“Less is More”: Credit Default Swaps and Firm Cyclicality

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Abstract

Firm cyclicality decreases by around 40% after the inception of credit default swap (CDS) trading. The effect is due to CDS firms’ lower asset growth-GDP growth sensitivity in good times and stronger for firms facing a more severe exacting creditor problem. The cyclicality-reducing effect of CDS trading cannot be explained with bank lending cyclicality or market beta. The result remains robust when we alternatively employ outstanding CDS positions, firm employment growth, or state-/industry-level cyclicality. Moreover, CDS trading impedes unhealthy growth and enhances profitability and market value. The evidence highlights an important disciplining effect of CDS on corporate growth.

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1. Introduction

Credit default swaps (CDSs) have been considered as the most important financial innovation from the past two decades. However, there has been debate about the real effects of CDS. CDS trading enables firms to obtain more debt and longer debt maturity (Saretto and Tookes, 2013) and increase innovation (Chang, Chen, Wang, Zhang and Zhang, 2019). But, CDS trading also increases corporate credit risk (Bolton and Oehmke, 2011; Subrahmanyam, Tang and Wang, 2014) and cash holdings (Subrahmanyam, Tang and Wang, 2017). Danis and Gamba (2018) show that the average effect of CDS trading on firm value is positive, but that the individual effects can be positive or negative. These findings suggest a tension between better access to credit and higher credit risk due to CDS trading. If the former (latter) effect dominates, CDS firms are expected to grow more (less) than non-CDS firms. Surprisingly, the literature does not provide evidence on the net effect of CDS trading on corporate growth over the business cycle. Does the inception of CDS trading influence firm growth and cyclicality? If yes, why and how? What would be the resulting impact on firm value? In this paper, we seek to address these questions.

Firm cyclicality refers to the sensitivity of firm growth to the growth of the entire economy. At the economy-wide level, the welfare cost of business cycles is huge (Bai and Zhang, 2021). Therefore, moderate or low macro-economic fluctuations and cyclicality are preferred from a welfare perspective when economic agents are risk-averse. Many economic policies, rules and regulations (e.g., fiscal and monetary policies, financial market regulations, accounting standards, banking regulations such as capital adequacy standards) reflect this preference and aim at reducing volatility or cyclicality of economic variables. At the firm level, cyclicality is a source for volatility and has been attributed to firm size, industry, credit supply and other effects (e.g., Becker and Ivashina, 2014; Bernanke and Gertler, 1989). Importantly, high firm growth over the business cycle can create or destroy firm value. If firms follow a shareholder value-maximizing strategy and invest in all available positive NPV projects, then higher relative corporate growth creates more value, everything else equal. However, if firms deviate from the optimal strategy because of agency problems, managerial entrenchment, behavioral biases or other reasons, then high corporate growth can become unhealthy and detrimental to shareholders (Jensen and Meckling, 1976). There is evidence that corporate expansion (contraction) is followed by periods with abnormally low (high) stock returns (Cooper, Gulen and Schill, 2008; Mortal and Schill, 2015). Moreover, the literature has shown that corporate growth through M&A tends to be unhealthy for relatively large firms but not for small firms (e.g., Moeller, Schlingemann and Stulz, 2004; Moeller, Schlingemann and Stulz, 2005).

CDSs are a financial innovation that makes it possible to separate the allocation of capital and risk and therefore can have important feedback effects on corporate finance and real economy activity. On the one hand, (low-risk) firms benefit from lower cost of debt, higher leverage, more long-term debt and lower financing frictions after the inception of CDS trading (e.g., Ashcraft and Santos, 2009; Saretto and Tookes, 2013; Chava, Ganduri and Ornthanalai, 2019). On the other hand, CDS trading increases the credit risk of the underlying firm (Subrahmanyam, Tang and Wang, 2014). This finding is explained with the existence of exacting creditors, also known as empty creditors (Hu and Black, 2008; Bolton and Oehmke, 2011; Danis, 2017). These creditors have less or no "skin in the game" because of CDS protection and therefore have low or no incentives to restructure firms in financial distress.[1] Subrahmanyam, Tang and Wang (2017) show that firms increase their cash holdings after the inception CDS trading to avoid negotiating with exacting creditors. Batta and Yu (2019) find that investments increase at the onset of CDS trading but decrease subsequently due to higher credit risk and debt overhang. Amiram, Beaver, Landsman, and Zhao (2017) find that banks as

[1] Creditors that hedge their credit risk exposures with CDS have also lower incentives to monitor CDS firms. Such reduction in lenders' monitoring incentives might increase corporate growth if it dominates the exacting creditor effect.

lead arrangers retain a larger share of syndicated loans and charge higher loan rates after the inception of CDS trading on firms' debt. Narayan and Uzmanoglu (2018) show a negative effect of CDS trading on firm value.

To investigate the impact of CDS trading on firm cyclicality, we collect data on publicly listed US firms during the period 2000-2018. Financial statement, employment and stock market data are gathered from Compustat and CRSP. We collect macro-economic data (GDP growth and other variables) from the Board of the Governors of the Federal Reserve System. Based on CDS data from Markit, we identify firms that are traded in the CDS market and the time when their first CDS trading started. Our final sample consists of 266,065 firm-quarter observations from 8,994 firms.

We measure firm cyclicality as asset (employment) growth sensitivity to GDP growth. To study the impact of CDS trading, we employ an indicator variable that equals one after CDS trading on a firm's debt has started and zero otherwise and interact this variable with GDP growth. The interaction term is our main variable of interest. A positive (negative) coefficient of this term would indicate that CDS trading increases (decreases) firm cyclicality.

We find three main results. We first show that firm cyclicality decreases by around 40% after the inception of CDS trading on firms' debt. This result is based on panel data regressions with a comprehensive set of firm controls, firm (or industry) fixed effects and time fixed effects. CDS firms' lower cyclicality leads to their lower asset growth compared to non-CDS firms. The average quarterly asset growth in our sample is 1.4% for CDS firms and 1.8% for non-CDS firms. Our main result is not due to selection effects and robust in instrumental variable regressions and propensity score matched (PSM) samples where we address the potential endogeneity between CDS trading and firm characteristics. Following related studies (Saretto and Tookes, 2013; Subrahmanyam, Tang and Wang, 2014; Chang, Chen, Wang, Zhang and Zhang, 2019), we control for differences between CDS traded vs. not traded firms and employ the share of FX derivatives of firms' main bank lenders as the instrument for firms' CDS trading status. We also find that our main finding persists when we control for firms' M&A activity.

In the next step, we show that the lower cyclicality due to CDS trading is systematically related to the exacting creditor problem. Our main result is significantly stronger for CDS firms that are more exposed to the exacting creditor problem, i.e., those with powerful shareholders, high industry market-to-book ratio, high liquidation costs and low credit ratings. The evidence suggests these firms reduce their asset growth strategically to strengthen their position vis-à-vis the exacting creditors. This finding is novel and complements the recent evidence on shareholder bargaining power (Colonnello, Efing and Zucchi, 2019) and preemptive cash holdings (Subrahmanyam, Tang and Wang, 2017).

We then consider two alternative explanations for our main result. First, the cyclicality of CDS firms might be lower because they exhibit lower systematic risk in the stock market, i.e., it is a low market beta effect in disguise. To investigate this possibility, we repeat our main analysis for high and low market beta firms. We find that the cyclicality-reducing effect of CDS trading is similar and highly significant in both subsamples. Hence, we rule out the market beta explanation of our results. Second, our main finding might be driven by bank lending cyclicality. If bank loans become costlier for CDS firms in good times but not for non-CDS firms, then CDS firms would grow less and exhibit a lower cyclicality. We show that this explanation is not supported by the data. The average loan spreads of CDS firms are always lower than those of PSM matched non-CDS firms. Hence, bank lending cyclicality cannot serve as an explanation for our main finding.

We perform several robustness tests. Our main result is robust in the periods before and after the global financial crisis. It remains qualitatively similar when we employ the continuous CDS net and gross positions instead of the binary CDS trading dummy. We also confirm our main result using state-level or industry-level business cycle measures instead of national GDP growth. Furthermore, we find a qualitatively similar impact of CDS trading on yearly employment growth. Precisely, CDS trading reduces employment growth sensitivity to GDP growth by 57%.

In the final step, we conduct a series of tests to understand whether the lower cyclicality is ultimately favorable or unfavorable for CDS firms. We show that the reduction of firm cyclicality due to CDS trading occurs only during good times (e.g., quarters with a GDP growth rate higher than the median of the whole sample period). In good times, many firms grow fast or even excessively, increase risk-taking and have stronger incentives for strategic default. Higher firm performance and the resulting pooling of high and low-quality firms in good times facilitate access to finance and may promote unhealthy growth. This reasoning is in line with the old bankers' wisdom that "bad loans are made in booms, not in recessions". At the same time, as shown in the model of Campello and Matta (2020), the likelihood of CDS overinsurance is higher in economic upturns, making the exacting creditor problem stronger. Our finding suggests that some of the excessive and potentially unhealthy corporate growth during good times is cut back due to CDS trading. In contrast, during bad times new hedging with CDS is more expensive because of higher default risk and corporate growth opportunities are limited. As a result, lenders reduce their outstanding CDS positions because of significantly higher marginal costs of hedging and firms are unlikely to grow strongly. These effects reduce the severity of the exacting credit problem and CDS firms have little incentives to lower their asset growth.

We further differentiate between firms from more and less cyclical three-digit SIC code industries. We confirm our main result only for the less cyclical industry subsample. This finding suggests that CDS trading is unlikely to reduce healthy growth and likely to be beneficial to the underlying firm. Moreover, we find a strong CDS trading effect for firms that exhibit high asset growth but low market-to-book ratio. Firms' high asset growth is likely to be unhealthy when the stock market is pessimistic about their investment opportunities, making them more vulnerable to exacting creditors. After the onset of CDS trading, these firms become more disciplined and reduce their asset growth. Furthermore, we find an inversely U-shaped relation between asset growth and firm profitability (ROA). Most of the firms are located at the left of the maximum, displaying a positive growth-profit relation. However, at the right of the optimal growth the relation is negative, i.e., more growth becomes unhealthy. CDS trading significantly increases the likelihood of healthy asset growth. Finally, we investigate whether the lower asset growth affects the equity value of CDS firms compared to non-CDS firms. We examine the asset growth-return anomaly (Cooper, Gulen and Schill, 2008), indicating that higher asset growth is followed by periods of lower stock returns. We first confirm this anomaly with our sample and then show that it is significantly reduced after the onset of CDS trading. Overall, these five tests consistently indicate benefits: CDS firms grow less to avoid unhealthy growth that would otherwise reduce shareholder value.

