on the voting rights of the overinsured creditors to address the bankruptcy bias caused by the empty creditor problem (Hu and Black (2008) and Bolton and Oehmke (2011)). In contrast, our main finding - the beneficial disciplining effect of empty creditors on firm cyclicality - speaks against constraining the rights of empty creditors.

APPENDIX A

Variable Definitions and Data Sources

AG: A firm's quarterly asset growth rate. Source: Compustat

EG: Yearly employment growth rate, defined as the percentage change in the number of employees. Source: Compustat

CDSTrading: A dummy variable that indicates CDS firms. It is equal to 1 for a firm starting the first quarter in which the firm has CDS trading, and for all quarters thereafter. The variable is equal to zero otherwise. Source: Markit

CDSTraded: A dummy variable equal to one for a firm for all quarters if there is a CDS market for the firm's debt at any quarter during the 2001-2018 sample period. The variable is equal to zero otherwise. Source: Markit

Net CDS: Calculated as $ln(net\ notional\ CDS\ amounts + 1)$.The net notional CDS amounts are reported by the DTCC. Source: DTCC

Gross CDS: Calculated as $ln(gross\ notional\ CDS\ amounts + 1)$.The gross notional CDS amounts are reported by the DTCC. Source: DTCC

ΔGDP: Quarterly gross domestic product growth rate, calculated as one fourth of the seasonally adjusted annual growth rate. Source: Federal Reserve Bank of St. Louis

ΔIP: Quarterly industrial production growth rate. Source: Federal Reserve Bank of St. Louis

ROA: Net income before extraordinary items, scaled by total assets. Source: Compustat

Size: The natural logarithm of total assets of a firm, in billions of dollars. Source: Compustat

Net PPE: Net property, plant, and equipment, scaled by total assets. Source: Compustat

Leverage: Book leverage, calculated as the book value of debt (short-term debt plus long-term debt) divided by total assets. Source: Compustat

Working Capital: Current assets minus current liabilities, scaled by total assets. Source: Compustat

Cash: Cash and cash equivalent, scaled by total assets. Source: Compustat

CAPX: Capital expenditure, scaled by total assets. Source: Compustat

Asset Turnover: Sales scaled by total assets. Source: Compustat

Retained Earnings: Retained earnings, scaled by total assets. Source: Compustat

Volatility: Annualized standard deviation of the trailing 252-trading-day stock returns before the fiscal quarter-end. Source: Compustat

Return: 12-month stock return.

Excess Return: 12-month stock return less the 12-month market return. Source: CRSP

Investment-grade: A dummy variable that takes the value of 1 if a firm's long-term S&P issuer-level credit rating is BBB or higher, and zero otherwise. Source: Compustat

Rated: A dummy variable that takes the value of 1 if a firm has an active long-term S&P issuer-level credit rating, and zero otherwise. Source: Compustat

Market to Book: Market to book ratio, calculated as the market value of assets (the market value of equity plus book value of liabilities) divided by the book value of assets. Source: Compustat

Lender FX Usage: A measure of the average FX hedging activities carried out by a firm's lending banks and underwriters. Source: Dealscan, FISD, Call Report

TAIO: Total active institutional ownership, defined as percentage of shares outstanding of a firm held by all institutional investors, excluding the quasi-indexers as defined in Bushee (2001). Source: Thomson Reuters 13-F database

INDQ: Industry Q, defined as the median market to book ratio of a firm's industry. Source: Compustat

LC: Liquidation costs, calculated as $1 - asset\ tangibility$, where asset tangibility is estimated as expected exist value of assets upon liquidation (see Berger, Ofek, and Swary (1996)). Source: Compustat.

$$0.715 \times Receivables + 0.547 \times Inventory + 0.535 \times capital + 1 \times \ Cash\ Holdings$$

ΔGoodwill: The change in goodwill, scaled by total assets. Source: Compustat

MADummy: A dummy variable that takes the value of 1 if a firm announces a M&A in a quarter, and 0 otherwise. Source: SDC Platinum

ΔGDP^{low}: This variable takes the value of quarterly GDP growth rate when the growth rate is below the median rate during the sample period. It is equal to 0 when the GDP growth rate is above or equal to the median rate. Source: Federal Reserve Bank of St. Louis

ΔGDP^{high}: This variable takes the value of quarterly GDP growth rate when the growth rate is above the median during the sample period. It is equal to 0 when the GDP growth rate is below or equal to the median. Source: Federal Reserve Bank of St. Louis

Healthy: A dummy variable that takes the value of 1 when a firm's asset growth rate is relatively low (e.g., lower than a threshold AG^*), and 0 otherwise. The threshold (AG^*) is obtained by estimating the regression specification (1) in Table 11: $2 \times (-0.099) \times AG^* + 0.064 = 0$. $AG^* = 0.32$. Source: Calculated by the authors.

