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Aggregate Risk in the Term Structure of Corporate Credit

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Abstract

Recent global crises have brought to light the risks that corporate credit markets are exposed to, particularly in the tails of the distribution. Using firm-level, credit default swap (CDS) data across maturities, we discuss two stylized facts. First, while the term structure of credit spreads is upward sloping on average, firms that are close to default exhibit a negative slope. Second, shorter-term credit spreads display greater counter-cyclicality to aggregate risks, a fact that is driven by the behavior of financially constrained firms. To better understand these dynamics, we construct a novel, dynamic model of firm behavior where corporations issue short and long maturity debt to finance investment. The model generates an endogenous credit spread term structure that matches these facts across a distribution of firms. Moreover, we find that dis-investment by the most financially constrained firms, in order to gain additional cash in recessions, can actually amplify stress.

Keywords: Credit Spreads, CDS, Term Structure, Tail Risk, Debt Maturity

JEL Classification: E43, G01, G12, G32

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1 Introduction

Through financial crisis episodes over the last two decades, economic policymakers and researchers have witnessed large tail risks manifest themselves in the real and financial activity of corporations. In the 2007-09 Global Financial Crisis, for example, financially constrained firms were hit the hardest as they were forced to draw on available credit lines and forego profitable investment opportunities (Campello, Graham, and Harvey, 2010). Such inequalities also appeared in credit markets amid the COVID-related turbulence in 2020, as high yield debt markets sunk at a faster pace than investment grade markets prior to government interventions in March (Haddad, Moreira, and Muir, 2021). Separate from these recent events, long-standing literature argues that corporate debt maturity management allows firms to cushion themselves against liquidity runs in downturns. This has been shown to be an optimal strategy in classical models of debt maturity (e.g., Diamond, 1991) and empirically relevant in studies of firm-level capital structure decisions.[1]

In this paper we connect these ideas and study how aggregate risk is priced in the term structure of credit spreads. In particular, we examine the cyclicality of the term structure of credit spreads, and how it differs for safe and risky firms. We start by examining these questions in the data using non-financial, corporate credit default swaps (CDS) across multiple maturities, from late 2001 through mid-2021. We find two key stylized facts. First, while the average firm's term structure of credit spreads is upward sloping, firms that are close to default exhibit a switch in the sign of their term structure slope. That is, short-term credit spreads become larger than long-term ones. Second, we find that spreads at the short run tend to be *more counter-cyclical* with respect to aggregate risks, than spreads at the long end. This second finding is particularly driven by sensitivities of the riskiest firms in recessions and is robust to measurement of aggregate risk.

To better understand the potential mechanisms that determine these facts, we design a dynamic, heterogeneous firm economic model, where corporations finance investment using debt and equity issuance. Corporations elect to use debt due to a tax shield and distress cost tradeoff that is standard in the literature (Hennessy and Whited, 2005), while equity is issued as a last resort due to its high issuance costs. The model contains aggregate shocks which drive business cycles while idiosyncratic shocks drive cross-sectional dispersion. What makes the model unique is that each period, firms have access to two pari-passu debt contracts (one quarter and five-year securities) with endogenous default risk. Firm default constitutes a

[1] A managerial survey paper by Bodnar, Graham, Harvey, and Marston (2011) suggests that CFO's are concerned about issuing new loans in bad times. Both Mian and Santos (2018) and Xu (2017) discuss how corporations try to refinance shorter maturity debt into longer term debt when credit conditions are strong, to hedge off liquidity risks in recessions.

failure to pay both contracts. Default risk is fairly priced in both contracts by intermediaries, and costly default and a convex stochastic discount factor (SDF) help to generate substantial, countercyclical credit spreads. Most importantly, because the model *simultaneously* features time-varying spreads at multiple maturities, it allows us to directly speak to the empirical facts we earlier mentioned.[2] The multiple maturity choice also separates our work from other literature where the model only contains one debt contract with longer maturity or a setting where maturity choice is implicitly determined through the rate of debt retirement.[3]

We calibrate the model to match key moments in the data including leverage, the long-term debt share, default and recovery rates, and equity and long-term debt issuance frequencies. At a high level, the model produces pro-cyclical aggregate investment and debt issuance, with countercyclical credit spreads across both debt maturities. In the cross-section, the model also matches the stylized empirical facts from the CDS data. While the term structure is positively sloped for the large majority of firms, the slope reduces and turns negative for a small fraction of financially constrained firms. Additionally, the shorter end of the credit spread curve is more sensitive to business cycle fluctuations for these very firms.

How does the model match these cross-sectional patterns in credit spreads? As the weakest firms become financially constrained in recessions, they become more needy of cash on hand due to reductions in profits. Additionally, due to a leverage ratchet effect (Admati, Demarzo, Hellwig, and Pfleiderer, 2018), these firms keep rolling over their long-term debt and maintain a high leverage ratio, which further increases their riskiness. While debt issuance is preferred relative to equity issuance, these firms effectively get priced out of both short and long-term debt markets, as the level of spreads sharply increases due to credit risk. Furthermore, the slope of the term structure turns increasingly negative as unconditional short-term probabilities of default are higher than longer-term conditional probabilities.[4] As a result, the most constrained firms end up, dis-investing (on net) out of their capital stock to avoid having to issue costly equity. The dis-investment channel amplifies the movement

[2] While speaking to the credit spread data, the model also implies that firms with an intermediate risk profile use short-term debt as bridge financing: if they receive positive shocks in the future, they can roll over short-term debt into long-term debt, while if they receive negative shocks, short-term debt allows them to deleverage fast. This is consistent with recent empirical literature (e.g., Kahl, Shivdasani, and Wang (2015)).

[3] Kuehn and Schmid (2014) features a corporate finance model where firms have access to a single, long-term security. Meanwhile, Chen, Xu, and Yang (2021) allow for reissuance of debt with a new maturity structure, but only with one contract at a time. In the sovereign default literature, using a model with long-term debt, Arellano and Ramanarayanan (2012) explain how issuing long-term debt helps hedge movements in sovereign credit spreads.

[4] Because the shocks that push financially constrained firms to the default boundary are transitory in the model, annualized long-run default probabilities for these very firms are lower than short-run default probabilities. For the same reason, annualized long-run default probabilities are higher than short-run probabilities for relatively unconstrained firms.

towards default as cash flows, which are a function of total invested capital, reduce further. Moreover, endogenous investment plays a significant role in the default and term structure dynamics.

Beyond our main contributions, there are other findings of interest. In the empirical section, we show that a decomposition of corporate credit spreads into expected losses (pure compensation for default risk) and credit risk premia (a residual that accounts for covariation of risk aversion and default) yields interesting results. Following the Berndt, Douglas, Duffie, and Ferguson (2018) methodology, expected losses explain a greater proportion of level and cyclicality effects at the short horizon of the CDS curve, while risk premia dominate CDS spreads at the longer end. Moreover, while the term structure of credit risk premia becomes increasingly upward sloping for the riskiest of firms, the slope of expected losses is even more so negative.

In the model section, we further explore the mechanisms that govern firm behavior. We find that investor risk aversion and equity issuance costs play a strong disciplining role in debt markets. In an environment where market participants are risk neutral, equilibrium leverage increases dramatically as credit investors and equity holders no longer overweight the risk of being financially constrained in recessions. Similarly, when equity issuance is costless, firms know they can raise capital cheaply when close to default. As a result they end up taking on more risk through leverage. The model also shows interesting interaction effects between the two key state variables – current net worth and long-term debt. This leads to a rich, endogenous cross-section of credit spreads.

Having described key results in the paper, we close the section by comparing our work to some relevant and existing literature. In the next section we discuss empirical evidence regarding term structure data for CDS. In the third and fourth sections, we introduce the model and present its quantitative results. In the final section we conclude.

Related Literature

In our empirical section we examine the macroeconomic information contained in credit markets. While we study contemporaneous relationships using correlated credit measures in CDS markets, Gilchrist and Zakrajšek (2012) examine the predictive nature of bond-based credit spreads towards aggregate macroeconomic variables such as GDP and investment growth. Similarly, Faust, Gilchrist, Wright, and Zakrajšsek (2013) look at the real-time forecasting ability of real variables using credit spreads and find that the inclusion of spread measures is vital for prediction. In a paper that uses the same dataset as us, Han, Subrahmanyam, and Zhou (2017) discuss that the term structure of credit default swaps has predictive power for future stock returns. More specifically, the authors show that firms with a higher slope of CDS spreads have relatively lower stock returns over the future 6 months. Higher CDS slopes also predict a future reduction in credit quality. Augustin (2018) shows for sovereign debt that countries with a negative CDS term structure slope potentially display adverse economic outcomes in the near future. Our work can be thought of as an extension of this idea to corporate bond markets. In the empirical section of Chen et al. (2021), the authors also describe a link between debt maturity and systematic risk and show that firms with greater systematic risk (market beta) are those that have higher long-term-debt ratios. In contrast, we show that firms that are riskier ex-ante, as determined by their CDS ranking, are those whose spreads price greater aggregate risk.

Our work also contributes to the structural literature on long-term debt models and debt maturity. To our knowledge, our model is the first dynamic asset pricing model with aggregate risk, endogenous investment, and two fairly priced debt contracts of varying maturity. This allows us to address our novel facts about the term structure of credit spreads and study its implications for corporate policies. Merton (1974), Leland (1994), and Leland and Toft (1996) involve the optimization of firm cash flows with (single maturity) debt contracts, however they all take cash flows to be exogenous and assume commitment of the total stock of debt (i.e., constant repayment and issuance). We show that endogenous investment interacts significantly with debt maturity choice and that the lack of commitment adds to the level of credit spreads.

Greenwood, Hanson, and Stein (2010) produce a gap-filling theory with habitat investors to explain the pro-cyclical nature of long-term debt issuance. To better understand the great reliance of financial firms on short-term debt, Brunnermeier and Oehmke (2013) discuss a theoretical model where creditors optimally reduce their offered maturity in response to the diluting actions of other creditors. Kuehn and Schmid (2014) embed a long-term debt contract into an investment-based framework with Epstein-Zin preferences. He and Milbradt (2016) is like our paper in that they discuss a debt-rebalancing problem with short and long-term debt simultaneously. However, the authors focus on circumstances where the fundamental aggregate state is deteriorating and a debt shortening equilibrium emerges. Also, they fix the total amount of debt (the sum of short and long), whereas we allow for full flexibility.

In highly related work that involves endogenous investment, Jungherr and Schott (2021) embed two simultaneous, risky debt contracts without commitment at different maturities. While they focus on the model's general behavior and compare to a setting with a single short-term debt contract, our goal is to study the implications of the model for corporate credit spreads. For this purpose, we embed a countercyclical stochastic discount factor to better align asset prices to credit spread data and discuss the behavior of firms that are closer to default. The model in Chen et al. (2021) allows for reissuance of debt with endogenous maturity choice at each point in time. In contrast with our work, cash flows are taken to be exogenous. Newly issued debt wipes away existing debt and doesn't allow for a comparison across a firm's term structure. Hu, Varas, and Ying (2021) present a model of endogenous maturity management, but without endogenous investment.