Our paper contributes to the literature in the following ways. First, we show an important disciplining effect: CDS firms reduce their cyclicality by engaging in lower growth to be better able to cope with exacting creditors. We further show that such behavior of CDS firms impedes unhealthy growth and increases firm value. Hence, "less is more". Our findings complement and extend research on the cost and benefits of CDS for firms (e.g., Chang, Chen, Wang, Zhang and Zhang, 2019; Danis and Gamba, 2018; Narayanan and Uzmanoglu, 2018; Subrahmanyam, Tang and Wang, 2014). In particular, we add to recent studies showing that the negative exacting creditor effect can be offset by increased cash holdings of CDS firms (Subrahmanyam, Tang and Wang, 2017) or interventions of CDS sellers (Danis and Gamba, 2019).

Second, our study provides a new perspective on firm cyclicality. To the best of our knowledge, the literature has not investigated whether cyclicality depends on financial innovation. CDS are important example of financial innovation because they make it possible to separate the allocation of capital and risk and therefore can create feedback effects on individual firms and the aggregate economy. Recent research has shown that high-growth startups (“gazelles”) contribute significantly to job creation and productivity growth in the US, but these firms have become less prevalent and less dynamic in recent years (Sterk, Sedláček and Pugsley 2021; Haltiwanger, Jarmin, Kulick, and Miranda, 2016). We focus on the other side of the firm size distribution: Firms whose debt is subject to CDS trading are significantly larger, more likely to be rated (and if rated: better rated) and more profitable than non-CDS firms and account for around 15% of all firms in our sample. We consider these differences in our econometric analysis and show that CDS trading reduces the asset (employment) growth cyclicality of the underlying firms. This effect likely reduces the amplitude and welfare cost of business cycles (Bai and Zhang, 2021).

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 presents our main empirical results on the impact of CDS trading on firm cyclicality as well as tests of alternative explanations and robustness tests. Section 4 shows that CDS trading impedes unhealthy growth and enhances profitability and market value. Section 5 concludes.

2. Data

We collect data from two main sources. We extract CDS trading data from the Markit database, and then merge this data with financial statement information from Compustat. Excluding firms that are either in the financial industry (standard industry classification code 6000-6999) or with missing financial information, we arrive at a final sample of 8,449 firms with 266,065 firm quarter observations, spanning the period from the last quarter of 2000 to the last quarter of 2018. We also use data from further sources, including the GDP data from the Federal Reserve St. Louis website, the Institutional ownership data from Thomson Reuters

13F holding, the mergers and acquisitions data from SDC, and the stock price data from CRSP, to gather additional variables.

Our main variable is CDSTrading, which is an indicator variable that equals one for a firm in the quarter in which CDS trading for the firm has started and for all subsequent quarters, and zero otherwise. Overall, we identify 849 CDS firms and 33,832 firm-quarter observations. Our main dependent variable asset growth (AG) is defined as the percentage quarterly change in the book value of a firm's total assets. To eliminate 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, Chen, Wang, Zhang and Zhang (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 shows variable definitions and Panel A of Table 1 reports summary statistics for the full sample.

(Insert Table 1 here)

In Panel B of Table 1, we compare the summary statistics of CDS firms with those of non-CDS firms. Importantly, the average quarterly asset growth rate of CDS firms (1.4%) is lower than the one of non-CDS firms (1.9%) and the difference is highly statistically significant (t-stat. = 5.9). In addition, CDS firms are very different from non-CDS firms regarding many firm characteristics. For example, CDS firms are on average larger, more levered, more profitable, less risky, and have higher Tobin's Q. Figure 1 displays the dynamics of quarterly asset growth for CDS firms and non-CDS firms during 2000-2018.

(Insert Figure 1 here)

The figure confirms that CDS firms exhibit a lower quarterly asset growth rate than other firms.[2] Interestingly, CDS firms mainly show lower asset growth than other firms in good times, i.e., when the GDP growth rate is relatively high. We investigate these descriptive results in formal econometric analyses in the remainder of the paper.

3. Empirical Analysis

In this section, we first investigate the impact of the onset of CDS trading on firm cyclicality using panel data regression analysis. Second, we address the potential selection bias and endogeneity issue in our analysis. Third, we investigate whether the CDS trading-induced reduction in cyclicality is achieved through cutting M&A transactions. Fourth, we examine the existence of exacting creditors as a potential channel through which CDS trading affects firm growth. Afterwards, we test two alternative explanations of the CDS trading effect on firm cyclicality. Finally, we report findings from several robustness tests.

3.1. Baseline results

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

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

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 the first quarter in which the firm has its CDS

[2] The beginning of the sample period is an exception, when there is a small - but rapidly growing - number of CDS firms. This was the period when the CDS market became a stable and reasonably liquid venue for trading corporate credit risk.

trading in the market and all subsequent quarters, and zero otherwise. ΔGDP_t is quarterly nominal gross domestic product growth rate.[3] [4] $\boldsymbol{X_t}$ is a vector of control variables and it incorporates the determinants of CDS introduction as specified in Subrahmanyam, Tang, and Wang (2014) and the determinants of firm asset growth (corporate investment) as in Chen and Chen (2012). $\boldsymbol{\varepsilon_{i,t}}$ is the i.i.d. residual term. All variables are defined in Appendix A. We are interested in the coefficient of the interaction term β_1, which indicates firms' cyclicality measured as asset growth-GDP growth sensitivity.

(Insert Table 2 here)

First, the positive and significant coefficient of ΔGDP (1.695) as shown in column (1) of Table 2 confirms the well observed firm asset growth cyclicality, suggesting that the total assets of a typical non-CDS firm in our sample grow by 1.695% when GDP increases by 1%. Second, the negative coefficient of the interaction term in column (1) shows that average asset growth of CDS firm is significantly lower than that of non-CDS firms. Importantly, firm cyclicality decreases by 38% (=-0.654/1.695) after the onset of CDS trading. The absolute value of the coefficient of the interaction term decreases when we progressively add controls and fixed effects, as shown in columns (2) through (5).[5] However, the coefficient of the interaction term remains negative and statistically highly significant and its economic significance even increases. Column (5) reports our baseline results, estimated from augmenting the regression

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

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

[5] The coefficient of GDP growth reflects firms' asset growth sensitivity to GDP growth (= cyclicality), the interaction indicates how the base effect is moderated by CDS trading. The time fixed effects capture the firm asset growth in every in year-quarter. The latter are not sufficient to measure cyclicality because the time fixed effects alone do not contain information about the GDP growth value in certain year-quarter observations.

specification (Equation 1) with both time (quarter) and firm fixed effects. Strikingly, the results show that CDS trading reduces firm cyclicality by 47% $(= -0.364/0.774)$, including a comprehensive set of time-varying firm controls, firm fixed effects and time fixed effects.

3.2. Selection effects and endogeneity

One challenge for any study on real effects of CDS trading on corporate decisions is that CDS firms might be different from non-CDS firms in ways that are related to how firms make various decisions. Specifically, CDS firms might be less cyclical even if there was no CDS trading on their debt. Our baseline approach indirectly addresses the problem by controlling for CDS introduction determinants and firm fixed effects. However, the selected CDS introduction determinants may not be exhaustive and there might be omitted variables that drive both CDS introduction and firm growth. To address this concern, we account for time invariant differences between CDS firms and non-CDS firms by adding $CDSTraded$ as additional control variable, following Saretto and Tookes (2013) and other related studies. $CDSTraded$ is an indicator variable that equals one for a firm if it has a traded CDS contract on its debt at any time during our 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 one regression specification enables us to utilize differences in the timing of CDS introduction across CDSTraded firms to estimate the impact of having CDS contracts (traded in the market) on asset growth cyclicality. Table 3 reports the results.

(Insert Table 3 here)

We find that CDSTraded firms make different asset growth decisions compared to non-

CDS firms. 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 $CDSTraded$, however, 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, e.g., via increased hedging demand. To deal with this issue, we need to identify variables that explain the hedging needs of firms' creditors but that are not directly related to firm growth. We follow the related literature (e.g., Saretto and Tookes, 2013; Subrahmanyam, Tang, and Wang, 2014; Subrahmanyam, Tang, and Wang, 2017; and Chang, Chen, Wang, Zhang and Zhang, 2019) and use $Lender\ FX\ Usage$ as the instrument to address this issue.[7] $Lender\ FX\ Usage$ 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. As the variable of interest is an interaction term, we adopt the control function (CF) approach instead of the usual two-stage least squares estimator (2SLS) (Wooldridge, 2015). Specifically, we first regress $CDSTrading$ on the instrument and the control variables. Next, we use the predicted values of $CDSTrading$ to compute the fitted residuals $\hat{\theta} = \text{CDSTrading} - \widehat{\text{CDSTrading}}$ and subsequently include $\hat{\theta}$ as an additional regressor in the baseline regression specification. Table 4 presents the results of the instrumental variable regressions.

(Insert Table 4 here)

Column (1) shows that econometrically the relevance condition is met as $CDSTrading$ is

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

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

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, Chen, Wang, Zhang and Zhang (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 the 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 $\hat{\theta}$ and the control variables from the baseline regression specification. The last column of Table 4 reports the results from the third-stage regression. Clearly, the interaction term $\mathrm{CDSTrading} \times \Delta GDP$ enters the regression with a coefficient of -0.357, which is statistically significant at the 1% level. It is noteworthy that the statistical and economic magnitude of the coefficient on the interaction term is almost identical to the one in our baseline analysis (see Table 2, column 5).

As an alternative approach for identification, we turn to propensity score matching (PSM). One advantage of the PSM method, as noted by Roberts and Whited (2013), is that it does not rely on a clear source of exogenous variation for identification and thus complements the IV analysis. The matching approach is based on the propensity score, defined as the conditional probability of receiving treatment (e.g., CDS trading). Specifically, for each treated firm (CDS firm), we find one matching non-CDS firm with the closest propensity score for CDS trading, calculated with the following probit model:

$$\mathrm{Prob}\big(\mathrm{CDS\ initiation}_{i,t} = 1\big) = \Phi\big(\alpha + \beta_1 \boldsymbol{X}_{i,t-1} + \beta_2 \mathrm{Industry}_j + \beta_3 Quarter_t\big) \dots \quad .(2)$$

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 it equals zero for non-CDS firms in all quarters. $\boldsymbol{X}_{i,t-1}$ include a variety of firm characteristics that determine the initiation of CDS trading on a firm as documented in the previous studies (e.g., Saretto and Tookes, 2013; Subrahmanyam, Tang and Wang, 2014): ROA, Size, Net PPE, Leverage, Working Capital, Cash, Asset Turnover, Retained Earnings, Volatility, Excess Return, $\text{Investment} - \text{grade}$, 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, Tang and Wang (2014), we estimate model (2) using all sample firms during the entire sample period 2000-2018 and exclude post-CDS initiation quarters of CDS firms. Appendix B reports 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.[8] The coefficients of the explanatory variables are generally consistent with those in previous studies (Saretto and Tookes, 2013; Subrahmanyam, Tang and Wang, 2014; Chang et al., 2019). For instance, larger firms, firms with higher leverage and less volatile stock returns, and rated firms are more likely to experience CDS trading. In Panel B, we compare the characteristics of CDS firms with those of their matches prior to the quarter of CDS trading initiation. The results clearly show that the matching is effective, as before the onset of CDS trading the treated and control firms are not significantly different for all firm characteristics. The insignificant difference in propensity score 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 dramatically to

[8] Note that our pseudo R^2, estimated using quarterly data, is smaller than those in the previous studies, which are based on yearly data. For example, the estimated pseudo R^2 is 0.39 in Subrahmanyam, Tang and Wang (2014) and 0.465 in Chang et al. (2019).