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FIGURE 1

Firm asset growth and GDP growth

The solid black (broken black) line plots the average quarterly asset growth (AG) of CDS firms (PSM matched non-CDS firms). The solid gray line plots the quarterly nominal GDP growth rate (ΔGDP). The sample period is from Q1 2001 to Q4 2018.

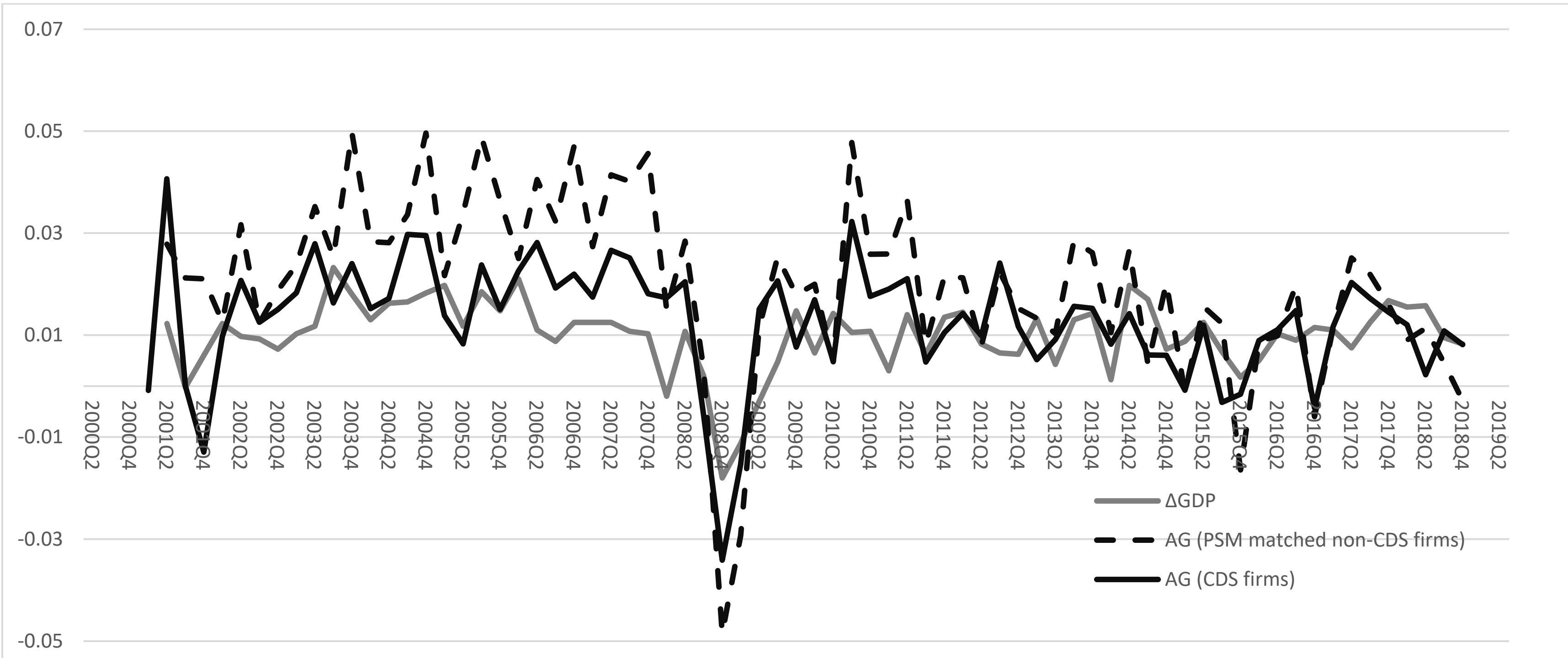

FIGURE 2

Placebo coefficient estimates on $CDSTrading^{Placebo} \times \Delta GDP$

This figure plots the histogram of the 1,000 placebo coefficient estimates of the interaction term $CDSTrading^{Placebo} \times \Delta GDP$. Instead of mapping the first CDS transaction dates to the corresponding CDS firms, we assign theses first dates to a randomly selected sample of firms that consists of CDS firms and the propensity-score matched non-CDS firms. We define a new dummy variable, $CDSTrading^{Placebo}$, that equals one for these counterfactual "CDS firms" after the CDS trading inception dates, and 0 otherwise. We then re-estimate our baseline regression (specification 4 in Table 2) using the new variable $CDSTrading^{Placebo}$. We repeat this exercise 1,000 times and obtain 1,000 coefficient estimates for the interaction term $CDSTrading^{Placebo} \times \Delta GDP$, each time with a randomly designated sample of "CDS firms". The point estimate from our baseline regression (-0.364) is represented by the dashed vertical line in the graph.