2 Empirical Evidence

In this section we document stylized facts related to cross-sectional and time series patterns of corporate credit spread data. Our goal is to understand the degree to which aggregate risk is priced in the term structure of credit spreads. We start with a brief description of the data, followed by a discussion of the various tests we conduct.

2.1 Data Summary

To proxy for corporate credit risk we primarily use credit default swap data. There are multiple reasons why CDS data are ideal for our study. First, as CDS are insurance contracts tied to default events of firms, they are directly reflective of a risk spread that is not dependent on the proper correction of a risk-free rate. Second, because CDS contracts are traded frequently by several institutions (hedge funds, banks, etc.) relative to corporate bonds that trade infrequently, they are less susceptible to pricing frictions that arise from illiquidity and imperfect information (see Bai and Collin-Dufresne (2019)). Hence, they are a purer measure of credit risk. Finally, because CDS contract terms and pricing conventions are more standardized, they allow for more direct comparison across firms (see Han et al. (2017)).

At the firm-level, we collect CDS quotes from Markit across three maturities (1Y, 5Y, 10Y) and insist that firms report all three maturities on a given day.[5] These data are available at the daily frequency, are firm-specific, and represent the bid-ask average from multiple reporting dealers. We use CDS that are linked to bonds that are senior and unsecured (Markit tier category SNRFOR) and are based on the no restructuring (XR) docclause. We remove all data that correspond to the *Financials, Utilities*, and *Government* sectors in Markit. These empirical specifications are very similar to those used in Berndt et al. (2018). In addition, to control for outlier values as done in Gilchrist and Zakrajšek (2012), we winsorize all data at the .5% level. All CDS data go from late 2001 to mid-2021 and we take month end values for each firm to generate a monthly, panel dataset.

[5]Markit data also makes available a 6M CDS in some cases but we choose to discard this as conditioning on its availability substantially shrinks our cross-section.

In subsequent tests we control for both firm-level accounting data and examine data related to physical probabilities of default. To do so, we merge in quarterly financial statement data from Compustat and daily default probability data from Moody's Analytics. The time-varying default probabilities (expected default frequencies or "EDF") from Moody's arise from a Merton (1974) or Leland (1994) style model, that depends on a firm's market value of equity and underlying return volatility. In these tests we additionally exclude financial firms (SIC codes 6000 – 6999), utility firms (SIC 4900 – 4999), and quasi-governmental and non-profit firms (SIC 9000 – 9999). Merging in both of these datasets cuts our sample roughly in half, so we conduct a number of tests with purely the CDS sample and check its robustness in the merged samples.

We report summary statistics of our CDS data in Table 1. Each row of the table reports the mean of cross-sectional moments, with respect to various maturities. In the top panel and first three columns, we show that the average 1Y, 5Y, and 10Y prices are given by 1.43, 2.21, and 2.44 annual percentage points respectively. This upward sloping term structure is robust to looking at the merged sample with Compustat data (middle panel), examining the merged sample with EDF data (bottom panel), or studying positive and negative growth states (middle and right panels).[6] As expected, negative states display higher CDS spreads across all maturities while positive states are lower. While the average term structure is upward sloping, the cross-sectional standard deviation is largely downwards sloping in the top panel; even more pronounced is the downwards slope of the skewness and kurtosis. These latter results will end up playing a role as we think about the pricing of aggregate risk.

The effect of the merge with Compustat or Moody's data is clear as both of these data focus on samples with larger firms and stronger credit profiles. This is displayed in Figure 1. In the figure each panel displays median values over time with respect to a particular maturity. The merged samples are consistently lower in value and the differences in CDS spreads are most noticeable during the 2007-09 financial crisis period. The number of firms shrinks by roughly one half between the CDS-only sample and the other two samples. As shown in Figure 2, the full sample averages roughly 500 firms each month while the two merged samples are closer to 250 and 200, respectively.

2.2 Credit Spread Term Structure

Our first object of interest is the credit spread term structure and how it varies across ex-ante, firm-level riskiness. Our work is, of course, not the first to study such topics. As Han et al. (2017) discuss, the credit spread slope can be informative of firm fundamentals. The authors

[6] Positive economic growth states are dates where quarterly industrial production growth falls in the top 25% of realized outcomes, while negative ones fall into the bottom 25%.

show that a lower slope predicts future decreases in default risk, increases in profitability, and higher future stock returns. Using sovereign CDS to study country-level credit risk, Augustin (2018) suggests that a country's term structure slope can provide information regarding the structure of underlying risk factors. Furthermore, countries that exhibit a negative slope can have adverse implications for future, country-specific economic growth. Our empirical results can be interpreted as an application of the latter findings to non-financial corporate firms.

2.2.1 Overall Dynamics

We start by sorting firms into quintile risk buckets based on their 1-month lagged 1Y CDS value.[7] Based on these quintile rankings, we examine average CDS values, Compustat moments, and EDF data as well. These values are displayed in Table 2 and reflect data from the matched CDS-Compustat sample. As expected, the one-, five-, and ten-year CDS spreads increase in average value as we move from risk group 1 to 5. Similarly, the slope of the term structure also increases as a function of ex-ante risk. In terms of accounting characteristics, leverage and the long-term debt ratio are both increasing in risk type.[8] For example, risk group 1 firms have a leverage of 28% while those in group 5 exhibit a 43% leverage rate. Intuitively, as risk increases, average book size, market size, market-book ratio, and investment growth all decrease. For group 5 firms, investment growth is actually negative on average.

Finally, the bottom panel of Table 2 displays information regarding the physical default probabilities. Overall, 1Y and 5Y EDF measures display average values of 1.22% and 1.04%, respectively. While this suggests a negative slope of EDF's, it is important to note that this does not suggest that the five-year cumulative probability of default is less than the corresponding one-year value. Rather, the EDF's are geometrically compounded annual probabilities that match up with maturity-specific cumulative default probabilities. This means that the negative EDF slope implies that short-term default probabilities are less than longer-term conditional probabilities (i.e., hazard rates). This negative EDF slope becomes particularly pronounced as we move to risk group 5 (slope of -1.43%).

2.2.2 Tails of the Risk Distribution

Sorting firms into coarse quintiles masks interesting dynamics in the extreme tails of risk. In Table 3, we look at firms that are in the top percentiles of risk, from 25 to 1%. Note that each data point reports the average value of a particular statistic, conditional on firms

[7] Similar results hold when we sort on the average level of CDS across maturities.

[8] Because we examine a merged sample that involves some of the largest firms, leverage and long-term debt ratios are larger than what is reported in other papers (for example, Kuehn and Schmid (2014)).

being in the top $X\%$ of lagged 1Y CDS spreads. In this portion of the distribution, we can observe that the slope of the term structure actually ends up flipping signs, moving from 141 b.p. at the 25% mark to -160 b.p. at the 1% mark. Even within the smaller Compustat and EDF-merged samples, we see that the slope decreases sharply and turns negative at the top percentile. A main reason for this might be the shape of the EDF term structure, which becomes extremely negatively sloped. This implies that short-term (physical) default probabilities are extremely large, relative to longer-term conditional probabilities. There are other interesting patterns that emerge from this table. Leverage spikes over 50% at the far-right tail and investment growth also turns steeply negative, as firms seem to begin dis-investing when they are this close to default.

We summarize the tail behavior of short and long-term credit spreads, as a function of firm-level ex-ante risk, in Figure 3. In the top panel we plot average 1Y and 5Y spreads as a function of cross-sectional tail percentage. Naturally, the higher a firm resides in its risk distribution the higher the average spread would be. What is more interesting, however, is that while the 1Y credit spread is consistently below the 5Y maturity, at a certain threshold it overtakes it. This is when the slope becomes negative and is consistent with data from the previous Table.

In the bottom subplot we show that in negative economic states (i.e., recessions) this switching slope dynamic is more severe and takes place for a larger chunk of firms. The solid blue line in this panel represents the difference between the two lines in the above panel. As one can see it is consistently positive until a threshold point. We examine this slope particularly in recessions (dot-marked, green line) and it is evident that it flips for a larger chunk of firms, close to 5%. This point takes place much earlier, especially when compared to positive states.

2.3 Cyclicality of Credit Spreads

Naturally, we would expect fundamental default risk to rise in adverse economic states, as firms get closer to default (a lower distance to default) and continue to experience a combination of negative cash flow and funding shocks. It can also be the case that for the same level of default risk, financial investors are more risk averse in adverse states. This form of counter-cyclical risk aversion can result in higher credit risk premia (e.g., Berndt et al. (2018)), which raises the overall credit spread. Such risk aversion plays a crucial role in modern asset pricing models (e.g., Chen (2010); Bansal and Yaron (2004)).

2.3.1 Full Sample

To test the degree of cyclicality in our credit spread panel, we examine regressions of the form:

$$s_{it}^{m} = \beta_M M_t + \beta_X' X_{i,t-1} + \varepsilon_{it}^{m} \tag{1}$$

where s_{it}^{m} is firm i's CDS spread at time t for maturity m and M_t is one of many possible aggregate risk measures. Meanwhile $X_{i,t-1}$ is a set of lagged controls that can include industry or firm fixed effects, or time-varying Compustat controls. We use a lagged version of these controls, as done in Chen et al. (2021), so that our measurement of β_M accounts for underlying, historical firm risks. The regressions are performed using monthly data. CDS values are taken from the end of the month, while the last known Compustat quarterly values are taken as of month end.

Our baseline results are presented in Table 4. From top to bottom, each panel provides results with respect to a different aggregate risk indicator (industrial production growth, nonfarm payroll employment growth, average VIX, and S&P market returns). All risk indicators are measured at a quarterly level (e.g., quarterly growth rates, averages, and returns) as we want to make sure that they properly capture lower-frequency movements in aggregate conditions. Going left to right within a panel, columns 1 – 3 account for industry fixed effects, columns 4 – 6 account for firm fixed effects, while the last 3 columns employ both fixed effects and Compustat controls from the second panel of Table 2.

If we focus our attention on columns 1 – 3 of the first panel, the interpretation is that a 1-σ movement in industry production growth is associated with a -.50%, -.44%, and -.37% movement in 1Y, 5Y, and 10Y CDS spreads respectively. These negative coefficients are statistically significant at the 1% level and in line with our economic intuition. This downward sloping, absolute sensitivity to aggregate risk consistently holds across all 4 risk indicators. For example, with the quarterly average of VIX, the sensitivities range from .92 to .63. When we include different controls such as firm fixed effects and Compustat controls, we continue to see these patterns.