0.171, confirming that the matching is successful.

We now re-estimate our baseline model using the propensity score-matched sample. Table 5 presents the regression estimates in column (1).

(Insert Table 5 here)

Consistent with the baseline results for the whole sample, the interaction term $CDSTrading \times \Delta GDP$ enters the regression with a negative coefficient, statistically significant at the 1% level. Interestingly, the economic significance of the CDS trading effect on firm cyclicality barely changes from that of the whole sample. We use matching with replacement (multiple matching) as a benchmark case as it allows for better matches. However, the advantage might be at the expense of precision if a few control firms dominate the control group, because they are best matches for too many treated firms, and thus drive the regression results. 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 this alternative matching criterion, as shown in column (2) of Table 5. Overall, the PSM results support our main findings from the whole sample: CDS trading reduces firm cyclicality.

Finally, we 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 then considered “CDS firms”. Specifically, 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. Utilizing the randomization of the CDS trading status, we create a placebo treatment and re-estimate our baseline regression (specification 5 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". We next plot a histogram of the estimated placebo coefficients. As shown in Figure 2, the actual interaction effect (-0.364), as reported in column 5 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, the majority of the placebo estimates are around zero, with an average of -0.02 and a standard deviation of 0.12. If anything, the placebo results suggest that the cyclicality-reducing effect we document is likely driven by the presence of CDS trading and unlikely by a treatment misidentification.

(Insert Figure 2 here)

In sum, the results obtained from the set of identification strategies are consistent and indicate that CDS trading indeed leads to a lower firm cyclicality.

3.3. M&A activity and firm cyclicality

Firm cyclicality might depend on corporate growth strategies. Firms grow because of regular investments in projects and/or M&A activity. There is evidence that firms tend to reduce their M&A activity after the onset of CDS trading (Batta and Yu, 2019). Hence, it is important to check whether the cyclicality-reducing effect of CDS trading we document is driven by firms adjusting M&A activities as a precautionary response to the potential exacting creditor problem. To address this point, we consider two M&A variables in our analysis. First, we define a dummy variable MA_Dummy, which is equal to one if a firm announces an M&A event in a quarter, and zero otherwise. MA_Dummy is a relatively coarse measure of M&A activities as it does not distinguish large M&A deals from small ones. We therefore consider a second measure of M&A activities, which is the change in goodwill (ΔGoodwill). This measure might be more informative as it captures the magnitude of an M&A deal. We first add to our baseline regression model MA_Dummy or/and ΔGoodwill as control variables for asset growth. We next exclude firm-quarter observations, for which MA_Dummy equals one and conduct a subsample analysis. Table 6 reports the corresponding regressions results.

(Insert Table 6 here)

In columns (1) and (2), we control for MA_Dummy and ΔGoodwill, respectively. In column (3), we add both M&A controls at the same time. 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 MA_Dummy equals one, and estimate the model (5) from Table 2 on this slightly smaller sample that is free of any asset growth due to M&A activity. The coefficient of the interaction term CDSTrading × ΔGDP is negative and highly significant, confirming the findings of our baseline regression in Table 2. Overall, the analysis suggests that CDS trading is likely to have implications across a variety of firm investment decisions and the cyclicality-reducing effect we document is not driven by firms cutting M&A transactions after the inception of CDS trade.

3.4. CDS trading, firm cyclicality and exacting creditors

The empirical results, thus far, suggest that firms change their asset growth strategy following the inception of CDS trading to become less cyclical. Theoretically, CDS can change creditors' incentives in multiple ways. Our findings are consistent with the effect of exacting creditors documented in the literature. As modeled in Bolton and Oehmke (2011), ex post, when a firm is in distress exacting creditors, being protected by CDS contracts, tend to be tougher and are motivated to push the firm into bankruptcy. Anticipating this incentive of exacting 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 economic downturns. This theory immediately leads to two empirical predictions. First, we expect that the CDS trading effect we found above is more prominent for CDS firms facing a more severe exacting creditor problem. Second, the cyclicality-reducing effect of CDS trading should materialize during "good times", when the economy grows fast. We focus in this section on testing the first prediction and leave the test of the second prediction to Section 5.

We identify firms for which the pressure from exacting creditors is higher and expect a greater impact of CDS trading on cyclicality for these firms as they are more likely to take precautionary actions. Specifically, we split the sample into two sub-samples based on various partitioning variables. In the related literature, it has been shown that firms with powerful shareholders, greater industry Q, higher liquidation costs, and higher credit risk are more likely to suffer the exacting creditor problem (e.g., Kim, 2016; Colonnello, Efing, and Zucchi, 2018). Accordingly, we use measures of institutional ownership (total institutional ownership and motivated monitors' ownership), industry Q, liquidation costs, and Investment-grade, respectively, as the partitioning variable to split the whole sample.[9] We next re-estimate the baseline regression model as specified in column (5) of Table 2 for each sub-sample and present the results in Table 7.

[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 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 as twice risky as IG firms when we measure default risk based on their 5-year CDS spreads.

(Insert Table 7 here)

Comparing column (1) with column (2), we find that, as expected, the absolute magnitude of β_1 (the coefficient of the interaction term) is higher for firms with larger total institutional ownership (TIO). This finding is further strengthened when we use motivated monitors' ownership (MMO) to replace TIO as a measure of shareholders' bargaining power, as shown in columns (3) and (4).[10] Also consistent with our expectation, results in columns (5) through (10) confirm that the cyclicality-reducing effect of CDS trading is more prominent for (only exists in) firms with more severe 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 a variety of partitioning variables, suggesting that our main result – the lower asset growth cyclicality of CDS firms – can be interpreted as a precautionary strategy of CDS firms to mitigate the exacting creditor problem.

3.5. Alternative explanations

After having established the exacting creditor problem as the main channel of the CDS trading effect on firm cyclicality, we test two alternative explanations in this section. We show that they are unlikely to explain our main result.

3.5.1. Market beta and firm cyclicality

The probit regression results in Appendix B show that firms with low stock return volatility are more likely to induce CDS trading on their debt. To the extent that systematic risk accounts

[10] One may argue that MMO is a better measure of shareholders' bargaining power than TIO, see for example, Fich, Harford, and Tran (2015).

for a significant proportion of volatility, our variable CDSTrading may simply pick up low market beta firms. In other words, the cyclicality-reducing effect of CDS trading might be a market beta effect in disguise, e.g., low beta firms are less cyclical. Hence, a possible explanation of our findings based on beta deserves a further analysis. Specifically, at each quarter we define our sample firms as high-beta firms and low-beta firms, based on a split using the median market beta of all firms. Market betas are calculated from the Capital Asset Pricing Model (CAPM) using the past 5 years' monthly returns of individual stocks and returns of the market portfolio. As shown in the last row of Table 8, high-beta firms, on average, have a beta that is about three times that of low-beta firms (1.835 vs. 0.634). We next re-estimate the baseline regression on the two subsamples: the high-beta subsample and the 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 low-beta subsample. However, in Table 8 we find that the interaction term coefficient estimates for the two subsamples are not only highly significant but also similar in magnitude. A formal statistical test further confirms that the two coefficients are not significantly different from each other. The results of this analysis rule out that firm beta can serve as an explanation of the CDS trading effect on firm cyclicality.

(Insert Table 8 here)

3.5.2. Bank lending cyclicality and firm cyclicality

Research has documented that bank lending is procyclical, e.g., banks tend to loosen lending standards, reduce loan rates and increase supply credit supply during economic upturns (e.g., Dell'Ariccia and Marquez, 2006; Mian and Sufi, 2009; Becker and Ivashina, 2014). Such lending cyclicality makes it easier for firms to grow during good times and thus induces firm growth cyclicality. However, if the inception of CDS trading either forces or helps banks to put a correct (and higher) price tag on their loans when they are reluctant or not able to do so otherwise, then CDS firms may exhibit a lower cyclicality than non-CDS firms. If banks charge higher loan spreads for CDS firms in economic upturns but not for non-CDS firms, then this effect could explain CDS firms reduce their asset growth and cyclicality. Does bank lending cyclicality explain our main findings? In other words, does it become costlier for CDS firms compared to non-CDS firms to borrow from banks during good times? We investigate this question in the remainder.

In Figure 3, we plot the quarterly average borrowing costs for CDS firms (the solid black line), non-CDS firms (the solid light-gray line) and propensity score-matched (PSM matched) non-CDS firms (the solid gray line) over time, together with the average 5-year CDS spreads for CDS firms (the broken gray line). Firm borrowing costs are measured by the average All-in Spread Drawn (AISD), obtained from Thomson Reuters Dealscan. AISD is the spread the borrower pays to the lender in basis points over LIBOR for each dollar drawn down. It includes the spread of the loan and any annual (or facility) fee paid to the bank.

(Insert Figure 3 here)

Two interesting observations emerge from Figure 3. First, during 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 to price corporate loans (e.g., Norden and Wagner, 2008; Ashcraft and Santos, 2009). Second, the loan spreads of CDS firms are always lower than those of non-CDS firms (and PSM matched non-CDS firms) during the entire sample period, including economic upturns. These findings rule out that bank lending cyclicality can explain our main result. 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 cannot explain our results.

3.6. Robustness tests

In this section, we carry out a number of additional tests to study the robustness of our findings. We consider sub-periods, the amount of outstanding CDS positions, alternative measures of the business cycle and the cyclicality of employment growth.