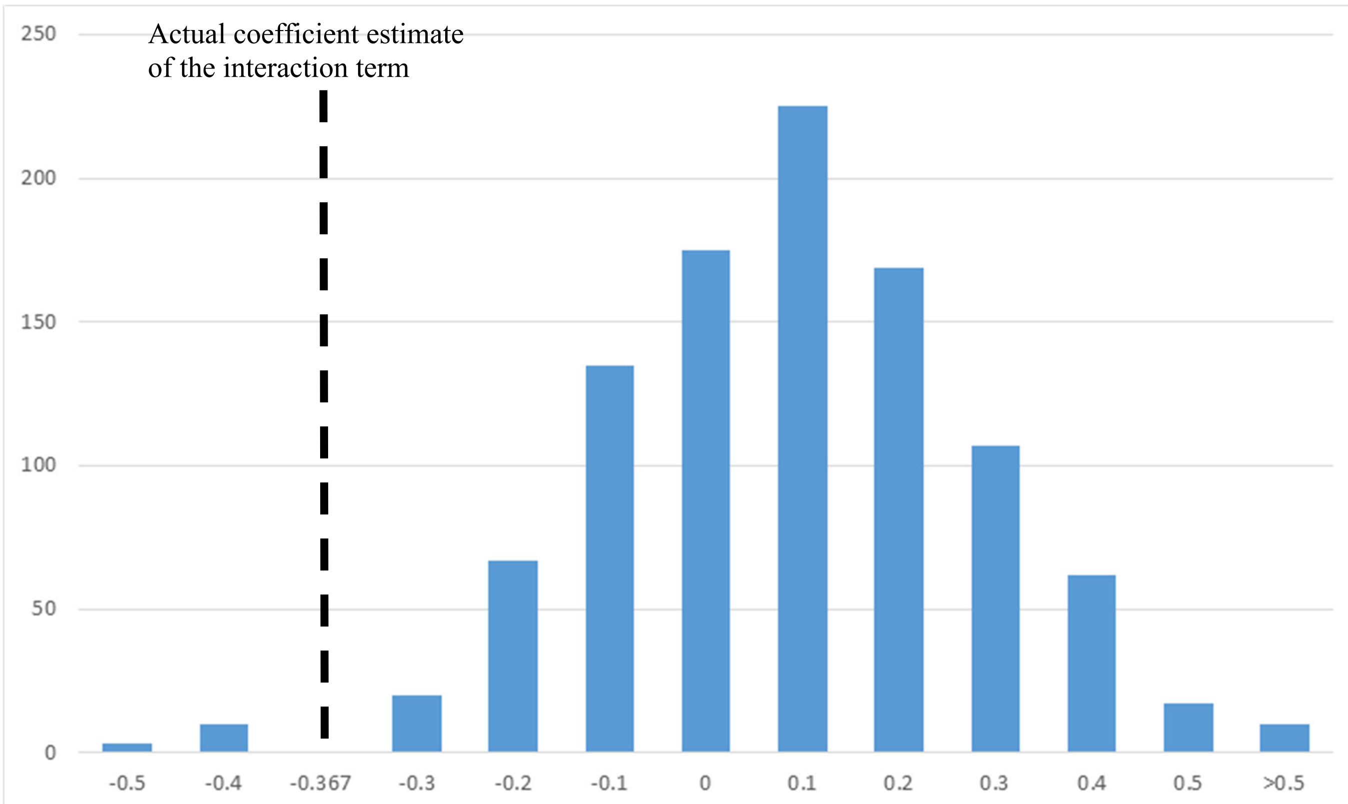

FIGURE 3

The dynamics of CDS spreads and loan spreads

This figure plots the average 5-year CDS spreads (in basis points) for CDS firms and the average loan spreads (in basis points), measured by All-in Spread Drawn (AISD) obtained from Thomson Reuters Dealscan, for CDS firms, and propensity-score matched (PSM matched) non-CDS firms from Q1 2002 to Q4 2018..