The most surprising part of these findings is that longer term spreads are less sensitive to macroeconomic risk. In particular, Giesecke, Longstaff, Schaefer, and Strebulaev (2011) discuss the idea (using a long sample) that corporate defaults tend to cluster, and that adverse macroeconomic news (both real and financial market data) coincide with credit risk. Furthermore Berndt et al. (2018) suggest of an aggregate component in credit risk premiums. Combining both of these, we would expect that the upward sloping term structure of CDS would coincide with an increasing sensitivity to aggregate risk. To get a better sense as to where these empirical patterns arise from we look at finer cuts of the data.

2.3.2 Conditioning on Risk Group and Economic States

To get at the types of firms that are driving these results we separate firms based on ex-ante credit risk, like the summary statistics in Table 2. Using each grouped set of firms across time, we run similar regressions as earlier. Table 5 displays the results to these tests. Taking the first panel, we see the coefficients monotonically increase in absolute size from left (lowest risk group) to right (highest risk group). This makes sense – credit spreads and CDS are highly right skewed and firms that post higher ex-ante spreads are those that will be more sensitive to aggregate shocks (such as monetary policy). For the 1Y CDS contract, for example, the coefficient rises from -.02 to -.08 to -1.26%. Meanwhile for the 5Y swap, the loading goes from -.02 to -.09 to -1.00%. Clearly, short-term credit spreads are more counter cyclical than long-term ones, and the effects are concentrated in the riskiest set of firms. Similar results hold when we examine other risk indicators (see panels 2 through 4). In particular, results on VIX and market returns are quite pronounced as 1Y spreads are economically and statistically sensitive to aggregate risk drivers at a rate that is greater than longer maturities.

We add to this discussion by examining the type of economic states (booms vs. recessions) where these sensitivities are their largest. We continue to break up firms by their ex-ante risk group and condition on recession states (i.e., when industrial production growth is at a relative low). Table 6 displays the results of these specifications. In these tests we squarely focus on industrial production growth as the risk indicator. The top panel, which examines the overall cyclicality, displays identical results to those in the previous table. The middle panel focuses on adverse economic states and there are two conclusions that can be drawn. First, the average *absolute level* of sensitivities is higher for group 5 and group 3 firms. Second, for group 5, the absolute difference between 1Y and 5Y (10Y) grows substantially to roughly 39 b.p. (57 b.p.). In the unconditional results, group 5 displayed absolute differences in sensitivities of 26 b.p (43 b.p.) across maturities. These differences are important to note as they reflect the idea that not only are short-term credit spreads sensitive to recessions, but in recessions, *further bad news* can particularly harm shorter-term funding conditions. We also show, in the final panel that such effects are muted in non-recession periods. In Table 7 we show that the above effects are not only particular to industrial production growth as a risk indicator. When we examine nonfarm payroll growth or S&P returns as aggregate variables, we continue to see that in recession states these maturity-specific credit risk patterns emerge.[9]

[9]Similar results hold for VIX as well, but they are not displayed due to space constraints. They are

2.3.3 CDS Liquidity Effects

As with any financial market data, the lack of transaction volume and security liquidity can reduce the degree to which prices reflect fundamentals. The same applies in CDS markets as well, where trading positions have declined tremendously over the last 12 years. In particular, the reduction of gross notional positions in single-name CDS has driven the overall decline in CDS trading (e.g., Boyarchenko, Costello, and Shachar (2020)). As we exclusively use single name CDS in our analysis, this issue is potentially problematic for us if the most illiquid securities drive our results.

To address these issues, we focus our attention on a particular indicator – the count of broker dealer quotes for the 5Y CDS ("Composite Depth"), which combine to form the average CDS price we view in our data set. The intuition behind this measure is straightforward. As the number of quotes grow for a particular contract, this might be suggestive of a more liquid market, as a larger number of dealers are willing to transact with counterparties. Further, the number of dealer quotes are provided for each firm, at each point in time, which allows us to perform a detailed analysis in the cross-section of CDS market depth.

Figure 4 displays the distribution of CDS liquidity over time. For the purposes of the figure, we compute the median, 10%, and 90% quantiles, and display three month rolling averages of these values over time. A few patterns stick out from the figure. While the earlier mentioned notional sizes have declined over time, it is not clear that the number of participating dealers has. In fact, in recent times (post 2016) it seems that the distribution of CDS quotes has shifted upwards. Furthermore, the number of quotes for larger firms, as given through the median of the matched CDS-Compustat sample is almost always greater than the full sample median. This result is intuitive as we would expect greater participation in the larger, more well-known issues.

We analyze whether liquidity affects our cross-sectional cyclicality results by conducting our earlier regressions as a function of the number of dealer quotes. Table 8 provides the results of these tests, where the middle and bottom panels condition on the number of quotes provided. Focusing on the fifth risk group, it is clear that the most liquid CDS contracts actually make our empirical specification even stronger. At the 1Y horizon, for example, a baseline sensitivity of -1.26 increases in absolute value to -1.50 if we condition on the most liquid. Moreover, it does not seem that illiquid observations are driving our cyclicality results; if anything, it goes the other way.[10]

available upon request.

[10]The aforementioned table also shows that when we place additional liquidity constraints, the number of high risky securities substantially decreases, relative to safer securities. While not the focus here, this suggests that CDS risk and liquidity, proxied for by market depth, are negatively correlated.

2.4 Term Structure of Expected Losses and Risk Premia

Fundamentally, credit spreads can be decomposed into two sources: (1) compensation due to expected losses in default and (2) a risk premium residual that accounts for co-variation between the stochastic discount factor and losses in default. In this sub-section we examine patterns in expected losses and credit risk premia across the term structure and further study the sources of our cyclicality results.

To decompose CDS spreads into these two components we follow the methodology in Berndt et al. (2018), which we describe briefly here. The CDS spread at a given maturity is the annualized rate C_t, such that:

$$\Delta C_t \sum_{k=0}^{K-1} \mathbb{E}_t \left[(1 - D_{t,k\Delta}) \frac{M_{t+(k+1)\Delta}}{M_t} \right] = \sum_{k=0}^{K-1} \mathbb{E}_t \left[L_{t+k\Delta,\Delta} D_{t+k\Delta,\Delta} \frac{M_{t+(k+1)\Delta}}{M_t} \right] \tag{2}$$

where the left-hand side reflects premium payments conditional on non-default of the firm, and the right-hand side the potential protection against losses in default. Δ is the period of repayment in years and K is the total number of periods.[11] $D_{t,y}$ indicates a default indicator of default occurs between t and $t+y$. Similarly, $L_{t,y}$ indicates losses in default if it occurs between t and $t+y$. Finally, M_k is the cumulative discount factor from t to k.

Under three assumptions (risk neutrality of time discount rates, conditional independence of recovery rates from realized default, and martingale nature of recovery rates), we can transform the above equation to receive:

$$EL_t = \frac{L_t \sum_{k=0}^{K-1} d_{t,(k+1)\Delta} \mathbb{E}_t \left[D_{t+k\Delta,\Delta} \right]}{\Delta \sum_{k=0}^{K-1} d_{t,(k+1)\Delta} \mathbb{E}_t \left[1 - D_{t,k\Delta} \right]}$$

where EL_t is the expected loss component and $d_{t,k\Delta}$ is the time t discount rate of a cash flow at $t + k\Delta$. Note that the implied expected loss component depends on three pieces of data: (1) zero-coupon bond yields, (2) expected default probabilities, and (3) recovery rates which imply a loss rate. For the first item we use estimates from Gürkaynak, Sack, and Wright (2007). For the second we calibrate a Nelson-Siegel-Svensson model of default probabilities using a term structure of Moody's EDF data for each firm-date and apply it to the horizon of choice.[12] For the third item, we take recovery values from the Markit database. After computing the expected loss component, EL_t from the formula above, the credit risk premium is defined as $CRP_{it}^m = s_{it}^m - EL_{it}^m$. Inherent in this expression is that

[11] As premium payments are generally quarterly, for a 5-year CDS contract, $\Delta = .25$ and $K = 20$.

[12] We use an identical procedure as that in Berndt et al. (2018) to estimate default curves for each firm-date. For more details see their paper and Appendix.

the decomposition is firm, time, and maturity specific.

Figure 5 displays the cross-sectional median of this split, at each part of the term structure (1Y, 5Y, and 10Y). A few patterns are evident. First, at the 1Y horizon, the expected loss component makes up a larger proportion of the total CDS *level*. Meanwhile at the 5Y and 10Y horizon, this proportion shrinks. Second, variation in credit spreads are much less explained by expected losses at the longer horizons. This is evidenced by the relative smoothness of the expected loss components at longer horizons.

We can numerically confirm these observations and examine tail behavior in Table 9. Similar to earlier we zoom in on firms that are particularly risky and examine the decomposition of their spreads and the *slope* of their CDS curves. Focusing on the last panel of the table, it is clear that the riskiest of firms display a negatively sloped term structure of expected losses. This is precisely where the negative slope of overall CDS comes from. These results are intuitive from the standpoint that the expected loss component relates more to the physical probability of default. To the extent that these risky firms are more likely to immediately default, this negative slope is consistent.

Finally, we replicate our cyclicality analysis, within each sub-component of credit spread data. In Table 10 the middle and bottom panels examine the following two regression specifications, respectively:

$$\begin{aligned} EL_{it}^m &= \beta_{IP}\Delta IP_t + \beta_X' X_{it} + \varepsilon_{it}^m \\ CRP_{it}^m &= \gamma_{IP}\Delta IP_t + \gamma_X' X_{it} + \eta_{it}^m \end{aligned}$$

Focusing on the first three columns ("Overall"), we see that the degree of countercyclicality at the 1Y horizon, is relatively evenly split between expected losses and risk premia (-.15 vs. -.13). Meanwhile at longer horizons we see that risk premia are much more countercyclical (-.03 vs. -.18). Naturally, these results are driven by the riskiest of firms ("Risk Group 5"), where the even split of cyclicality is again seen at the 1Y horizon. The asymmetric split is very clearly present at the 5Y and 10Y horizons, as well.

2.5 Credit Risk Dynamics from March 2020

To provide a clear example of the dynamics we observe in the full sample, we focus on evidence from the COVID-related turbulence that took effect in US financial markets, during the first quarter of 2020. As this was a time period where financial markets were becoming increasingly stressed, and certain types of firms were disproportionately hurt (e.g., firms in the travel, retail, and energy sectors), it serves as a laboratory to study our broad sample findings.

Using the CDS data alone, we start by sorting firms by their 2019 year-end average spread values, where the values are defined by the average of firm-specific CDS values across maturity – $\frac{1}{3} \times (CDS_{1Y} + CDS_{5Y} + CDS_{10Y})$. After conducting these sorts, we examine two variables: (1) the shift in levels of the CDS from December 2019 to March 2020 and (2) the shift in slope between the two dates. In order to minimize the relaxing effects of US monetary policy that might take away from our use of the time period, we use data as of March 20, shortly prior to the March 23 announcement by the Federal Reserve that announced plans to create a secondary market corporate credit facility. We present our results in Figure 6. The bottom axis of both figures indicates statistics that relate to the riskiest percentage of firms.