3.6.1. Sub-period analysis

CDS contracts were initially conceived as a hedging tool for firms' creditors to manage credit risk. Big shocks in financial markets, such as financial crises, may temporarily or fundamentally change investors' and firms' risk attitudes and thus have short-term or long-term impact on the behavior of exacting creditor and firms. As the cyclicality-reducing effect of CDS trading documented in this study results from firms' precautionary response to potential threats (actions) of exacting creditors, it may be influenced by financial crises. Using the 2007-08 global financial crisis as an experiment, we investigate whether such influence can be detected in the data. Specifically, we split the full sample period into two sub-periods: one that starts in Q4 2000 and ends in Q2 2007, and the other that starts in Q3 2007 and ends in Q4 2018. The baseline regression results estimated for the two sub-periods are reported in Table 9.

(Insert Table 9 here)

We find, in Panel A of Table 9, a negative and significant coefficient of the interaction term for both sub-periods, suggesting that the cyclicality-reducing effect of CDS trading remains in the aftermath of the global financial crisis. It is worth noting, though, that the pre-crisis effect of CDS trading on firm cyclicality (-0.607) is more than twice as large as the post-crisis effect (-0.246). If we consider that pre-crisis period was a period with relatively high GDP growth, this finding indicates that the CDS trading effect is stronger during good times.

3.6.2. Outstanding CDS positions and firm cyclicality

The dummy variable $CDSTrading$ does not distinguish CDS firms with large outstanding CDS positions from those with small positions, nor does it capture the dynamics of outstanding CDS positions for a given CDS firm. To explore the outstanding CDS position heterogeneity across CDS firms and over time, we obtain detailed CDS position information from the Trade Information Warehouse of the Depository Trust & Clearing Corporation (DTCC). The DTCC discloses both the aggregate gross notional CDS positions (gross amount), as well as the aggregate net notional positions (net amount) on a particular reference entity with a weekly frequency from October 31, 2008.[11] We focus on the net notional amount, as it is a more meaningful measure of the amount of credit risk transferred by CDS contracts and thus more relevant to the exacting credit problem. We define a new variable, $Net\ CDS = ln(net\ amount + 1)$ and re-estimate our baseline regression, replacing $CDSTrading$ with $Net\ CDS$. Panel B of Table 9 shows the regression results in column (1). The coefficient of the interaction term is negative and significant, showing that our main results are robust to using the continuous measure of outstanding CDS positions. As an additional robustness check, instead of using $Net\ CDS$ we use $Gross\ CDS = ln(gross\ amount + 1)$ in the regression in column (2) and obtain similar results.

[11] For a particular reference entity, the gross notional amount is calculated as the sum of all long (or equivalently, short) CDS contracts. Similarly, the net notional amount is calculated as the sum of net protection bought by counterparties that are net buyers of protection.

3.6.3. *Alternative measures of business cycle*

In the above analyses, we use national GDP growth to measure the business cycle for all firms, regardless in which industry or geographic area a firm operates. Although correlated, different industries or geographic areas may exhibit business cycle patterns that differ from national GDP growth. If the CDS-induced cyclicality reduction is CDS firms' response to mitigate potential pressure from exacting creditors, it should remain robust when we consider alternative measures of the business cycle at the industry or state levels. This view is confirmed by the data. As shown in Panel C of Table 9, the interaction term remains significantly negative when we replace the country-level measure of business cycle (ΔGDP) with the industry level measure (ΔIAG) in column (1) or the state level measure (ΔGDP^{State}) in column (2).[12]

3.6.4. *Employment growth cyclicality*

Total asset growth is arguably the most comprehensive measure of firm growth. Nevertheless, we consider employment growth (EG) as an alternative measure as it directly reflects firms' labor market decisions and capital and labor intensity vary across firms and time. Although asset growth and employment growth are positively correlated in the long term, it is not necessarily the case that CDS trading impacts both growth measures in the same way. For example, facing exacting creditors, firms may decide to reduce asset growth temporarily but maintain their current employment level as it can be costly to fire now and hire later employees. To understand the implications, if any, of CDS trading on employment growth cyclicality, we perform further regression analysis by replacing asset growth (AG) as the dependent variable in the baseline model with employment growth (EG).[13] Panel D of Table 9 presents the results

[12] For a firm i that operates in industry j and state k, at quarter t, $\Delta IAG_{i,j,t}$ is calculated as the average asset growth of all firms in industry j, excluding firm i; and $\Delta GDP^{State}_{i,k,t}$ is measured as the GDP growth rate of state k.

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

for the models with firm controls, time fixed effects and industry or firm fixed effects, respectively. We find a negative CDS trading effect on employment growth cyclicality in column (1) and column (2), confirming the robustness of our main results on firm cyclicality based on asset growth.

4. CDS trading and healthy vs. unhealthy corporate growth

We have rationalized our empirical findings with the role of exacting creditors, following the model of Bolton and Oehmke (2011). The same model also predicts, as discussed in the previous section, that CDS firms have incentives to grow at a relatively lower rate during economic upturns. Figure 1 and the results in Panel A of Table 10 support this prediction. We now conduct a formal empirical analysis to test this implication, using the following regression model:

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

where $\Delta GDP^{high}{}_t$ is a variable that takes the value of the quarterly GDP growth rate when the growth rate is above the median during the sample period. It is equal to zero when the GDP growth rate is below or equal to the median. Similarly, $\Delta GDP^{low}{}_t$ is a variable that takes the value of the quarterly GDP growth rate when the growth rate is below the median during the sample period. 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 10 presents the corresponding regression results.

(Insert Table 10 here)

The negative and highly significant coefficient β_1^{high}, and the insignificant β_1^{low} in all specifications indicate that indeed CDS firms adjust their cyclicality only during the high growth regime of the economy, confirming the exacting creditor problem mechanism. Importantly, this empirical finding also signals that firms might benefit from the 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).

Firm asset growth on average tends to be cyclical. However, there is substantial variation in cyclicality across firms. Measuring firm cyclicality as correlation between firm asset growth and ΔGDP during our sample period, we find that firm cyclicality is positive with a mean of 0.10 and a standard deviation of 0.18, ranging from -0.84 to 0.91. Given this large dispersion of firm cyclicality, firms may react differently to the inception of CDS trading depending on their level of cyclicality. Does CDS trading reduce the cyclicality for more cyclical firms or less cyclical firms or all firms? This question is interesting because its answer may indicate whether the CDS effect is likely to be beneficial or detrimental to the underlying firm. Assuming firms maximizing their values, being a more cyclical firm implies that the firm is more likely to benefit from high asset growth cyclicality. In other words, for more cyclical firms, the benefits of growing strongly during economic upturns are more likely to exceed the potential costs imposed by exacting creditors in economic downturns. Hence, reducing cyclicality is more likely to be beneficial for less cyclical firms.

We divide our sample into a more cyclical subsample and a less cyclical subsample, performing a median split based on the cyclicality of the firm's three-digit SIC industry. In this analysis, we use industry cyclicality to distinguish between more or less cyclical firms to mitigate potential concerns of endogeneity between firm cyclicality and CDS trading. We then re-estimate our baseline regression on the two subsamples. Table 11 reports the results.

(Insert Table 11 here)

We find the cyclicality-reducing effect of CDS trading only for the firms from the less cyclical subsample. This finding suggests that CDS trading is unlikely to reduce healthy growth and thus likely to be beneficial to the underlying firm.

In the remainder, we conduct three additional and more direct empirical tests to provide further evidence that CDS trading reduces unhealthy growth. First, firms with unjustified (by investment opportunities) high asset growth are more exposed to the exacting creditor problem and would benefit the most from reducing (unhealthy) growth. Thus, we expect to observe 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. We see a firm as 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). 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 the greater investment opportunities mitigate the potential threats from exacting creditors. We perform regression analysis for the two sub-samples (vulnerable firms and neutral firms), respectively, using the following model:[14]

[14] In this analysis and the following ones, we investigate whether the CDS trading-induced reduction in firm asset growth (during good times) is value-enhancing or value-destroying and therefore focus on $CDSTrading$ alone, not the interaction term, as the variable of interest.

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

As shown in columns (1) and (2) of Table 12, we only detect a significant CDS trading effect on asset growth for vulnerable firms, lending support to the view that CDS trading reduces unhealthy growth.

(Insert Table 12 here)

One may argue that a firm's high growth might be justified, and thus be healthy, as long as 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 replace Q with $Q^{Dev.}$ To identify vulnerable versus neutral firms and repeat the regression analysis. We obtain similar results, as displayed in columns (3) and (4).

Next, if CDS trading indeed reduces unhealthy asset growth, we would expect that CDS firms are more likely to be healthy firms. We define firms as healthy versus unhealthy based on the asset growth-profitability (AG-ROA) relation. A firm is healthy if the AG-ROA relation is positive, and unhealthy otherwise. We postulate that for a typical firm in our sample the AG-ROA relation is positive when AG is low and becomes negative when AG exceeds a certain threshold (e.g., when firms reach a too high growth rate). To identify the turning point, we conduct regression analysis with the following model:

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

Table 13 presents the regression results.

(Insert Table 13 here)

Consistent with our expectation, we detect an inversely U-shaped AG-ROA relation from the positive (and significant) β_1 and the negative (and significant) β_2 in column (1) of Table 13. The coefficients of AG and its squared term enable us to derive the turning point: $AG^* = \frac{0.145}{2\times 0.150} = 0.48$. It indicates that when a firm's quarterly asset growth is lower than 0.48, a further increase in asset growth increases profitability (e.g., the firm is healthy), whereas when a firm's quarterly asset growth is higher than 0.48, a further increase in asset growth decreases profitability (e.g., the firm is unhealthy). Turning to whether CDS firms are more likely to be on the left side of the inversely U-shaped AG-ROA relation, we first define a dummy variable $Unhealthy$, which is equal to one when a firm's asset growth is higher than AG^*, and 0 otherwise. We next regress $Unhealthy$ on $CDSTrading$ and control variables. The negative coefficient of $CDSTrading$ reported in column (2) of Table 13 suggests that CDS firms are, consistent with our prediction, more likely to be healthy firms.

Lastly, we examine the impact of CDS trading on relation between asset growth and stock returns. The asset growth anomaly implying that firms with high asset growth rates earn negative subsequent risk-adjusted returns has first been documented in Cooper, Gulen, and Schill (2008). The authors associate the anomaly to investment-related mispricing and show evidence that the negative abnormal returns of high-growth firms are consistent "with the idea that the asset growth effect arises in part from managerial overinvestment and related investor underappreciation of managerial empire building." Following Cooper, Gulen, and Schill (2008), we predict that if CDS trading indeed reduces unhealthy growth (e.g., overinvestment and/or empire building) as we have illustrated before, the negative asset growth effect on stock returns should be weaker for CDS firms. To test this prediction, we first estimate the regression specification of Model 1 in Table III of Cooper, Gulen, and Schill (2008) and we next estimate a modified model with two more explanatory variables: interaction term $CDSTrading \times AG^{annual}$ and CDSTrading. Table 14 reports the results.[15]

(Insert Table 14 here)

The negative and highly significant coefficient of AG^{annual} in column (1) confirms the documented asset growth anomaly during our sample period. More important, as shown in column (2), CDS trading has a dampening effect on the anomaly, reducing the absolute magnitude of the AG^{annual} coefficient by 56%. This finding indicates that cyclicality-reducing effect of CDS trading has a beneficial impact, resulting in relatively higher stock returns and market value for CDS firms.