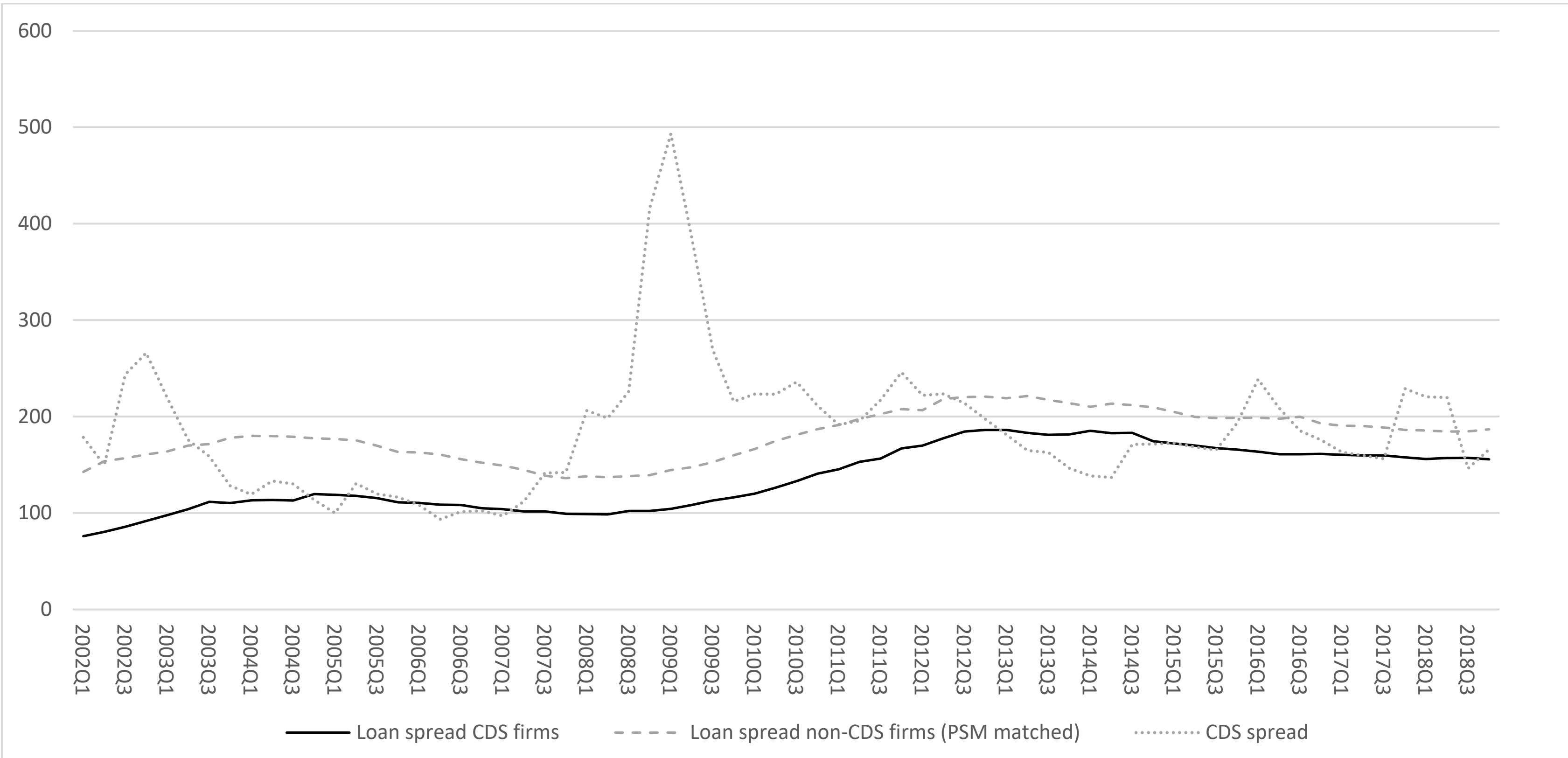

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TABLE 1

Matching Results and Summary Statistics

Panel A of this table presents the results of probit regression on the probability of CDS trading initiation. All explanatory variables are one-quarter lagged and are defined in Appendix A. The sample period is from Q4 2000 to Q4 2018. Heteroskedasticity-robust t-statistics adjusted for clustering within firms are reported in brackets. Panel B provides summary statistics of CDS firms and PSM-matched non-CDS firms. T-tests are performed on the differences in mean values between the two subsamples (CDS vs non-CDS firms) and t-statistics are reported in brackets. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Probit regression results on the probability of CDS trading initiation

Dep. Var.:	P(CDS initiation$_{i,t}$ = 1)
AG	0.257** [2.03]
CAPX	1.029** [2.23]
ROA	0.000 [0.00]
Size	0.251*** [24.11]
Net PPE	-0.014 [-0.13]
Leverage	0.890*** [10.56]
Working Capital	0.269** [2.01]
Cash	-0.180 [-1.13]
Asset Turnover	0.357*** [2.91]
Retained Earnings	-0.020 [-1.06]
Volatility	-0.416*** [-4.52]
Excess Return	-0.024 [-0.66]
Investment-grade	-0.039 [-0.79]
Rated	0.221*** [4.65]
Constant	-5.556*** [-17.58]
Time Fixed Effects	Yes
Industry Fixed Effects	Yes
Number of observations/$Pseudo\ R^2$	194,410/0.278

Panel B: Summary statistics of CDS and PSM-matched non-CDS firms prior to CDS trading