From the top figure, we can see that there was an expected positive shift in spread levels, from December 2019 to March 2020, as firm-level credit risk increased. The shift in levels was most significant for the riskiest of firms – a finding that is relatively unsurprising given the convex surface of firm credit risk. Perhaps more interesting is the bottom chart, which displays that the slope shrank across the distribution, but reduced into negative territory for some of the riskiest firms. While these very firms had displayed a positive slope of the term structure prior to the crisis, the change in dynamic is stark and serves as validation to the larger sample effects we presented earlier. We should also mention that the firms in the bottom 10%, which display a negative slope, include firms that would certainly face challenges in a COVID environment. Notable examples include Neiman Marcus, Chesapeake Energy, Frontier Communications, and J.C. Penney.[13]

2.6 Summary

In this section, we show evidence that as firms get particularly close to default, the slope of their credit spread curve switches signs. Furthermore, credit spreads at the shorter end of the curve are more sensitive to adverse economic news and these results are driven by the riskiest firms particularly in negative states of the world. More generally, the dynamics we examine here are reflective of broader concepts of *self-fulfilling* rollover risk. While the credit default swap contracts are not necessarily reflective of bonds of these exact maturities (i.e., the insurance-related spreads on debt with exactly these maturities), they do convey the market pricing of credit risk. As a result, their prices tell a story consistent with weaker firms getting priced out in short-term markets in crisis episodes. For example, if these firms approached short-term investors to gain access to fresh capital, the efficient pricing of credit risk and default probabilities would likely make short-term debt very costly to obtain. Of

[13]The cross section of credit default swaps that we examine over the period includes 473 firms which suggests that the roughly 10% that display an average negative slope ($\sim$ 47 firms) is a sizable number.

course, these firms would also face greater costs for longer debt maturities as well, however the issues are the most acute and pressing at shorter horizons. This type of story and interpretation will be important as we draw parallels to the dynamic model of firm behavior in the next section.

3 Model

3.1 Technology

Firms use capital k to produce output y according to the following production function:

$$y = Zk^{\alpha} - \psi. \tag{3}$$

The production function has decreasing returns with parameter $\alpha \in [0, 1]$. ψ is a fixed cost of production. Z is an aggregate productivity process that evolves according to

$$\ln Z = (1 - \rho^Z)\mu^Z + \rho^Z \ln Z_{-1} + \eta \tag{4}$$

where ρ^Z is the persistence of the productivity process. The innovations η are normally distributed with mean zero and volatility σ^Z. μ^Z is the unconditional mean of the log productivity process, which we set to $\mu^Z = -\frac{1}{2}(\sigma^Z)^2$ to ensure that Z has an unconditional mean of one.

Capital evolves according to the law of motion

$$k' = (1 - \delta)(1 + \varepsilon)k + i, \tag{5}$$

where δ is the rate of depreciation and i is investment. $\varepsilon \sim N(0, \sigma^{\varepsilon})$ is a firm-specific capital quality shock that shifts the capital stock of the firm. Such a capital quality shock is standard in the literature (e.g., Jungherr and Schott (2020), Ottonello and Winberry (2020)). It represents factors that we do not explicitly model that vary the value of capital. Examples are machines becoming obsolete or breaking down. We include the capital quality shock as it helps the model to generate realistic default rates.

Cash flows are discounted with a stochastic discount factor (SDF). Following Zhang (2005) and Jones and Tuzel (2013), we directly parametrize the SDF as a function of the aggregate state according to

$$\ln M(Z, Z') = \ln \beta - \Gamma(Z) \left[\ln Z' - (1 - \rho^Z)\mu^Z - \rho^Z \ln Z \right] - \frac{\Gamma(Z)^2}{2} (\sigma^Z)^2 \tag{6}$$

$$\Gamma(Z) = \gamma_0 + \gamma_1 \ln Z. \tag{7}$$

$\gamma_0 > 0$ is associated with the risk aversion of the representative investor. γ_1 governs the sensitivity of the risk aversion to the business cycle. $\gamma_1 < 0$ implies that risk aversion is higher if productivity today is low, i.e. in recession states. This SDF has the intuitive explanation that states in which productivity growth is positive are discounted more than states in which productivity growth is negative. Moreover, discounting is stronger if productivity is low today. This yields a counter-cyclical Sharpe ratio, which is in line with the data (e.g. Lustig and Verdelhan (2012)). Finally, we subtract the term $\frac{\Gamma(Z)^2}{2}(\sigma^Z)^2$ to ensure that the stochastic discount factor has a constant expected mean, which leads to a constant risk-free rate. This allows us to abstract from modelling time-variation in risk-free coupon rates and helps to focus the model on the default risk premiums that are the main focus of our analysis.

3.2 Financing

3.2.1 Debt Financing

Firms can issue short-term debt, b_S, and long-term debt, b_L, at state-contingent prices Q_S and Q_L on competitive bond markets. Short-term debt is a one period contract: if a firm issues one unit of short-term debt today, it needs to repay $1 + c$ in the next period, where c is a coupon rate. We model long-term debt following Leland (1994), Hackbarth, Miao, and Morellec (2006) and Kuehn and Schmid (2014) as a recursive contract with maturity $1/\mu$: if a firm issues one unit of long-term debt today, it needs to repay $\mu + c$ in the next period, while $1 - \mu$ is rolled over at the next period's market price Q'_L. The stock of the firm's long-term debt evolves according to

$$b'_L = (1 - \mu) b_L + j_L, \tag{8}$$

where j_L is long-term debt issuance. When issuing debt, firms have to pay linear debt issuance costs ξ_S and ξ_L, respectively. These debt issuance costs reflect, for example, intermediation fees.

3.2.2 Equity Financing

Income is taxed with corporate income tax τ. Income net of taxes is defined as

$$\tilde{y} = (1-\tau)(ZK^{\alpha} - c(b_S + b_L) - \delta(1+\varepsilon)k - \psi). \tag{9}$$

That is, there is a tax deduction for both depreciation and interest expenses. The net worth of the firm is given by

$$n = \tilde{y} + (1+\varepsilon)k - b_S - \mu b_L. \tag{10}$$

The equity payout e of the firm is defined residually by the firm's budget constraint:

$$\begin{aligned} e = {} & n - k' \\ & + \left[Q_L - \xi_L 1(b'_L > (1-\mu)b_L)\right]\left[b'_L - (1-\mu)b_L\right] \\ & + \left[Q_S - \xi_S 1(b'_S > 0)\right] b'_S. \end{aligned} \tag{11}$$

If firms issue equity, that is, $e < 0$, they have to pay a linear equity issuance cost. In conjunction with the debt issuance cost, this equity issuance cost creates a wedge between the value of internal and external financing. The total payout to shareholders d, which includes the equity issuance cost, is thus given by

$$d = e\left[1 + \phi 1(e \leq 0)\right]. \tag{12}$$

3.2.3 Default

Firms can default on their outstanding debt. This takes place when the (market) value of the firm reaches 0. In default, the firm is liquidated, shareholders receive nothing, and creditors receive the liquidation proceeds of the firm, which are given by

$$n^* = \chi(Z)\left[(1-\tau)\left[Zk^{\alpha} - \delta(1+\varepsilon)k - \psi\right] + (1+\varepsilon)k\right]. \tag{13}$$

A fraction $1-\chi(Z)$ of the firm's assets is destroyed in default. Following Chen (2010), we allow the recovery parameter to co-move with the aggregate state, according to

$$\chi(Z) = \chi_0 + \chi_1 \ln Z + \chi_2/2(\ln Z)^2. \tag{14}$$

We assume that $\chi_1 > 0$ and $\chi_2 < 0$, such that the recovery parameter is increasing and concave in the aggregate state. Pro-cyclical recovery rates reflect for example fire sale discounts that tend to rise asymmetrically during recessions.

Note that, consistent with the US tax code, there is no deductibility of interest expenses in the case of default. There is a cross-default clause, so firms cannot default selectively on either only short-term debt or long-term debt. Moreover, there is a pari-passu clause, so owners of short-term debt and long-term debt receive equal shares of the firms liquidation proceeds. The recovery rate of the creditors is given by

$$r = \frac{n^*}{b^S + b^L}. \tag{15}$$

As will be defined shortly, the market value of the firm at any point in time will be given by $v\left(n, b^L, Z\right)$. It is possible to show that the optimal default policy of the firm is defined by a cutoff for the idiosyncratic capital quality shock $\underline{\varepsilon}$, which is implicitly defined by

$$0 = v((1-\tau)\left[Zk^\alpha - \delta(1+\underline{\varepsilon})k - cb - \psi\right] + (1+\underline{\varepsilon})k - b_S - \mu b_L, b_L, Z). \tag{16}$$

Put differently, this will be the shock ε at which the owners of the firm will be indifferent between continuing to operate or to default and walk away.

3.3 Equity financing constraint

One difficulty in a model with defaultable long-term debt and positive recovery rates is that firms that are very close to default might want to "gamble for resurrection". In such a situation, firms might find it optimal to choose low levels of capital and high levels of debt, $k' = \underline{k}$ and $b' = \overline{b}$. Under this corner solution, the firm will naturally have a high equity payout today and default in the next period. This corner solution is undesirable for two reasons: first, it implies empirically unrealistic behavior. Second, it can create convergence issues in the quantitative solution of the model if the solution algorithm jumps back and forth between the interior solution and the corner solution.

To eliminate the corner solution, we follow Jungherr and Schott (2021) and impose a constraint on equity financing. We add a constraint such that the continuation value of the firm to shareholders must be at least as high as a fraction κ of the end of period capital stock:

$$v(n, b^L, Z) - d \geq \kappa k'. \tag{17}$$

This constraint can be motivated by a simple moral hazard problem (e.g., Gertler and Kiyotaki (2011)): suppose that the shareholders of the firm can run away with a fraction κ of the capital stock of the firm. To ensure that this will not happen in equilibrium, creditors can impose an incentive compatibility constraint that states that the value to shareholders of continuing to operate the firm must be at least as high as the gain from diverting assets. This incentive constraint thus takes the form of equation 17. In simulations of the model, the incentive constraint is almost never binding or close to binding.

3.4 Bond prices

Both bond prices, short and long, are determined by a break-even condition such that total current proceeds to the firm equal the total expected payment to intermediaries in the future. The short-term bond price is given by

$$Q_S(k', b'_L, b'_S, Z) = \int_{-\infty}^{\infty} M(Z, Z') \left[\int_{\underline{\varepsilon}}^{\infty} (1+c)\, dG(\varepsilon) + \int_{-\infty}^{\underline{\varepsilon}} r' dG(\varepsilon) \right] dF(Z'). \tag{18}$$

That is, it will be the expectation of cash flows to creditors in non-default states, $1 + c$, and default states, r, where the expectations are taken over the idiosyncratic capital quality shock and the aggregate productivity shock. Future cash flows are discounted with the stochastic discount factor. The bond price depends on the decisions of the firm through the endogenous default policy $\underline{\varepsilon}$ of the firm and the firm's recovery value r'.