5. Conclusion

In this paper, we investigate whether CDS trading affects the cyclicality of U.S. firms during the period 2000-2018. CDS trading can have benefits due to higher credit availability and longer debt maturities but also costs such as higher credit risk due to the exacting credit problem. The net effect likely affects firms' asset and employment growth over the cycle.

We find three novel results. First, firm cyclicality decreases by at least 40% after the inception of credit default swap (CDS) trading on firms' debt. CDS firms' lower cyclicality leads to their lower asset growth compared to non-CDS firms. Second, this finding is significantly stronger for CDS firms that are more exposed to the exacting creditor problem, i.e., those with powerful shareholders, high industry market-to-book ratio, high liquidation costs and low credit ratings. We also show that our main finding cannot be explained with systematic risk (market beta) or bank lending cyclicality. Third, we provide extensive evidence

[15] We use yearly data for this analysis to obtain comparable results with those in Cooper, Gulen, and Schill (2008).

that the lower cyclicality is beneficial to CDS firms. The reduction of firms' asset growth due to CDS trading occurs in economic upturns, when firms are more likely to grow excessively and the effect only exists for firms from less cyclical industries and those exhibiting high asset growth and low market-to-book ratio. Furthermore, CDS trading increases the likelihood of healthy asset growth and significantly reduces the asset growth-return anomaly. The results of these tests consistently suggest that the lower cyclicality due to CDS trading is beneficial to firms, hence "less is more".

The main contribution of our study is that we uncover an important disciplining effect of CDS trading that mitigates the exacting credit problem. CDS firms reduce their growth to better cope with exacting creditors and such strategy pays off as it increases firm profitability and market value. Our findings have macro-economic and policy implications. CDS trading makes it possible to separate the allocation of capital and risk in the economy and therefore can create feedback effects on corporate finance and real economy activity. Our study highlights such effect on the cyclicality of individual firms, which we expect to be relevant for macro-economic fluctuations as well. Finally, financial regulators and policymakers should take our findings into account when designing, evaluating, or changing rules and regulations that affect the scale and scope of CDS trading.

Appendix A. Variable definitions and data sources

Variable	Definition	Source
AG	A firm's quarterly asset growth rate.	Compustat
EG	Yearly employment growth rate, defined as the percentage change in the number of employees.	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.	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.	Markit
Net CDS	It is calculated as $ln(net\ notional\ CDS\ amounts + 1)$.The net notional CDS amounts are reported by the DTCC.	DTCC
Gross CDS	It is calculated as $ln(gross\ notional\ CDS\ amounts + 1)$.The gross notional CDS amounts are reported by the DTCC.	DTCC
ΔGDP	Quarterly gross domestic product growth rate, calculated as one fourth of the seasonally adjusted annual growth rate.	Federal Reserve Bank of St. Louis
ΔIP	Quarterly industrial production growth rate.	Federal Reserve Bank of St. Louis
ROA	Net income before extraordinary items, scaled by total assets.	Compustat
Size	The natural logarithm of total assets of a firm, in billions of dollars.	Compustat
Net PPE	Net property, plant, and equipment, scaled by total assets.	Compustat
Leverage	Book leverage, calculated as the book value of debt (short-term debt plus long-term debt) divided by total assets.	Compustat
Working Capital	Current assets minus current liabilities, scaled by total assets.	Compustat
Cash	Cash and cash equivalent, scaled by total assets.	Compustat
Asset Turnover	Sales scaled by total assets.	Compustat
Retained Earnings	Retained earnings, scaled by total assets.	Compustat
Volatility	Annualized standard deviation of the trailing 252-trading-day stock returns before the fiscal quarter-end.	Compustat
Return	12-month stock return.	
Excess Return	12-month stock return less the 12-month market return.	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.	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.	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.	Compustat
Lender FX Usage	A measure of the average FX hedging activities carried out by a firm's lending banks and underwriters.	Dealscan, FISD, Call Report
TIO	Total institutional ownership, defined as percentage of shares outstanding of a firm held by all institutional investors, excluding the quasi-indexers as identified by Bushee (2001).	Thomson Reuters 13-F database

MMO	Motivated monitors' ownership, defined as percentage of total shares outstanding of a firm held by motivated monitors. Motivated monitors are institutional investors whose holding value in a firm is in the top 10% of their portfolio.	Thomson Reuters 13-F database
INDQ	Industry Q, defined as the median market to book ratio of a firm's industry.	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): $0.715 \times Receivables + 0.547 \times Inventory + 0.535 \times capital + 1 \times\ Cash\ Holdings$	Compustat
ΔGoodwill	The change in goodwill, scaled by total assets.	Compustat
MA_Dummy	A dummy variable that takes the value of 1 if a firm announces a M&A in a quarter, and 0 otherwise.	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.	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.	Federal Reserve Bank of St. Louis
Unhealthy	A dummy variable that takes the value of 1 when a firm's asset growth rate is too high (higher than a threshold AG^*) that a further increase in asset growth reduces ROA, and 0 otherwise. The threshold (AG^*) is obtained by estimating the regression specification (1) in Table 8: $2 \times (-0.150) \times AG^* + 0.145 = 0$. $AG^* = 0.48$.	Calculated by the authors.

Appendix B. Probit regression results and comparison of firm characteristics

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 compares the firm characteristics of CDS firms with those of 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.:	$\text{Prob}(\text{CDS initiation}_{i,t} = 1)$
ROA	0.600
	[1.27]
Size	0.222***
	[25.54]
Net PPE	-0.005
	[-0.08]
Leverage	0.845***
	[11.17]
Working Capital	0.236**
	[2.19]
Cash	-0.256*
	[-1.92]
Asset Turnover	0.187**
	[1.97]
Retained Earnings	-0.016
	[-0.76]
Volatility	-0.430***
	[-5.28]
Excess Return	-0.033
	[-0.95]
Investment-grade	-0.035
	[-0.75]
Rated	0.221***
	[4.98]
Constant	-5.283***
	[-16.80]
Time Fixed Effects	Yes
Industry Fixed Effects	Yes
Number of observations/$Pseudo\ R^2$	231,368/0.278

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

Firm Characteristics	(1) CDS firms	(2) Non-CDS firms	(3) Difference (t statistics)
ROA	0.006	0.007	-0.001 [-0.81]
Size	8.614	8.636	-0.022 [-0.29]
Net PPE	0.372	0.374	-0.002 [-0.19]
Leverage	0.351	0.355	-0.004 [-0.41]
Working Capital	0.104	0.104	-0.000 [-0.05]
Cash	0.086	0.081	0.005 [0.87]
Asset Turnover	0.227	0.223	0.004 [0.46]
Retained Earnings	0.087	0.051	0.036 [0.96]
Volatility	0.404	0.411	-0.007 [-0.65]
Excess Return	0.113	0.129	-0.016 [-0.74]
Investment-grade	0.440	0.410	0.031 [1.2]
Rated	0.584	0.589	-0.005 [-0.21]
Propensity score	0.063	0.063	0.000 [0.01]

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Figure 1. Firm asset growth and GDP growth

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

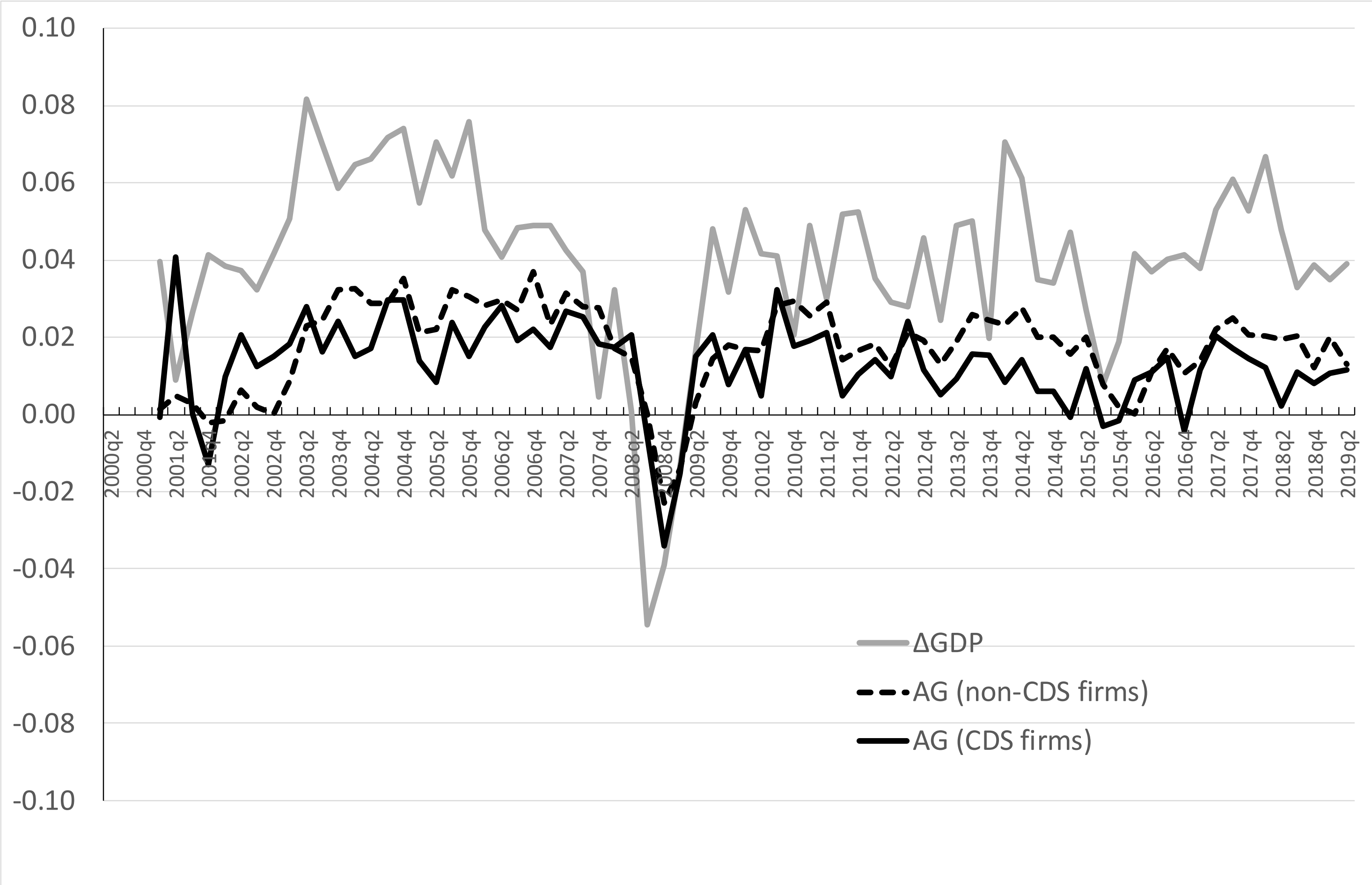

Figure 2. Placebo coefficient estimates on $CDSTrading^{Placebo} \times \Delta GDP$

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. 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 5 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.