Firm Characteristics	1 CDS firms	2 Non-CDS firms	3 Difference (t statistics)
AG	0.030	0.021	0.008 [1.28]
CAPX	0.043	0.044	-0.001 [-0.31]
ROA	0.005	0.006	-0.001 [-0.49]
Size	8.590	8.563	0.027 [0.35]
Net PPE	0.371	0.373	-0.002 [-0.14]
Leverage	0.353	0.359	-0.006 [-0.61]
Working Capital	0.105	0.104	0.001 [0.10]
Cash	0.086	0.085	0.001 [0.12]
Asset Turnover	0.227	0.238	-0.011 [-1.11]
Retained Earnings	0.084	0.074	0.010 [0.27]
Volatility	0.403	0.407	-0.004 [-0.33]
Excess Return	0.116	0.100	0.016 [0.71]
Investment-grade	0.442	0.397	0.044* [1.71]
Rated	0.586	0.557	0.029 [1.12]
Propensity score	0.065	0.064	0.000 [0.04]

TABLE 2

CDS Trading and Cyclicality

This table presents the results of regressions of firm asset growth (AG) on an interaction term between *CDSTrading* and GDP growth (ΔGDP), and control variables. All variables are defined in Appendix A. All independent variables, except ΔGDP, are one-quarter lagged. The sample period is from Q4 2000 to Q4 2018. The sample consists of CDS firms and the propensity-score-matched non-CDS firms. Heteroskedasticity-robust t-statistics adjusted for clustering within firms are reported in brackets. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Dep. Var.: *AG*	1	2	3	4
CDSTrading × Δ*GDP*	-0.413***	-0.415***	-0.419***	-0.367***
	[-2.72]	[-3.02]	[-3.05]	[-2.71]
CDSTrading	-0.004**	-0.002	-0.002	0.004
	[-2.24]	[-1.29]	[-1.06]	[1.64]
Δ*GDP*	1.410***	1.068***	1.061***	0.910***
	[11.47]	[9.43]	[9.38]	[8.09]
ROA		0.096***	0.092***	0.094***
		[3.65]	[3.51]	[3.65]
Size		-0.003***	-0.003***	-0.022***
		[-6.17]	[-6.62]	[-10.49]
Net PPE		0.024***	0.028***	0.055***
		[8.82]	[7.14]	[4.93]
Leverage		-0.016***	-0.014***	-0.030***
		[-4.38]	[-3.70]	[-4.14]
Working Capital		0.011*	0.019***	0.050***
		[1.84]	[2.77]	[4.32]
Cash		-0.018**	-0.025***	-0.060***
		[-2.03]	[-2.62]	[-3.29]
Asset Turnover		-0.001	0.007	0.001
		[-0.24]	[1.25]	[0.04]
Retained Earnings		0.000	0.000	0.002
		[0.12]	[0.18]	[0.67]
Volatility		-0.019***	-0.021***	-0.026***
		[-6.90]	[-7.30]	[-8.58]
Excess Return		0.021***	0.020***	0.013***
		[14.88]	[14.49]	[9.66]
Investment-grade		-0.001	-0.000	0.003
		[-0.33]	[-0.19]	[1.48]
Rated		0.005***	0.006***	0.004**
		[2.72]	[3.24]	[2.09]
Market to Book		0.013***	0.014***	0.019***
		[11.36]	[11.75]	[11.33]
Constant	0.008***	0.016***	0.002	0.167***
	[4.92]	[2.64]	[0.27]	[7.31]
Industry Fixed Effects	No	No	Yes	No
Firm Fixed Effects	No	No	No	Yes
Number of observations	54,939	54,939	54,939	54,939
R^2	0.009	0.049	0.055	0.060

TABLE 3
CDS Trading and Cyclicality: Tests on Endogeneity

Panel A of this table presents the results of regressions of firm asset growth (*AG*) on an interaction term between *CDSTrading* and GDP growth (ΔGDP), *CDSTraded,* and other control variables. Panel B presents the results of instrumental variable (IV) regressions of firm asset growth (*AG*) on an interaction term between *CDSTrading* and GDP growth (ΔGDP), and control variables. We use *Lender FX Usage* as the instrument for *CDSTrading*. *Lender FX Usage* 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. Residual included in column 2 (3) is the residual from the first-stage (second-stage) regression of the CF (3-stage) procedure. Controls are the same as those included in specification (4) of Table 2. All variables are defined in Appendix A. All independent variables, except ΔGDP and *CDSTraded*, are one-quarter lagged. The sample consists of CDS firms and the propensity-score matched non-CDS firms. The sample period is from Q4 2000 to Q4 2018. Heteroskedasticity-robust t-statistics adjusted for clustering within firms are reported in brackets. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Control for *CDSTraded*

Dep. Var.: *AG*	1	2	3
CDSTrading × ΔGDP	-0.451***	-0.446***	-0.427***
	[-2.97]	[-3.23]	[-5.36]
CDSTrading	-0.012***	-0.006***	-0.007***
	[-4.99]	[-3.02]	[-4.03]
ΔGDP	1.453***	1.099***	1.083***
	[11.69]	[9.64]	[24.69]
CDSTraded	0.012***	0.008***	0.008***
	[5.64]	[3.99]	[4.05]
Constant	0.003*	0.014**	-0.000
	[1.79]	[2.38]	[-0.00]
Controls	No	Yes	Yes
Industry Fixed Effects	No	No	Yes
Number of observations	56,081	54,939	54,939
R^2	0.011	0.049	0.055