The long-term bond price is given by

$$\begin{aligned} Q_L(k', b'_L, b'_S, Z) = \int_{-\infty}^{\infty} M(Z, Z') \Bigg[& \int_{\underline{\varepsilon}}^{\infty} \left(\mu + c + (1-\mu) Q_L(k'', b''_L, b''_S, Z')\right) dG(\varepsilon) \\ & + \int_{-\infty}^{\underline{\varepsilon}} r' dG(\varepsilon) \Bigg] dF(Z'). \end{aligned} \tag{19}$$

Like the short-term bond price, the long-term bond price is the expectation of the cash flows to creditors in non-default states, $\mu + c + (1 - \mu)Q_L(k'', b''_L, b''_S, Z')$, and default states, r'. Differently to short-term debt, the long-term bond price depends on the future long-term bond price, which in turn depends on future firm policies.

As in Kuehn and Schmid (2014), we compute quarterly credit spreads in the model as:

$$\frac{\mu + c}{Q_L(k', b'_L, b'_S, Z)} - \frac{\mu + c}{Q_L(Z)^{RF}} \tag{20}$$

for long-term debt and

$$\frac{1 + c}{Q_S(k', b'_L, b'_S, Z)} - \frac{1 + c}{Q_S(Z)^{RF}} \tag{21}$$

for short-term debt. In the above equations, $Q_S(Z)^{RF}$ and $Q_L(Z)^{RF}$ are risk free prices of short and long debt that pay off $1 + c$ next period and $\mu + c$ into perpetuity, respectively.

Credit spreads are computed for those firms that actually do issue debt (defaulting firms are removed).

3.5 Firm problem

The firm's problem has three state variables: the net worth of the firm, n, its level of outstanding long-term debt b_L and the state of aggregate productivity Z. Firms maximize shareholder value

$$v(n, b_L, Z) = \max_{k', b'_L, b'_S, e, \underline{\varepsilon}} \left\{ d + \int_0^\infty M(Z, Z') \int_{\underline{\varepsilon}}^\infty v(n', b'_L, Z') dG(\varepsilon) dF(Z') \right\}, \tag{22}$$

subject to dividend payouts 12, the budget constraint 11, the definition of net worth 10, laws of motion for the aggregate state 4, capital 5 and debt 8 and the equity financing constraint 17. They take the stochastic discount factor defined in equations 6 and 7, as well as the bond prices 18 and 19 as given.

Rewriting the budget constraint yields, in case of long-term debt issuance:

$$\begin{aligned} k' = & \underbrace{n - \frac{d}{1 + \phi 1(d \le 0)}}_{\text{equity financing}} \\ & + \underbrace{\left[Q_L(k', b'_L, b'_S, Z) - \xi_L 1(b'_L > (1-\mu) b_L)\right] \left[b'_L - (1-\mu) b_L\right]}_{\text{long-term debt financing}} \\ & + \underbrace{\left[Q_S(k', b'_L, b'_S, Z) - \xi_S 1(b'_S > 0)\right] b'_S}_{\text{short-term debt financing}} \end{aligned} \tag{23}$$

This implies that firms can finance their capital stock with either equity, short-term debt or long-term debt. The cost of equity financing are equity issuance costs, if the firm has insufficient internal funds. The costs of debt financing are debt issuance costs and endogenous default premiums.

4 Quantitative Results

4.1 Calibration

As the model has no closed-form solution, we resort to numerical methods to solve the model and employ techniques similar to those in Hatchondo, Martinez, and Sosa-Padilla (2016). We treat the investment, debt and debt maturity choices as continuous choices instead of discretizing them on a grid. Similarly, we treat the idiosyncratic shock as continuous. We discretize the aggregate state using a five-state Markov chain. To calibrate key parameters, we divide the model's parameters into two groups. The first group of parameters is calibrated to external targets, while the second group is calibrated internally to match moments from model simulations to cross-sectional moments from Compustat. The frequency of the model's calibration is quarterly.

Panel 11a of Table 11 displays the externally calibrated parameters. We set the depreciation rate δ to match the average depreciation rate in Compustat. We set the returns to scale of the production function α to a value of 0.65, following Cooper and Ejarque (2003) and Hennessy and Whited (2007). The corporate tax rate τ is set to 0.35, which is the corporate tax rate over most of the sample period. The persistence ρ^Z and volatility σ^Z of the aggregate shock are set to 0.95 and 0.007, respectively, following Cooley and Prescott (1995) and Zhang (2005). We set β to target a risk-free rate of 4 percent. The maturity of long-term debt μ is set to 0.05, implying that the average maturity of long-term debt is $\frac{1}{\mu} = 20$ quarters or 5 years.

Panel 11b of Table 11 displays the internally calibrated parameters. The parameters of the stochastic discount factor γ_0 and γ_1 are set to match a Sharpe ratio of 0.2 as well as an equity premium of 6 percent. We choose the equity issuance cost ϕ to measure a quarterly frequency of equity issuance of 5 percent. We choose the debt issuance costs ξ_S and ξ_L to match a frequency of long-term debt issuance of around 30 percent and a long-term debt share of around 90 percent. The fixed cost ψ and the volatility of the firm-specific capital quality shock σ^ε are set to match a default rate of one percent per year and a leverage of around 30 percent. Finally, the parameters of the recovery in default χ_0, χ_1 and χ_2 are set to target a recovery rate of 40 percent, a volatility of the recovery rate of 8 percent and a correlation of the recovery rate with the default rate of -0.8, in line with Chen (2010).

Panel 11c of Table 11 shows the model fit in terms of the targeted moments. Overall, the model, while highly non-linear, can match the calibration targets reasonably well.[14] Firms issue equity in around 6 percent of quarters and debt in around 30 percent of quarters, similar to the data. Firms have leverage ratios of 28.5 and a long-term debt share of 97 percent. The default rate is around 126 basis points per annum and the recovery rate is 51 percent. The model's performance regarding the volatility of the recovery rate and its correlation with the default rate, as well as regarding the equity risk premium can still be improved. Given the endogenous default intensities and recovery rates of the model, the counter-cyclical stochastic discount factor helps to amplify risk in the model. This intuition is in line with much of the asset pricing literature.

[14]The current calibration is preliminary, and the model fit can still be improved.

4.2 Model Moments and Behavior

4.2.1 Cross-sectional and Business Cycle Moments

To further evaluate the model fit, we use model simulations. We simulate a panel of 1000 firms for 2000 periods, discarding the first 1000 periods, and then compute cross-sectional moments from the simulated data. Table 12 displays the results. The model does a good job at replicating key cross-sectional moments of firms' real and financial policies in Compustat data. Notably, the model replicates both the (targeted) level and the (untargeted) volatility of the leverage and long-term debt share in the data well.[15] The model also generates realistic ratios for un-targeted ratios like the investment/capital ratio, debt issuance/capital ratio and the equity issuance/capital ratio. The model also produces empirically plausible cross-sectional standard deviations for these variables. In particular, the cross-sectional standard deviation on investment / capital is relatively low considering we do not use capital adjustment costs, which are popular in the literature (e.g., Zhang (2005)). Finally, we test the model's cross-sectional predictions for leverage by running a leverage regression, where we regress leverage on the firm's size, market-to-book ratio and profitability. As in the data, market-to-book and profitability are negatively related to leverage. The coefficient of size in the data is small and insignificant, while it is slightly negative in the data.

Table 13 shows the ability of the model to match cyclicalities of average variables in the cross section. While the model is highly stylized and only contains few frictions, it produces empirically plausible aggregate movements, in both quantities and prices. The model generates pro-cyclical investment and debt maturity. While not reported here, the pro-cyclical debt maturity is driven by greater long-term debt issuance in positive aggregate states, and greater short-term debt issuance in adverse states of the world. Finally, the model generates counter-cyclical default rates and credit spreads, as to be expected.

4.2.2 Firm Policies

To better understand the behavior of the model across the state space, we take our model simulations and examine the average values of key policy variables, within buckets of the state space. Figure 7 displays the policies of firms as a function of their net worth and their outstanding long-term debt. Each bucket in an individual panel reflects the behavior of firms within a 5% interval of long-term debt, crossed with a 5% interval of net worth. Meanwhile as colors range from blue to yellow, this reflects a gradient shift of a low outcome into a high

[15] As the firms we look at in our merged data set are some of the largest in the Compustat universe, it turns out that leverage rates and long-term debt shares (in the data) are even larger relative to what is commonly quoted.

outcome.

The top row shows firms' debt and equity financing policies: this shows clearly that the firm's policy is characterized by two inaction regions: in the dimension of net worth, high net worth firms pay dividends, firms with intermediate net worth retain all earnings and firms with low net worth issue additional equity. In the dimension of long-term debt, firms with low leverage issue additional debt, firms with intermediate leverage do not adjust their leverage and firms with high leverage either repurchase debt or default, depending on their net worth.

The second row takes a closer look at the realized short-term debt and long-term debt financing decisions of firms: it shows the revenue from short-term debt issuance and long-term debt issuance. Due to debt issuance costs, firms generally prefer long-term debt issuance to short-term debt issuance, but substitute to short-term debt financing in two cases: first, when the cost of long-term debt financing is very high and second (to a lesser degree), when they are relatively unlevered. Short-term debt serves as bridge financing: firms issue short-term debt, when long-term debt is relatively expensive for them. They roll over short-term debt into long-term debt if they experience a sequence of positive shocks. If they experience a sequence of negative shocks, short-term debt allows them to commit do deleverage swiftly.

The third row of Figure 7 shows the firms' credit spreads as a function of net worth and outstanding long-term debt. Credit spreads are highly non-linear: firms with lower net worth and higher long-term debt face larger credit spreads. Put differently, there is a clear interaction effect between net worth and long-term debt. It is also clear from the second figure in the row that the interaction effect works both ways. Finally, the credit spreads of long-term debt are more sensitive to the state variables of the firm than the credit spreads of short-term debt. More generally, these charts suggest that firms are priced out of using debt, both short-term and long-term, when they are in high-leverage, low net-worth states. This creates endogenous roll-over risk in the model.

4.3 The Distribution of Credit Spreads: Model vs Data

4.3.1 Unconditional Moments

How well does the model replicate the distribution of credit spreads? Table 14 shows the implication of the model for credit spread moments. Panel 14a displays unconditional moments. The model succeeds in producing an unconditionally upward sloping term structure of credit spreads. As the model currently stands, the *average* level of the term structure is less than what is in the data. At the short and long horizons, model spreads are 42 and 51 basis points versus 144 and 222 basis points in the data. While these are low, some of the issues arise from the calibration of the SDF and the lack of capital adjustment costs. As discussed in Kuehn and Schmid (2014), properly accounting for both of these has a significant effect on model dynamics. For example, capital adjustment costs to capital can create greater risks to the downside that are priced into credit spreads, as firms lose the ability to disinvest in recessions and gain access to cash.[16]

Two areas where the model does well are related to the counter-cyclicality of credit spreads and the tail risks of short term vs. long-term spreads. In the middle and bottom panels of Table 14 we show that positive states from the simulation (the top 2 out of 5 aggregate states) reflect lower spreads across the distribution, on average. Meanwhile negative states (the bottom 2 out of 5 aggregate states) reflect higher spreads. The slope of the term structure of credit spreads in the model is higher in booms than in recessions, as in the data: unconditionally, the slope is 9 basis points, in booms, it rises to 15 basis points, while in recessions, it falls to 6 basis points.