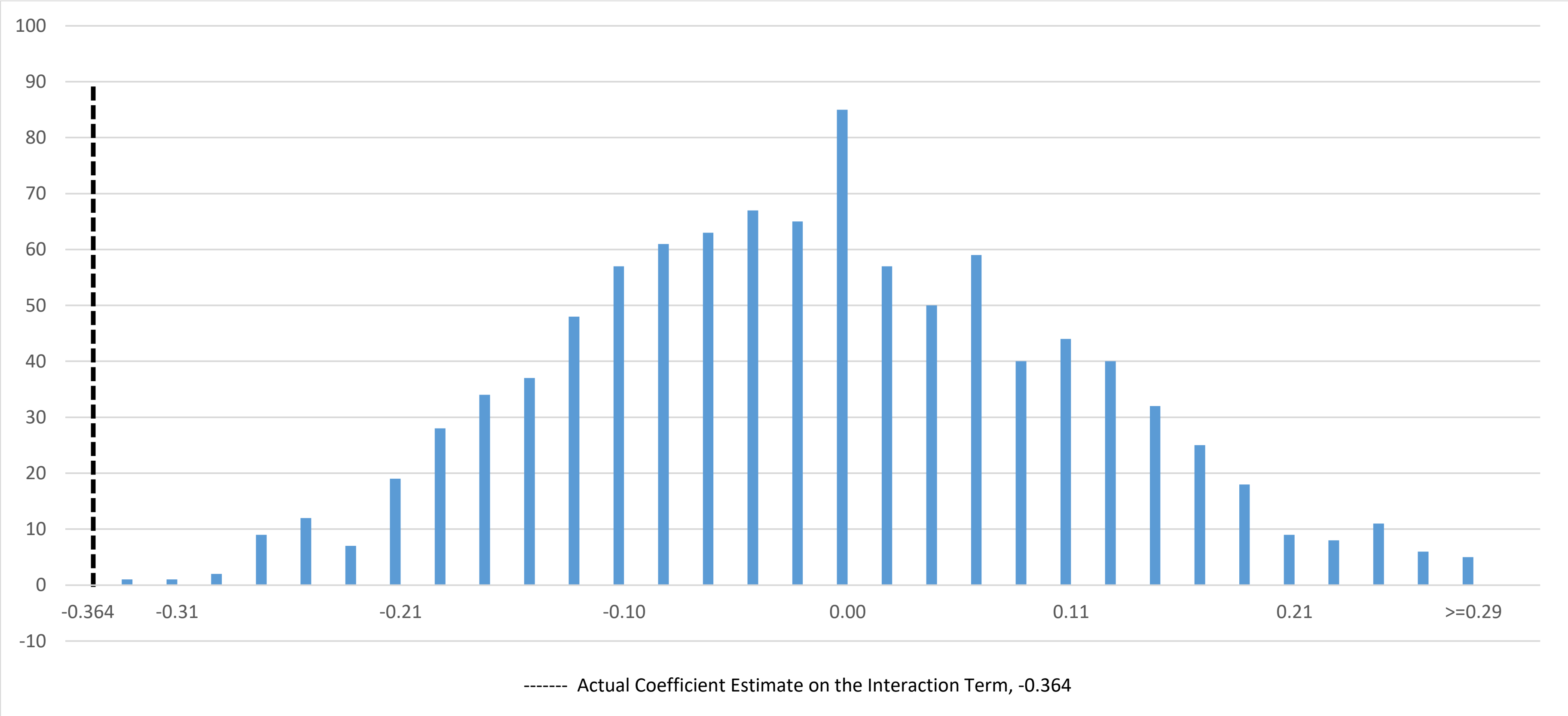

Figure 3. The dynamics of CDS spreads and loan spreads

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, non-CDS firms, and propensity-score matched (PSM matched) non-CDS firms from Q1 2002 to Q4 2018..

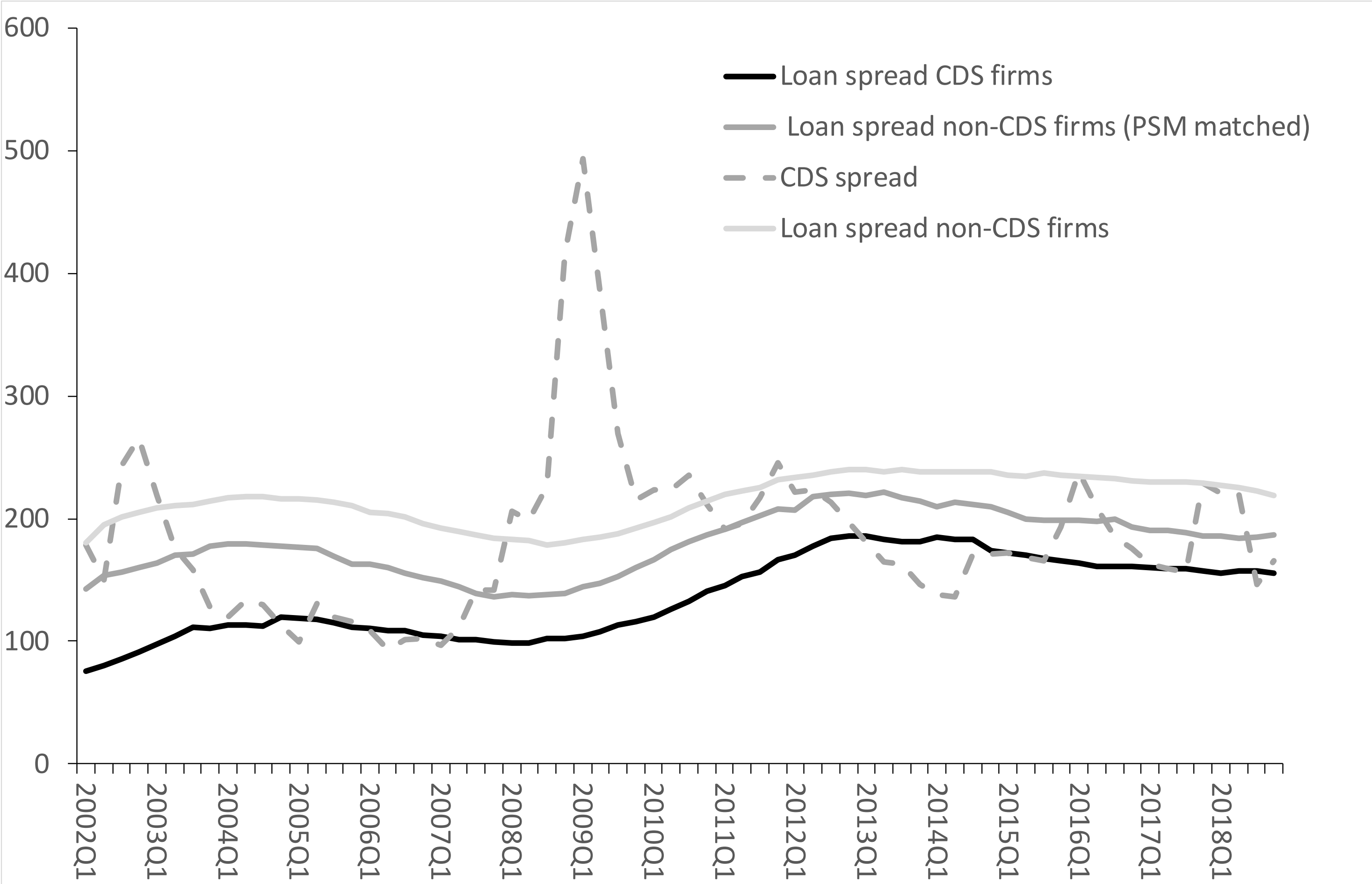

Table 1. Summary statistics

This table provides the summary statistics for the major variables used in our study. Panel A is dedicated to all sample firms, whereas panel B presents the statistics for CDS firms and non-CDS firms, separately. The sample period is from Q4 2000 to Q4 2018. The definitions of the variables are provided in Appendix A.

Panel A: Full sample

Variable	Number of observations	Mean	SD	p2.5	p25	Median	p75	p97.5
AG	266,065	0.018	0.142	-0.318	-0.030	0.005	0.040	0.875
EG	72,770	0.065	0.382	-0.955	-0.043	0.019	0.106	5.705
CDSTrading	266,065	0.124	0.330	0.000	0.000	0.000	0.000	1.000
CDSTraded	266,065	0.160	0.367	0.000	0.000	0.000	0.000	1.000
ΔGDP	266,065	0.010	0.007	-0.018	0.007	0.011	0.014	0.023
ΔIP	266,065	0.002	0.013	-0.056	0.000	0.006	0.010	0.020
Size	266,065	6.183	2.154	1.808	4.566	6.098	7.678	11.386
Net PPE	266,065	0.268	0.251	0.000	0.069	0.175	0.409	0.917
Leverage	266,065	0.221	0.220	0.000	0.009	0.179	0.350	1.017
Working Capital	266,065	0.252	0.259	-0.424	0.051	0.215	0.424	0.905
Cash	266,065	0.215	0.241	0.000	0.035	0.118	0.315	0.960
Asset Turnover	266,065	0.242	0.194	0.000	0.106	0.200	0.325	1.005
Retained Earnings	266,065	-0.729	2.568	-17.152	-0.468	0.038	0.296	0.942
ROA	266,065	-0.015	0.079	-0.475	-0.014	0.007	0.019	0.098
Volatility	266,065	0.559	0.338	0.136	0.324	0.469	0.693	1.945
Excess Return	266,065	0.048	0.570	-0.889	-0.290	-0.038	0.242	2.699
Investment-grade	266,065	0.078	0.269	0.000	0.000	0.000	0.000	1.000
Rated	266,065	0.135	0.341	0.000	0.000	0.000	0.000	1.000
Market to Book	266,065	2.009	1.579	0.502	1.103	1.491	2.276	10.418

Table 1 (cont'd)