Panel B: IV approach

	1	2	3
Dep. Var.:	*CDSTrading*	*AG* (CF)	*AG* (3-stage)
Lender FX Usage	2.762***		
	[7.79]		
CDSTrading × ΔGDP		-0.415***	-0.300***
		[-3.28]	[-2.61]
CDSTrading		0.021	0.021***
		[1.21]	[6.06]
ΔGDP	-1.057***	0.978***	0.918***
	[-3.32]	[10.06]	[8.81]
Residual		-0.016	-0.027***
		[-0.96]	[-6.54]
Constant	-1.263***	0.183***	0.188***
	[-7.79]	[4.84]	[8.98]
Controls	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Number of observations	55,040	54,939	53,961
R^2	0.158	0.060	0.060

TABLE 4

CDS Trading, Cyclicality and M&A Activity

This table presents the results of regressions of firm asset growth (*AG*) on an interaction term between *CDSTrading* and GDP growth (ΔGDP), M&A variables, and control variables. Controls are the same as those included in the specification in column (4) of Table 2. All variables are defined in Appendix A. All independent variables, except ΔGDP, and the M&A variables, are one-quarter lagged. The sample consists of CDS firms and the propensity-score matched non-CDS firms. The sample period is from Q4 2000 to Q4 2018. Heteroskedasticity-robust t-statistics adjusted for clustering within firms are reported in brackets. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Dep. Var.: *AG*	1	2	3	4
CDSTrading × ΔGDP	-0.420***	-0.430***	-0.431***	-0.391***
	[-3.08]	[-3.22]	[-3.24]	[-2.84]
CDSTrading	0.005**	0.007***	0.007***	0.004
	[2.01]	[3.19]	[3.27]	[1.56]
ΔGDP	0.954***	0.948***	0.944***	0.939***
	[8.47]	[8.58]	[8.56]	[8.26]
MADummy	0.015***		0.015***	
	[8.61]		[8.59]	
ΔGoodwill		0.265***	0.265***	
		[8.55]	[8.54]	
Constant	0.159***	0.163***	0.161***	0.150***
	[7.06]	[7.20]	[7.14]	[6.29]
Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Number of observations	54,939	54,939	54,939	49,950
R^2	0.062	0.072	0.073	0.061

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TABLE 5

Additional Analyses on Corporate Growth

This table presents the regression results of a number of additional tests, examining CDS trading effects on the cyclicality of M&A, inventory growth, cash growth, payables growth, receivables growth and employment growth in columns 1 through 6, respectively. Controls are the same as those included in specification (4) of Table 2. All variables are defined in Appendix A. All independent variables, except ΔGDP, are one-period lagged. The sample consists of CDS firms and the propensity-score matched non-CDS firms. The sample period is from Q4 2000 to Q4 2018. We use yearly data in column 1 and quarterly data in columns 2 through 6. Heteroskedasticity-robust t-statistics adjusted for clustering within firms are reported in brackets. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Dep. Var.:	1 M&A	2 Inventory Growth	3 Cash Growth	4 Payables Growth	5 Receivables Growth	6 Employment Growth
CDSTrading × ΔGDP	0.028	-0.734***	-3.829***	-0.873*	-0.313	-0.574*
	[0.08]	[-2.73]	[-2.79]	[-1.68]	[-0.95]	[-1.87]
CDSTrading	-0.009	0.010***	0.029	0.012	0.010**	0.029*
	[-1.32]	[2.89]	[1.40]	[1.61]	[2.21]	[1.75]
ΔGDP	0.346	1.544***	1.422	1.676***	1.585***	0.723***
	[1.36]	[7.24]	[1.32]	[5.04]	[7.99]	[2.78]
Constant	0.145***	0.218***	1.253***	0.427***	0.351***	0.681***
	[3.10]	[5.81]	[7.71]	[6.83]	[6.33]	[8.11]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	55,061	45,188	54,907	51,587	50,806	7,033
R^2	0.003	0.021	0.034	0.008	0.019	0.050