Finally, we show through model simulations that the skewness and kurtosis of short-term spreads are both larger than those of long-term values, regardless of state. These patterns are qualitatively consistent with the data and they will be directly reflective of the empirical findings we discussed in Section 2, as discussed below.

4.3.2 Credit Spread Dynamics

In the empirical section, we document two stylized facts related to the dynamics of short- and long-term spreads. As firms get increasingly close to default and display greater risk, the slope of their credit spread term structure diminishes dramatically and sometimes turns negative. Further, the cyclicality of shorter-term credit spreads becomes increasingly negative, especially when compared to that of long-term spreads. In our eyes, the success of the model mainly hinges on matching these qualitative patterns, and we explore those dynamics here.

In Figure 8, we replicate similar charts as those in Figure 3, using model simulated values. The bottom axis in all the figures refers to quantiles of the distance to default. There are 20 quantiles that separate groups of firms. Meanwhile the vertical axis relates to the realized credit spread. Across all figures, the one quarter credit spread is depicted as a solid line, while the five-year credit spread is depicted as a dashed line. Credit spreads during recessions are depicted in red, credit spreads during booms in blue.

The top panel 8a displays the levels of credit spreads. Credit spreads in recessions (red) are above credits spreads in booms (blue). Moreover, short-term credit spreads are mostly

[16] While not discussed here, we are currently implementing adjustment costs to capital and a subsequent version of the model will embed these.

information insensitive as the red and blue solid lines are on top of one another for a large portion of the firm distribution. Meanwhile the dashed lines reflect a slight premium for long-term debt in recessions, regardless of which quantile firms are in. For very risky firms however, where short-term debt is very sensitive to information, the lower maturity credit spreads jump dramatically. This jump is much larger in absolute size than the same difference for longer maturity debt. For example, the 5% riskiest of firms display a jump in short term spreads from 1.5 to 8.5%. Meanwhile these very same firms display a jump in long-term spreads from 1 to 2%. These firms are pushed close to default due to a sequence of negative, transitory idiosyncratic shocks. As firms' endogenous accumulation of net worth leads to endogenous mean reversion, the firms' short-run default probabilities are higher than the firms' long-run default probabilities, which is reflected in the inversion of the credit risk term structure.

The bottom panel 8b displays the slope of the term structure of credit spreads. For most distance to default quantiles, firms display a positively sloped credit spread curve. However, as we move towards the most financially constrained firms (lowest distance to default), we see that the slope flips sign. Furthermore, this sign flip takes place for a larger proportion of firms in recessions, as opposed to booms. This is consistent with the data.

To display the differential sensitivites of the spreads more directly by maturity, Table 15 revisits the panel regressions of Tables 4 and 5 in the model. We simulate a panel of firms, compute the credit spreads of each firm and then regress the credit spreads on the business cycle state. Panel 15a shows the results of the pooled panel regressions. Unconditionally, the cyclicality of the long-term credit spread is roughly equal to the cyclicality of the short-term credit spread. Panels 15b to 15d revisit the regressions by risk group. In the model, we measure risk by the equity value of the firm, though other measures would yield similar results. Consistent with the data, riskier firms have more cyclically sensitive credit spreads. Moreover, while the cyclicality of long-term credit spreads is higher than for short-term credit spreads for low-risk firms, the cyclicality of short-term credit spreads is higher than the one of long-term credit spreads for high-risk firms. This confirms the intuition that is given by the earlier Figure 8.

4.3.3 Firm Policies and Distance to Default: an Event Study

Up until this point we have focused on the prices of short and long debt, across the distribution of firms and over the business cycle. Figure 9 takes a closer look at firm policies as firms approach default. To do so, we use an event study approach. The results are also based on model simulations, similar to prior figures. The blue line plots the average policy of a firm that will eventually default during the 40 quarters prior to default. The dashed line is the unconditional mean of the respective policy.

The left panel in the first row plots the path of the exogenous capital quality shock that leads firms to default. Typically, default is preceded by a slight deterioration in capital quality for many periods, and then a sudden and dramatic fall in capital quality right before default. The right panel in the first row shows the investment policy of the firm: investment declines prior to default. Eventually investment falls below the depreciation rate, such that firms reduce their capital stock.

Why are firms forced to sell off capital and why can't they use alternative means of financing (debt or equity)? Certainly, firms increasingly issue equity as they get closer to default. Equity issuance is however very costly. Thus, marginally reducing the capital stock to avoid having to issue equity, while creating a costly deviation from their target size, is the less costly option for many firms. When it comes to debt issuance, very risky firms essentially get priced out of both short and long-term markets. When examining the issuance patterns, it is clear that firms issue short-term debt and long-term debt at intermediate distances to default. When they get very close to default, they neither issue short-term debt nor long-term debt. These quantity effects go hand in hand with the actual spreads across the curve skyrocketing and the term structure of credit spreads turning strongly negative (last three panels).

4.4 The Role of Frictions

To better understand which elements of the model are important for the level and cyclicality of credit spreads, we now switch various parameters off one by one. The main takeaway is that debt and equity issuance costs are essential to generate an upward-sloping term structure of credit spreads. Table 16 reports the results. The table reports moments for credit spreads, the default and recovery rate, leverage, the long-term debt share and the cyclicality of credit spreads across different models. Model 1 is the baseline model.

Column 2 reports moments for a model with risk-neutral investors. Surprisingly, credit spreads in this model decrease only slightly. This is due to the endogeneity of firm policy: with risk-neutral investors, credit spreads fall, holding firm policies constant. This encourages firms to use more leverage and a longer debt maturity structure. Default rates increase, and recovery rates decrease. Column 5 removes the counter-cyclicality of risk aversion. This leads firms to use more leverage, and more long-term debt. The intuition is similar to the model with risk-neutral investors.

Column 3 shows moments for a model in which there are no equity issuance costs. This leads to a large increase in short-term credit spreads, but not in long-term credit spreads.

The removal of equity issuance costs eliminates a cost of leverage, namely that firms might be forced to issue costly equity to repay outstanding debt if they have low internal funds. As a consequence, firms take on much more leverage. Default rates rise, and recovery rates fall.

The model in column 4 removes debt issuance costs. This leads firms to choose a much shorter debt maturity structure, which reduces credit spreads and default rates. This is, because short-term debt is not subject to a leverage ratchet effect, such that firms will deleverage more flexibly in bad states. This additional flexibility also implies that firms can take on more leverage. Note that this model is unable to generate an upward sloping term structure of credit spreads. Column 6 removes debt and equity issuance costs at the same time. The removal of debt issuance costs leads firms to use more short-term debt, and the removal of equity issuance costs leads firms to take on more leverage. In this model, the term structure of credit spreads becomes strongly downward-sloping.

Finally, the last column reduces the value of the equity financing constraint. This leads some firms to dilute debt and then default, which pushes up credit spreads and default rates substantially. As creditors price this behavior, the leverage capacity of firms falls. This last model implies higher credit spreads. However, it also implies higher default rates and lower recovery rates than in the data, and additionally it implies that firms issue substantial quantities of debt before they default, a behavior that is not confirmed in the data. Thus, ruling out this adverse behavior is crucial in quantitative models with defaultable long-term debt.

5 Conclusion

In this paper, we explore the term structure of corporate credit spreads in many different ways – slopes, time variation, cross-sectional dispersion, and sensitivities to aggregate risk. We find in the data that on average, investors price greater risks at the long end of the curve relative to the short end, however these risks become inverted for the most financially constrained firms in adverse economic states. To comprehend these facts, we construct a novel economic model with a counter-cyclical discount factor, endogenous investment, and two maturities of debt without commitment. The credit spreads and patterns that emit from the model are reasonable and broadly consistent with empirical data on firm-level quantities and prices. One of the more interesting implications of the model is that financially constrained firms are forced to dis-invest to gain additional access to cash, and this can lead to additional stress on the path to default. From a policy perspective, the implications of such real effects are important and further work is needed to assess the welfare effects of these real asymmetries.