Panel B: CDS firms and Non-CDS firms

Variable	CDS firms: Number of observations	CDS firms: Mean	CDS firms: SD	Non-CDS firms: Number of observations	Non-CDS firms: Mean	Non-CDS firms: SD	Difference in mean (Non-CDS − CDS)	t-stat
AG	33,832	0.014	0.084	232,233	0.019	0.148	0.005	5.9
EG	9,265	0.022	0.197	63,505	0.071	0.401	0.049	11.5
Size	33,832	9.143	1.252	232,233	5.752	1.904	-3.391	-314.0
Net PPE	33,832	0.350	0.246	232,233	0.256	0.249	-0.094	-63.6
Leverage	33,832	0.323	0.178	232,233	0.206	0.222	-0.117	-90.9
Working Capital	33,832	0.110	0.142	232,233	0.273	0.266	0.163	109.3
Cash	33,832	0.093	0.101	232,233	0.233	0.250	0.140	100.6
Asset Turnover	33,832	0.228	0.167	232,233	0.244	0.198	0.016	14.3
Retained Earnings	33,832	0.155	0.565	232,233	-0.857	2.717	-1.012	-67.6
ROA	33,832	0.011	0.027	232,233	-0.019	0.083	-0.030	-64.8
Volatility	33,832	0.343	0.197	232,233	0.591	0.343	0.248	129.0
Excess Return	33,832	0.043	0.366	232,233	0.049	0.594	0.006	2.5
Investment-grade	33,832	0.362	0.481	232,233	0.037	0.189	-0.325	-221.4
Rated	33,832	0.465	0.499	232,233	0.086	0.281	-0.379	-200.3
Market to Book	33,832	1.698	0.861	232,233	2.055	1.653	0.357	38.6

Table 2. CDS trading and asset growth 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. 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)	(5)
CDSTrading × ΔGDP	-0.654***	-0.429***	-0.432***	-0.413***	-0.364***
	[-7.55]	[-5.38]	[-5.42]	[-5.03]	[-4.40]
CDSTrading	0.002	-0.002*	-0.002*	0.008***	-0.002
	[1.59]	[-1.96]	[-1.66]	[3.92]	[-1.01]
ΔGDP	1.695***	1.084***	1.087***	0.996***	0.774***
	[36.03]	[24.76]	[24.80]	[21.70]	[11.22]
ROA		0.044***	0.044***	0.005	0.001
		[4.95]	[4.98]	[0.53]	[0.08]
Size		-0.001***	-0.001***	-0.025***	-0.030***
		[-4.17]	[-4.63]	[-21.92]	[-22.27]
Net PPE		0.023***	0.019***	0.049***	0.055***
		[13.93]	[8.15]	[7.30]	[8.19]
Leverage		-0.027***	-0.028***	-0.066***	-0.062***
		[-12.51]	[-12.70]	[-16.45]	[-15.16]
Working Capital		0.003	0.004	0.016**	0.018***
		[1.18]	[1.17]	[2.57]	[2.94]
Cash		-0.049***	-0.052***	-0.097***	-0.101***
		[-15.36]	[-15.30]	[-14.21]	[-14.66]
Asset Turnover		0.001	0.009***	0.004	-0.001
		[0.49]	[3.33]	[0.60]	[-0.17]
Retained Earnings		-0.001***	-0.001***	-0.005***	-0.004***
		[-3.92]	[-3.49]	[-8.53]	[-5.88]
Volatility		-0.024***	-0.025***	-0.022***	-0.023***
		[-16.96]	[-17.47]	[-12.26]	[-10.37]
Excess Return		0.026***	0.026***	0.014***	0.014***
		[37.25]	[36.85]	[18.56]	[19.17]
Investment-grade		-0.007***	-0.007***	0.003	0.005**
		[-4.87]	[-4.51]	[1.50]	[2.30]
Rated		0.008***	0.009***	0.005***	0.006***
		[6.74]	[7.05]	[2.83]	[3.43]
Market to Book		0.019***	0.019***	0.029***	0.029***
		[37.85]	[37.01]	[38.78]	[38.29]
Constant	0.001**	-0.003	-0.008	0.128***	0.131***
	[2.40]	[-1.01]	[-1.08]	[14.10]	[8.96]
Time Fixed Effects	No	No	No	No	Yes
Industry Fixed Effects	No	No	Yes	No	No
Firm Fixed Effects	No	No	No	Yes	Yes
Number of observations	266,065	266,065	266,065	266,065	266,065
R^2	0.006	0.073	0.075	0.090	0.094

Table 3. CDS trading and asset growth cyclicality considering selection effects

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. All variables are defined in Appendix A. All independent variables, except ΔGDP and CDSTraded, are one-quarter lagged. 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	-0.649***	-0.424***	-0.427***	-0.379***
	[-7.49]	[-5.32]	[-5.36]	[-4.71]
CDSTrading	-0.009***	-0.008***	-0.007***	-0.014***
	[-4.63]	[-4.15]	[-4.03]	[-7.54]
ΔGDP	1.690***	1.080***	1.083***	0.790***
	[35.92]	[24.65]	[24.69]	[11.22]
ROA		0.044***	0.044***	0.036***
		[4.96]	[5.00]	[4.07]
Size		-0.001***	-0.001***	-0.002***
		[-4.59]	[-5.06]	[-6.38]
Net PPE		0.023***	0.019***	0.020***
		[13.94]	[8.13]	[8.78]
Leverage		-0.027***	-0.028***	-0.027***
		[-12.61]	[-12.80]	[-12.06]
Working Capital		0.003	0.004	0.004
		[1.18]	[1.17]	[1.39]
Cash		-0.049***	-0.052***	-0.054***
		[-15.32]	[-15.28]	[-15.77]
Asset Turnover		0.001	0.009***	0.009***
		[0.50]	[3.29]	[3.12]
Retained Earnings		-0.001***	-0.001***	-0.001**
		[-3.86]	[-3.43]	[-2.31]
Volatility		-0.024***	-0.025***	-0.023***
		[-17.03]	[-17.55]	[-13.91]
Excess Return		0.026***	0.026***	0.027***
		[37.12]	[36.72]	[36.95]
Investment-grade		-0.008***	-0.007***	-0.005***
		[-5.14]	[-4.79]	[-3.51]
Rated		0.008***	0.008***	0.008***
		[6.39]	[6.70]	[6.37]
Market to Book		0.019***	0.019***	0.019***
		[37.84]	[37.00]	[36.58]
CDSTraded	0.011***	0.006***	0.006***	0.012***
	[6.38]	[3.49]	[3.62]	[6.67]
Constant	0.001*	-0.002	-0.007	-0.040***
	[1.70]	[-0.74]	[-0.97]	[-3.22]
Time Fixed Effects	No	No	No	Yes
Industry Fixed Effects	No	No	Yes	Yes
Number of observations	266,065	266,065	266,065	266,065
R^2	0.007	0.073	0.076	0.080

Table 4. IV regressions for CDS trading and asset growth cyclicality

This table 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 2SLS (3-stage) procedure. Controls are the same as those included in specification (5) of Table 2. 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. In column 1, heteroskedasticity-robust t-statistics adjusted for clustering within firms are reported in brackets. In columns 2 and 3, t-statistics calculated using bootstrapping standard errors as described in Papies, Ebbes, and Heerde (2017) are reported in brackets. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Dep. Var.:	(1) CDSTrading	(2) AG (2SLS)	(3) AG (3-stage)
Lender FX Usage	0.781***		
	[6.43]		
CDSTrading × ΔGDP		-0.364***	-0.357***
		[-4.55]	[-4.19]
CDSTrading		-0.005	0.013*
		[-0.11]	[1.83]
ΔGDP	-0.070**	0.773***	0.785***
	[-1.99]	[11.11]	[10.50]
Residual		0.002	-0.019**
		[0.06]	[-2.55]
Constant	-0.077**	0.131***	0.156***
	[-2.36]	[7.98]	[13.35]
Controls	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Number of observations	268,879	266,065	257,425
R^2	0.111	0.094	0.095

Table 5. PSM analysis of CDS trading and asset growth cyclicality

This table presents the baseline regression results with propensity score-matched samples constructed with multiple matching (column 1) and without multiple matching (column 2). The dependent variable is firm asset growth (AG) and the independent variables include an interaction term between CDSTrading and GDP growth (ΔGDP), and controls. Controls are the same as those included in specification (5) of Table 2. 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. 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	Matching with replacement	Matching without replacement
CDSTrading × ΔGDP	-0.367***	-0.356***
	[-2.71]	[-2.61]
CDSTrading	0.004	0.004*
	[1.64]	[1.75]
ΔGDP	0.910***	0.892***
	[8.09]	[7.86]
Constant	0.167***	0.168***
	[7.31]	[7.31]
Controls	Yes	Yes
Time Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Number of observations	54,939	55,866
R^2	0.060	0.060

Table 6. CDS trading, asset growth 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 controls, and other control variables. Controls are the same as those included in the specification in column (5) of Table 2. 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. 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	-0.378***	-0.335***	-0.349***	-0.344***
	[-4.57]	[-4.15]	[-4.32]	[-4.05]
CDSTrading	-0.002	-0.001	-0.000	-0.003
	[-0.75]	[-0.42]	[-0.18]	[-1.13]
ΔGDP	0.783***	0.731***	0.741***	0.778***
	[11.34]	[10.65]	[10.79]	[10.93]
MA_Dummy	0.036***		0.034***	
	[23.07]		[22.08]	
ΔGoodwill		0.352***	0.345***	
		[19.95]	[19.68]	
Constant	0.130***	0.137***	0.136***	0.126***
	[8.93]	[9.39]	[9.35]	[8.40]
Controls	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Number of observations	266,065	266,065	266,065	251,550
R^2	0.097	0.105	0.108	0.095

Table 7. CDS trading and asset growth cyclicality: 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 institutional ownership (TIO), motivated monitors' ownership (MMO), 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 (5) of Table 2. 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. 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)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. Var.: AG	High TIO	Low TIO	High MMO	Low MMO	High INDQ	Low INDQ	High LC	Low LC	IG	Non-IG or Not-rated
CDSTrading × ΔGDP	-0.416***	-0.241**	-0.336***	0.239	-0.846***	-0.082	-0.269***	-0.127	-0.134	-0.287***
	[-3.61]	[-1.99]	[-3.18]	[0.87]	[-6.26]	[-0.82]	[-2.82]	[-0.78]	[-0.68]	[-2.86]
CDSTrading	-0.003	0.001	-0.004	-0.016**	0.009**	-0.008***	-0.005*	-0.001	-0.004	-0.005**
	[-1.20]	[0.31]	[-1.35]	[-1.97]	[2.08]	[-3.37]	[-1.92]	[-0.16]	[-0.98]	[-2.00]
ΔGDP	0.955***	0.637***	0.809***	0.787***	0.789***	0.777***	0.658***	0.846***	0.341	0.788***
	[9.40]	[6.91]	[7.17]	[6.06]	[7.25]	[9.08]	[7.24]	[8.14]	[1.60]	[10.89]
Constant	0.185***	0.131***	0.225***	0.134***	0.094***	0.173***	0.174***	0.107***	0.263***	0.131***
	[10.20]	[7.64]	[10.53]	[7.69]	[4.20]	[8.58]	[9.88]	[4.38]	[4.51]	[8.21]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	135,455	130,610	111,556	112,221	131,878	134,187	134,460	131,605	20,587	245,478
R^2	0.097	0.097	0.087	0.107	0.103	0.085	0.083	0.099	0.065	0.096