TABLE 6

CDS Trading, Cyclicality and the Exacting Creditor Problem

This table presents the results of sub-sample regressions of firm asset growth (AG) on an interaction term between $CDSTrading$ and GDP growth (ΔGDP), and control variables. In columns 1 through 8, we split the whole sample into two sub-samples according to total active institutional ownership ($TAIO$), industry Q ($INDQ$), and liquidation costs (LC), respectively. Each firm-quarter observation is allocated into a sub-sample based on the median of the partitioning variable. In columns 9 and 10, we split the whole sample into two sub-samples according to a firm's credit rating. The IG sub-sample includes firms with an investment grade (S&P credit rating $> BB+$) and the Non-IG or Not-rated sub-sample includes firms with a credit rating that is lower than or equal to $BB+$ and firms that are not rated by S&P. Controls are the same as those included in specification (4) of Table 2. All variables are defined in Appendix A. All independent variables, except ΔGDP, are one-quarter lagged. The sample consists of CDS firms and the propensity-score matched non-CDS firms. The sample period is from Q4 2000 to Q4 2018. Heteroskedasticity-robust t-statistics adjusted for clustering within firms are reported in brackets. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Dep. Var.: AG	1 High TAIO	2 Low TAIO	3 High INDQ	4 Low INDQ	5 High LC	6 Low LC	7 IG	8 non-IG or not-rated
$CDSTrading \times \Delta GDP$	-0.480**	-0.270	-0.489**	-0.161	-0.559***	0.037	0.182	-0.423***
	[-2.42]	[-1.46]	[-2.42]	[-0.84]	[-3.02]	[0.17]	[0.55]	[-2.91]
$CDSTrading$	0.003	0.007**	0.010***	-0.007*	0.010***	-0.013***	0.012*	0.003
	[0.84]	[2.29]	[2.88]	[-1.84]	[3.32]	[-3.18]	[1.83]	[1.04]
ΔGDP	1.081***	0.769***	0.840***	0.509**	0.953***	0.754***	0.492*	0.979***
	[6.58]	[5.08]	[4.88]	[2.35]	[5.93]	[3.68]	[1.86]	[8.24]
$Constant$	0.199***	0.172***	0.175***	0.110***	0.175***	0.139***	0.182*	0.169***
	[7.78]	[5.33]	[5.69]	[2.60]	[6.17]	[3.50]	[1.91]	[6.95]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	27,558	27,381	27,265	27,674	27,528	27,411	3,248	49,224
R^2	0.066	0.054	0.053	0.087	0.050	0.075	0.053	0.061

TABLE 7

CDS Trading, Cyclicality and Debt Maturity

This table presents the results of sub-sample regressions of firm asset growth (AG) on ΔGDP and control variables in columns (1) through (4), and the results of an interaction term analysis in column (5). Controls are the same as those included in the specification in column (4) of Table 2. We split the whole sample into four sub-samples according to debt maturity and the status of CDS trading. A CDS (non-CDS) firm is classified as a long-term debt CDS (non-CDS) firm if its $\frac{long-term\ debt}{total\ debt}$ ratio is higher than the sample median of CDS (non-CDS) firms, and as a short-term debt CDS (non-CDS) firm otherwise. $LTD\ CDSTrading$ ($STD\ CDSTrading$) is a dummy variable that indicates long-term debt (short term debt) CDS firms. All variables are defined in Appendix A. All independent variables, except ΔGDP, are one-quarter lagged. The sample consists of CDS firms and the propensity-score matched non-CDS firms. The sample period is from Q4 2000 to Q4 2018. Heteroskedasticity-robust t-statistics adjusted for clustering within firms are reported in brackets. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Dep. Var.: AG	1 LTD CDS Firms	2 LTD non-CDS Firms	3 STD CDS Firms	4 STD non-CDS Firms	5 Interaction term Analysis
ΔGDP	0.683***	0.793***	0.537***	0.916***	0.871***
	[3.77]	[7.21]	[5.07]	[5.31]	[8.62]
$LTD\ CDSTrading \times \Delta GDP$					-0.019
					[-0.14]
$STD\ CDSTrading \times \Delta GDP$					-0.565***
					[-3.84]
Constant	0.286***	0.213***	0.252***	0.103*	0.168***
	[5.76]	[5.42]	[5.69]	[1.77]	[7.31]
Controls	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Number of observations	11,242	14,311	15,025	9,460	54,939
R^2	0.083	0.055	0.057	0.060	0.060

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TABLE 8

CDS Trading, Cyclicality and Asset Beta

This table presents the baseline regression results for two subsamples: high beta firms (column 1) and low beta firms (column 2). A firm is considered as a high (low) beta firm if its market beta is higher (lower) than the median across all sample firms. Market beta is calculated from the Capital Asset Pricing Model (CAPM), using the previous 5-year monthly returns. The dependent variable is firm asset growth (AG). Control variables are the same as those included in specification (4) of Table 2. All variables are defined in Appendix A. All independent variables, except ΔGDP, are one-quarter lagged. The sample consists of CDS firms and the propensity-score matched non-CDS firms. The sample period is from Q4 2000 to Q4 2018. The last row reports the average beta for each subsample. Heteroskedasticity-robust t-statistics adjusted for clustering within firms are reported in brackets. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	1	2
Dep. Var.: AG	High asset beta sample	Low asset beta sample
$CDSTrading \times \Delta GDP$	-0.493**	-0.316*
	[-2.47]	[-1.74]
$CDSTrading$	-0.000	0.008**
	[-0.04]	[2.51]
ΔGDP	1.415***	0.485***
	[8.48]	[3.11]
$Constant$	0.151***	0.175***
	[5.25]	[4.72]
Controls	Yes	Yes
Firm Fixed Effects	Yes	Yes
Number of observations	27,309	26,925
R^2	0.075	0.040
Average beta	1.679	0.590