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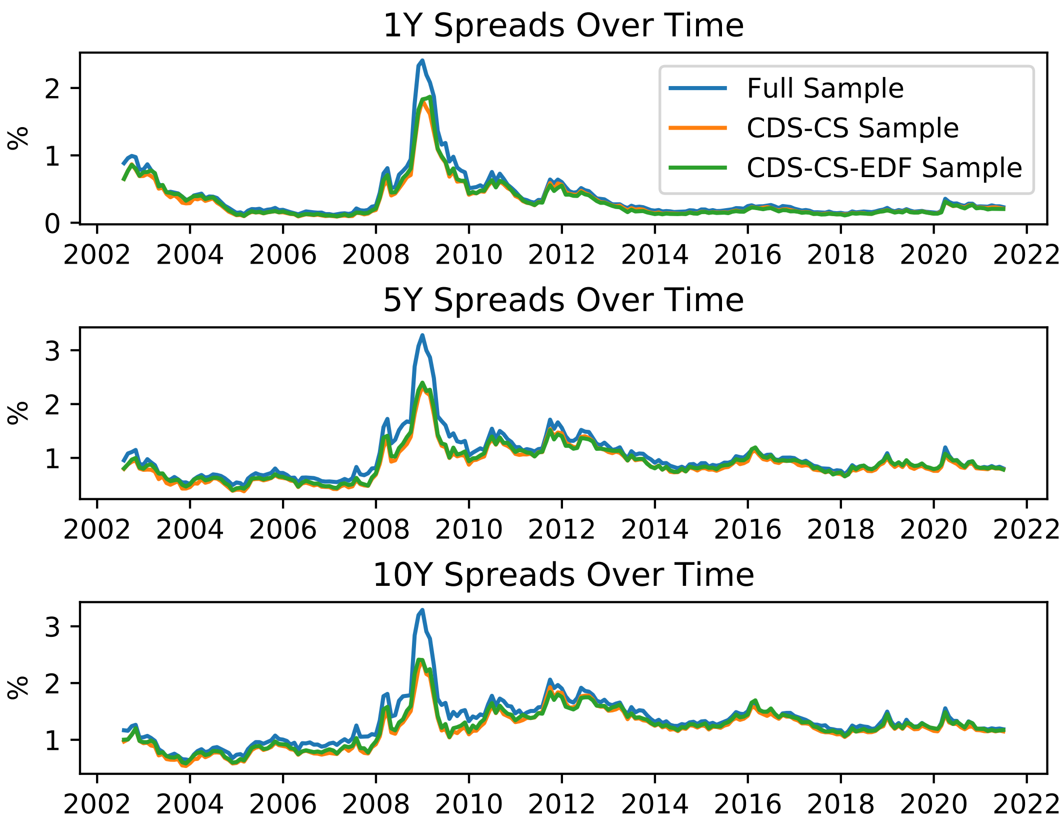
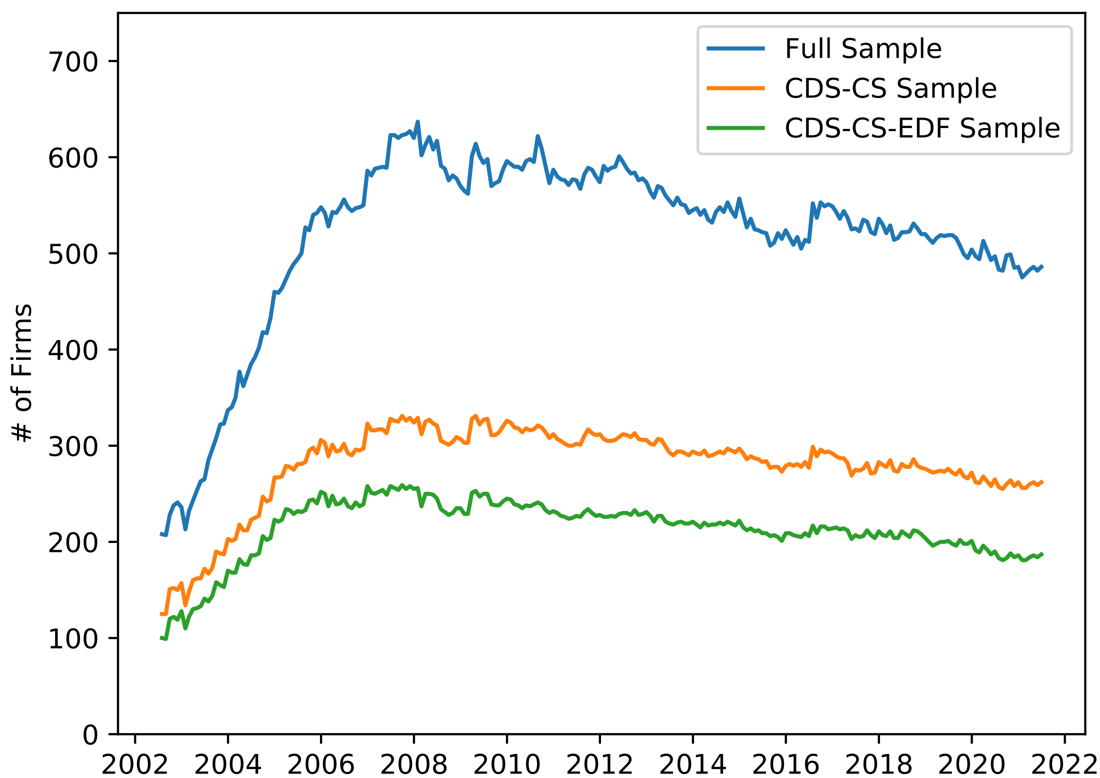
Figures

Figure 1: **Term Structure of Corporate CDS (2002 – Present)**



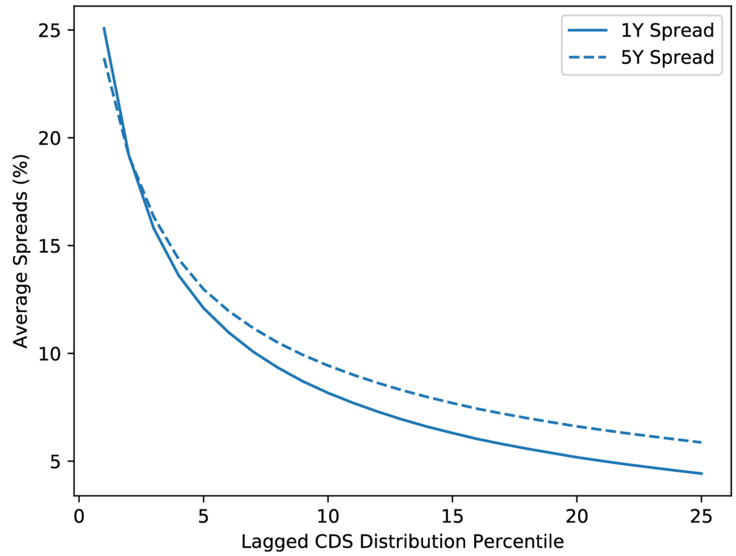
Each panel displays median values over time with respect to a particular maturity (1Y, 5Y, or 10Y). Within a panel, medians are computed across three samples – a Markit-only sample, a Compustat-Markit merged sample, and a Compustat-Markit-Moody's sample.

Figure 2: **Sample Firm Counts CDS**

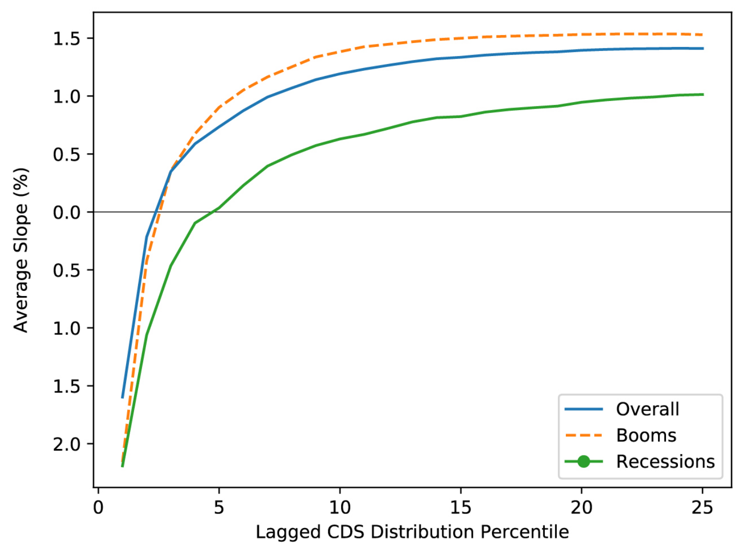


This figure displays the number of firms at each point in time. The three lines refer to the Markit, Compustat-Markit, and Compustat-Markit-Moody's merged samples.

Figure 3: **Term Structure of Credit Spreads and Firm-Level Risk**



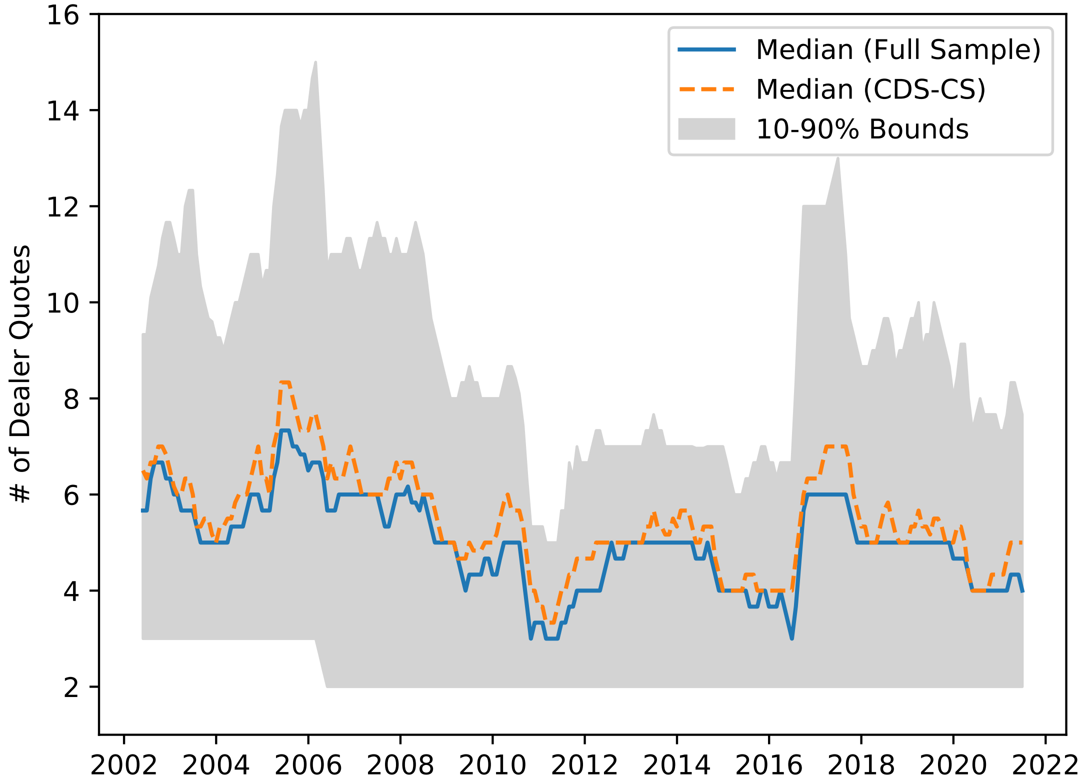
(a) Average Spreads vs. Firm Risk



(b) Average Slope vs. Firm Risk

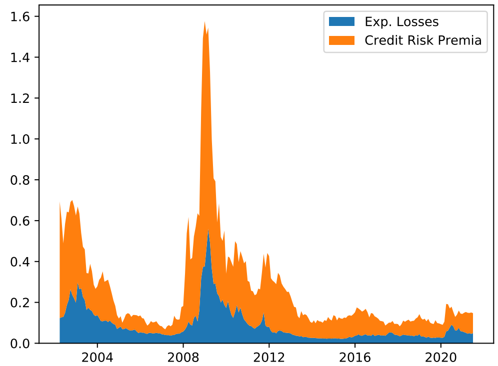
In each panel, we sort firms by their 1Y CDS spread as of the month prior and examine the average value of statistics within the riskiest X% of firms, as measured through the above CDS spread. The top panel examines 1Y vs 5Y spreads as a function of cross-sectional risk, while the bottom panel examines the slope. Additionally, in the bottom panel, the dashed line examines the slope in boom periods while the dotted line in recessions. All data are winsorized at the .5% level.

Figure 4: **CDS Liquidity Over Time**

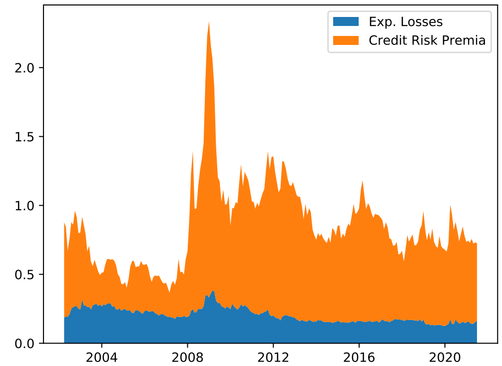


This figure displays the distribution of CDS liquidity over time, as measured by the number of broker dealer quotes per contract. At each point in time, the median, 10%, and 90% quantiles are computed. The blue solid line reflects the 3-month rolling average of the median count of dealer quotes, while the grey area reflects the 3-month rolling average of the 10%-90% bounds. Finally, the orange dashed line reflects the moving average of quotes in the CDS-Compustat sample.