Table 8. CDS trading and asset growth cyclicality: High vs. low beta samples

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 (5) of Table 2. 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 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 beta sample	Low beta sample
CDSTrading × ΔGDP	-0.390**	-0.374***
	[-2.32]	[-2.75]
CDSTrading	-0.005	0.000
	[-1.17]	[0.05]
ΔGDP	1.050***	0.370***
	[9.82]	[4.09]
Constant	0.095***	0.195***
	[3.28]	[9.57]
Controls	Yes	Yes
Time Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Number of observations	126,305	124,228
R^2	0.110	0.078
Average beta	1.835	0.634

Table 9. CDS trading and asset growth cyclicality: Robustness tests

This table presents the results of a set of robustness tests. The dependent variable is firm asset growth (AG) for Panels A through C, and firm employment growth (EG) for Panel D. All regressions include the same control variables as those used in specification (5) of Table 2. The sample period is from Q4 2000 to Q4 2018 for all panels, unless stated otherwise. All variables are defined in Appendix A. Independent variables, except ΔGDP, are one-period lagged. Panel A reports results of sub-period regressions. In column 1, the sample period is from Q4 2000 to Q2 2007 and in column 2 the sample period is from Q3 2007 to Q4 2018. Panel B reports the baseline regression results, in which the dummy variable $CDSTrading$ is replaced by measures of outstanding CDS amount. Outstanding CDS amount is measured as $Net\ CDS$ in column 1 and as $Gross\ CDS$ in column 2. The sample period is from Q4 2008 to Q4 2018, as the DTCC data is not available before Q4 2008. Panel C reports the results of regressions, in which cyclicality is measured with state GDP growth (column 1) and average industry asset growth (column 2). In column 1 the sample period is from Q1 2005 to Q4 2018, as the state-level GDP data is not available before Q1 2005. Panel D reports the results of regressions of yearly firm employment growth. 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: Sub-period analysis

Dep. Var.: AG	(1) Q4 2000 to Q2 2007	(2) Q3 2007 to Q4 2018
CDSTrading × ΔGDP	-0.607***	-0.246**
	[-2.75]	[-2.42]
CDSTrading	0.002	-0.005
	[0.60]	[-1.05]
ΔGDP	0.319**	0.934***
	[2.39]	[11.55]
Constant	0.288***	0.241***
	[11.31]	[12.64]
Controls	Yes	Yes
Time Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Number of observations	106,850	159,215
R^2	0.113	0.097

Panel B: Outstanding CDS positions and firm cyclicality

Dep. Var.: AG	(1) Net CDS	(2) Gross CDS
Net CDS × ΔGDP	-0.020**	
	[-2.02]	
Net CDS	0.000	
	[1.56]	
Gross CDS × ΔGDP		-0.017**
		[-2.02]
Gross CDS		0.000
		[1.51]
ΔGDP	0.886***	0.885***
	[10.97]	[10.97]
Constant	0.238***	0.238***
	[12.39]	[12.39]
Controls	Yes	Yes
Time Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Number of observations	151,570	151,570
R^2	0.097	0.097

Table 9 (continued)

Panel C: Alternative measures of business cycle

Dep. Var.: AG	(1) State ΔGDP	(2) Industry AG
CDSTrading$\times$ ΔGDP^{State}	-0.152**	
	[-2.20]	
CDSTrading$\times$ ΔIAG		-0.117***
		[-2.98]
CDSTrading	-0.009**	-0.003
	[-2.30]	[-1.21]
ΔGDP^{State}	0.175***	
	[5.25]	
ΔIAG		0.433***
		[23.60]
Constant	0.224***	0.132***
	[11.77]	[9.00]
Controls	Yes	Yes
Time Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Number of observations	169,105	265,853
R^2	0.095	0.099

Panel D: CDS trading and employment growth cyclicality

Dep. Var.: EG	(1)	(2)
CDSTrading $\times$ ΔGDP^{annual}	-0.505***	-0.441***
	[-4.14]	[-3.58]
CDSTrading	-0.004	-0.008
	[-0.73]	[-0.88]
ΔGDP^{annual}	1.061***	4.790***
	[13.82]	[6.10]
Constant	0.073*	0.568***
	[1.93]	[8.03]
Controls	Yes	Yes
Time Fixed Effects	No	Yes
Industry Fixed Effects	Yes	No
Firm Fixed Effects	No	Yes
Number of observations	72,770	72,770
R^2	0.029	0.046

Table 10. CDS trading and asset growth cyclicality: High vs. 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 (5) 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 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)	(5)
CDSTrading× ΔGDP^{high}	-0.747***	-0.500***	-0.506***	-0.496***	-0.410***
	[-8.62]	[-6.27]	[-6.33]	[-6.05]	[-4.94]
CDSTrading× ΔGDP^{low}	-0.188	-0.093	-0.084	-0.050	-0.145
	[-1.43]	[-0.74]	[-0.66]	[-0.39]	[-1.13]
CDSTrading	0.001	-0.003**	-0.002**	0.008***	-0.002
	[1.08]	[-2.25]	[-1.97]	[3.77]	[-1.14]
ΔGDP^{high}	1.677***	1.055***	1.059***	0.954***	0.722***
	[34.58]	[23.47]	[23.53]	[20.28]	[10.36]
ΔGDP^{low}	1.816***	1.281***	1.279***	1.277***	1.145***
	[27.19]	[19.89]	[19.85]	[19.50]	[11.59]
Constant	0.001**	-0.003	-0.008	0.128***	0.132***
	[2.09]	[-1.14]	[-1.12]	[14.12]	[9.00]
Controls	No	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	No	No	Yes
Industry Fixed Effects	No	No	Yes	No	No
Firm Fixed Effects	No	No	No	Yes	Yes
Number of observations	266,065	266,065	266,065	266,065	266,065
R^2	0.006	0.073	0.076	0.090	0.094

Table 11. More and less cyclical subsamples

This table presents the baseline regression results for more and less cyclical firms. The more cyclical subsample (less cyclical subsample) contains firms from three-digit industries whose average correlation between $asset\ growth$ and ΔGDP during the sample period is above (below) the median across all industries. The dependent variable is AG. Control variables are the same as those included in specification (5) of Table 2. 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. 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	More cyclical subsample	Less cyclical subsample
CDSTrading × ΔGDP	-0.046	-0.336***
	[-0.45]	[-3.92]
CDSTrading	-0.008***	0.003
	[-3.29]	[1.17]
ΔGDP	0.834***	0.444***
	[11.99]	[5.54]
Constant	0.080***	0.120***
	[5.06]	[7.38]
Controls	Yes	Yes
Time Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Number of observations	133,209	132,856
R^2	0.108	0.096

Table 12. 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 (5) 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. 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 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	-0.028***	-0.005	-0.031***	-0.004
	[-4.95]	[-1.56]	[-5.43]	[-1.31]
Constant	0.354***	0.223***	0.362***	0.222***
	[11.05]	[7.20]	[10.96]	[7.69]
Controls	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Number of observations	59,100	73,879	56,928	76,051
R^2	0.143	0.107	0.149	0.106

Table 13. Asset growth, CDS trading 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 regression of a dummy variable Unhealthy on CDSTrading, and control variables. All variables are defined in Appendix A. All independent variables are one-quarter lagged, except AG. 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	Unhealthy
AG	0.145***	
	[53.74]	
AG^2	-0.150***	
	[-43.20]	
CDSTrading		-0.005***
		[-2.59]
ROA	0.207***	-0.117***
	[37.04]	[-12.58]
Size	0.006***	-0.022***
	[11.73]	[-18.34]
Net PPE	-0.024***	-0.004
	[-8.86]	[-0.65]
Leverage	0.011***	-0.046***
	[6.49]	[-12.05]
Working Capital	-0.011***	-0.026***
	[-4.66]	[-4.98]
Cash	0.008***	-0.021***
	[2.80]	[-3.41]
Asset Turnover	0.058***	-0.023***
	[21.14]	[-4.14]
Retained Earnings	0.004***	-0.004***
	[15.40]	[-7.15]
Volatility	-0.005***	0.000
	[-5.88]	[0.02]
Excess Return	0.005***	0.003***
	[20.44]	[4.56]
Investment-grade	0.000	0.002
	[0.36]	[1.04]
Rated	-0.001**	0.007***
	[-2.10]	[4.36]
Market to Book	-0.000	0.022***
	[-0.36]	[30.32]
Constant	-0.042***	0.123***
	[-8.42]	[10.79]
Time Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Number of observations	264,501	268,879
R^2	0.303	0.052

Table 14. CDS trading and the asset growth anomaly

This table presents the results of regressions of yearly stock return (Return) on yearly asset growth (AG^{annual}), and control variables in column 1 and on an interaction term between CDSTrading and AG^{annual}, and control variables in column 2. AG^{annual} is the asset growth defined as the percentage change in total assets from the fiscal year ending in calendar year $t-2$ to fiscal year ending in calendar year $t-1$. BM is calculated using the Compustat data in the fiscal year ending in calendar year $t-1$ and is defined as in Davis, Fama, and French (2000). MV is the June (t) market value, BHRET6 is the buy-and-hold return over January (t) – June (t), BHRET36 is the 36-month buy and hold return over July ($t-3$) to June (t). The sample period is from 2001 to 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.: Return	(1)	(2)
AG^{annual}	-0.142***	-0.147***
	[-14.63]	[-14.43]
CDSTrading× AG^{annual}		0.082***
		[3.62]
CDSTrading		0.032*
		[1.96]
BM	0.368**	0.366**
	[2.57]	[2.54]
MV	-0.000***	-0.000***
	[-3.39]	[-3.43]
$BHRET6$	-0.071***	-0.072***
	[-7.22]	[-7.27]
$BHRET36$	-0.045***	-0.045***
	[-10.75]	[-10.72]
Constant	0.140***	0.142***
	[11.84]	[11.91]
Time Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Number of observations	56,149	56,149
R^2	0.127	0.127