TABLE 9

CDS Trading and Cyclicality by High and Low GDP Growth

This table presents the results of regressions of firm asset growth (*AG*) on an interaction term between *CDSTrading* and ΔGDP^{high}, an interaction term between *CDSTrading* and ΔGDP^{low}, and control variables. Controls are the same as those included in the specification in column (4) in Table 2. All variables are defined in Appendix A. All independent variables, except ΔGDP^{high} *and* ΔGDP^{low}, are one-quarter lagged. The sample consists of CDS firms and the propensity-score matched non-CDS firms. The sample period is from Q4 2000 to Q4 2018. Heteroskedasticity-robust t-statistics adjusted for clustering within firms are reported in brackets. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Dep. Var.: *AG*	1	2	3	4
$CDSTrading \times \Delta GDP^{high}$	-0.459***	-0.401***	-0.400***	-0.340***
	[-3.15]	[-3.01]	[-3.01]	[-2.58]
$CDSTrading \times \Delta GDP^{low}$	-0.393*	-0.368*	-0.362*	-0.292
	[-1.79]	[-1.78]	[-1.74]	[-1.40]
CDSTrading	-0.004**	-0.002	-0.002	0.004
	[-2.14]	[-1.32]	[-1.15]	[1.56]
ΔGDP^{high}	1.383***	1.017***	1.007***	0.836***
	[11.04]	[8.81]	[8.74]	[7.31]
ΔGDP^{low}	2.019***	1.662***	1.654***	1.540***
	[10.80]	[9.48]	[9.45]	[8.76]
Constant	0.007***	0.015**	0.001	0.162***
	[4.14]	[2.43]	[0.13]	[7.13]
Controls	No	Yes	Yes	Yes
Industry Fixed Effects	No	No	Yes	No
Firm Fixed Effects	No	No	No	Yes
Number of observations	54,939	54,939	54,939	54,939
R^2	0.011	0.050	0.055	0.061

TABLE 10

CDS Trading, Asset Growth and Tobin's Q

This table presents the results of sub-sample regressions of firm asset growth (AG) on *CDSTrading*, and control variables. Controls are the same as those included in the specification in column (4) of Table 2. We split the whole sample into four sub-samples according to AG and Tobin's Q (or $Q^{Dev.}$). $Q^{Dev.}$ is the deviation of a firm's q from the industry median q. Each firm-quarter observation is allocated into a sub-sample based on the medians of the partitioning variables, e.g., the HighAG & LowQ sub-sample (column 1) contains firms with high asset growth of the trailing one quarter and low q. All variables are defined in Appendix A. All independent variables, except ΔGDP, are one-quarter lagged. The sample consists of CDS firms and the propensity-score matched non-CDS firms. The sample period is from Q4 2000 to Q4 2018. Heteroskedasticity-robust t-statistics adjusted for clustering within firms are reported in brackets. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Dep. Var.: AG	1	2	3	4
	HighAG & LowQ	HighAG & HighQ	HighAG & Low$Q^{Dev.}$	HighAG & High$Q^{Dev.}$
CDSTrading	-0.011**	-0.002	-0.015***	-0.001
	[-2.20]	[-0.63]	[-2.60]	[-0.39]
Constant	0.312***	0.217***	0.296***	0.211***
	[5.39]	[5.72]	[4.51]	[5.97]
Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Number of observations	12,335	15,098	10,683	16,750
R^2	0.091	0.051	0.106	0.048

TABLE 11

CDS Trading, Asset Growth and Profitability

This table presents in column 1 the results of the regression of firm profitability (ROA) on asset growth (AG), its squared term (AG^2), and control variables, and in column 2 the results of the regressions of a dummy variable *Healthy* on *CDSTrading*, and control variables. Controls are the same as those included in the specification in column (4) in Table 2. All variables are defined in Appendix A. All independent variables are one-quarter lagged, except AG. The sample consists of CDS firms and the propensity-score matched non-CDS firms. The sample period is from Q4 2000 to Q4 2018. Heteroskedasticity-robust t-statistics adjusted for clustering within firms are reported in brackets. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	1	2
Dep. Var.:	*ROA*	*Healthy*
AG	0.064***	
	[8.30]	
AG^2	-0.099***	
	[-10.05]	
CDSTrading		0.004***
		[2.64]
Constant	0.020***	0.894***
	[2.72]	[48.07]
Controls	Yes	Yes
Firm Fixed Effects	Yes	Yes
Number of observations	54,673	55,096
R^2	0.210	0.015