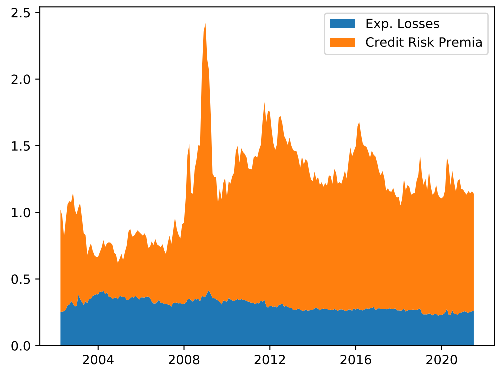
Figure 5: **Expected Losses and Credit Risk Premia Over Time**



(a) 1Y Spreads



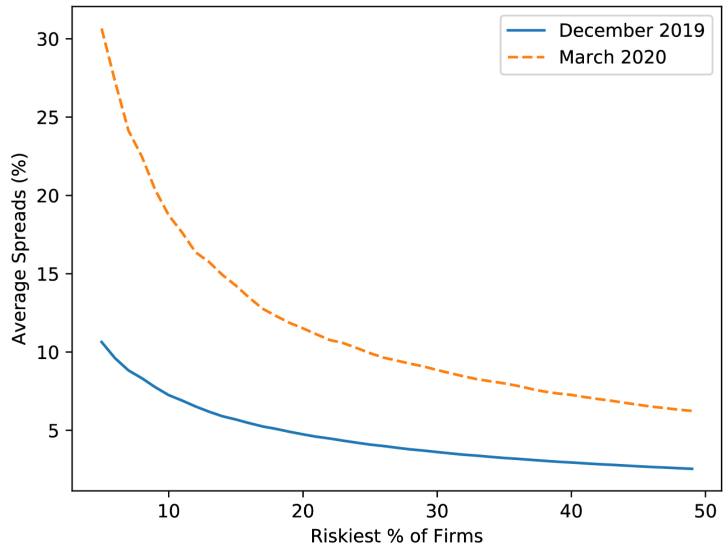
(b) 5Y Spreads



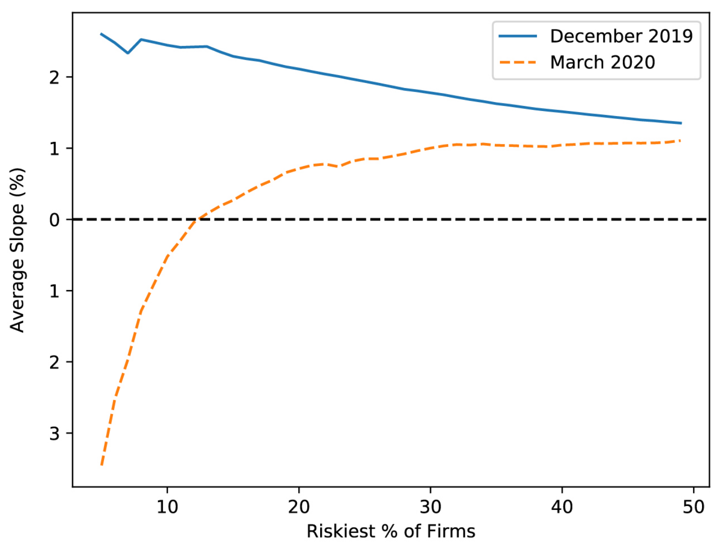
(c) 10Y Spreads

In each panel, we display the median expected loss component and credit risk premium of CDS spreads. The expected losses and credit risk premia are computed using the methodology in Berndt et al. (2018), for each firm across time, at varying maturities. For more details regarding variable construction see the main text.

Figure 6: **Credit Spread Dynamics in Early 2020**



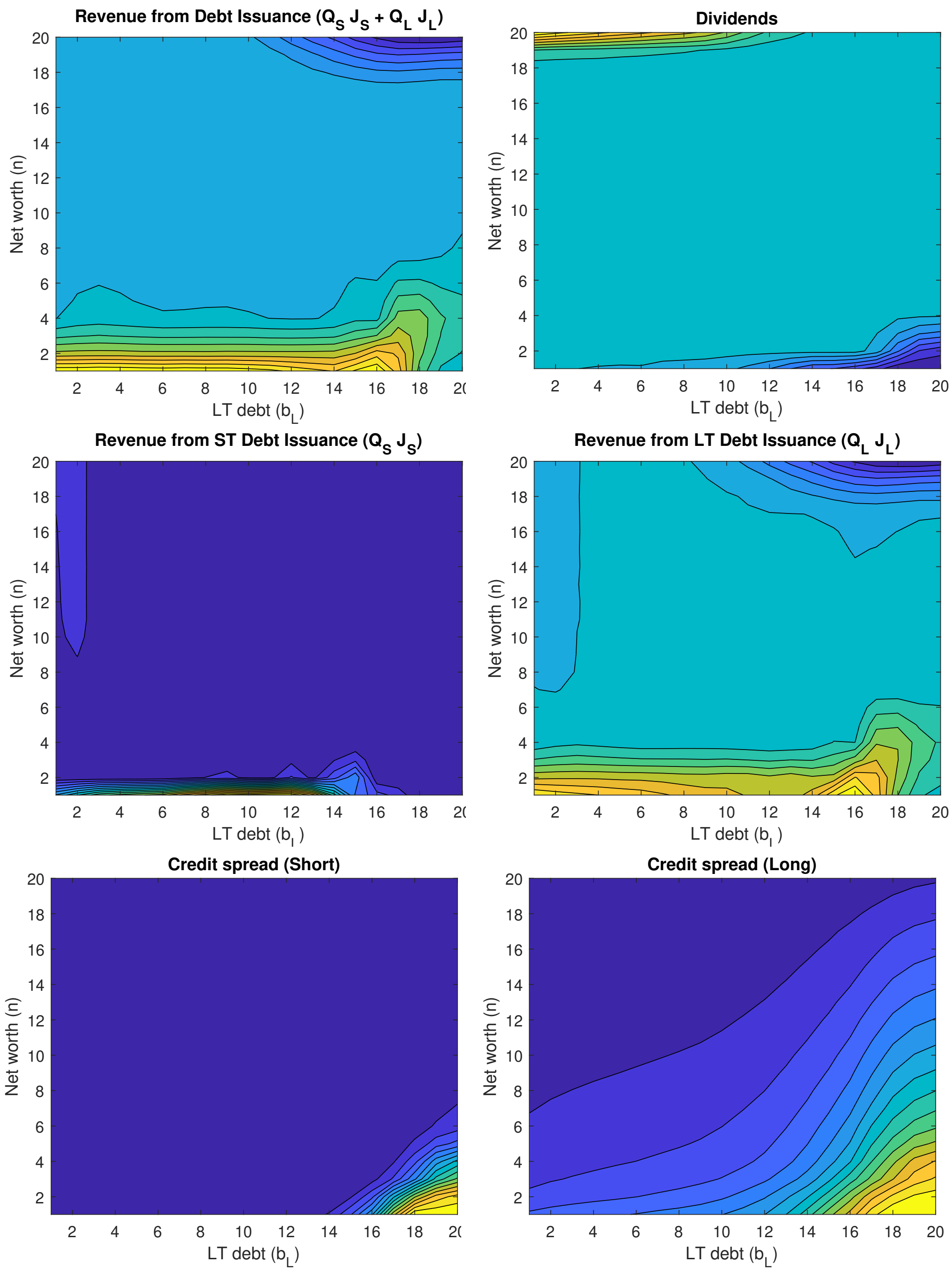
(a) Average Spreads vs. Firm Risk



(b) Average Slope vs. Firm Risk

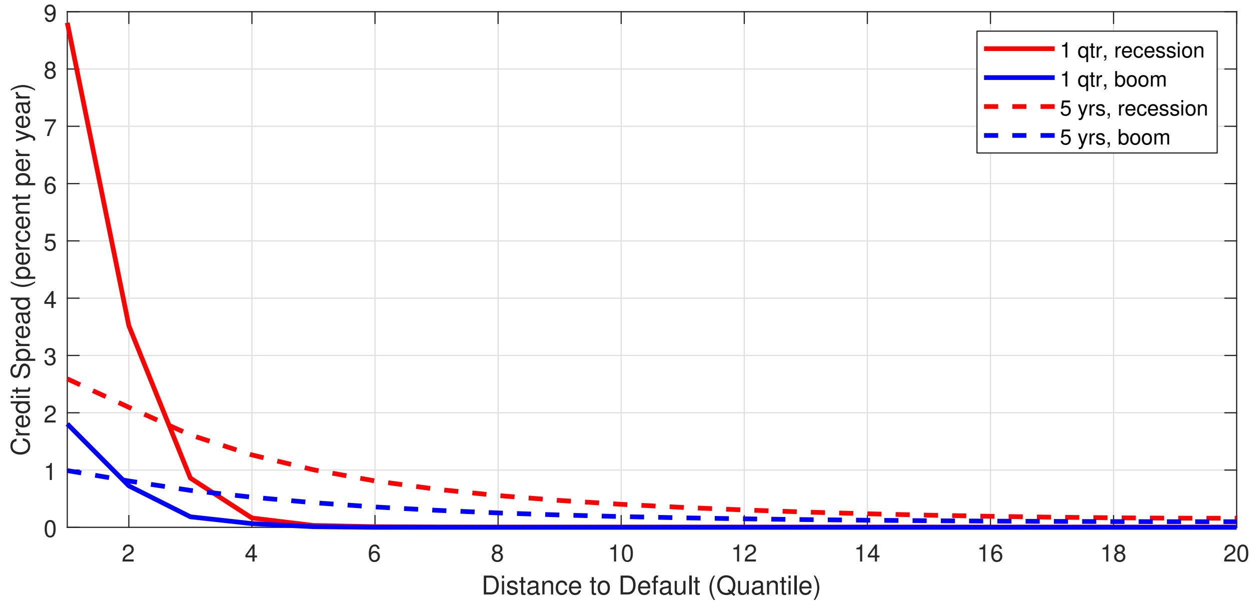
In each panel, we sort firms by their average CDS values (across 1Y, 5Y, and 10Y spreads) as of December 2019, and examine the average value of statistics within the riskiest X% of firms. The top panel examines the shift in average spreads from December 31, 2019 to March 20, 2020, while the bottom panel examines the shift in slope (5Y – 1Y spread) between the two dates. If data not available for these exact days, last available quotes are taken within 3 days prior. All data are winsorized at the 1% level.

Figure 7: **Realized Policy Choices Across the State Space**

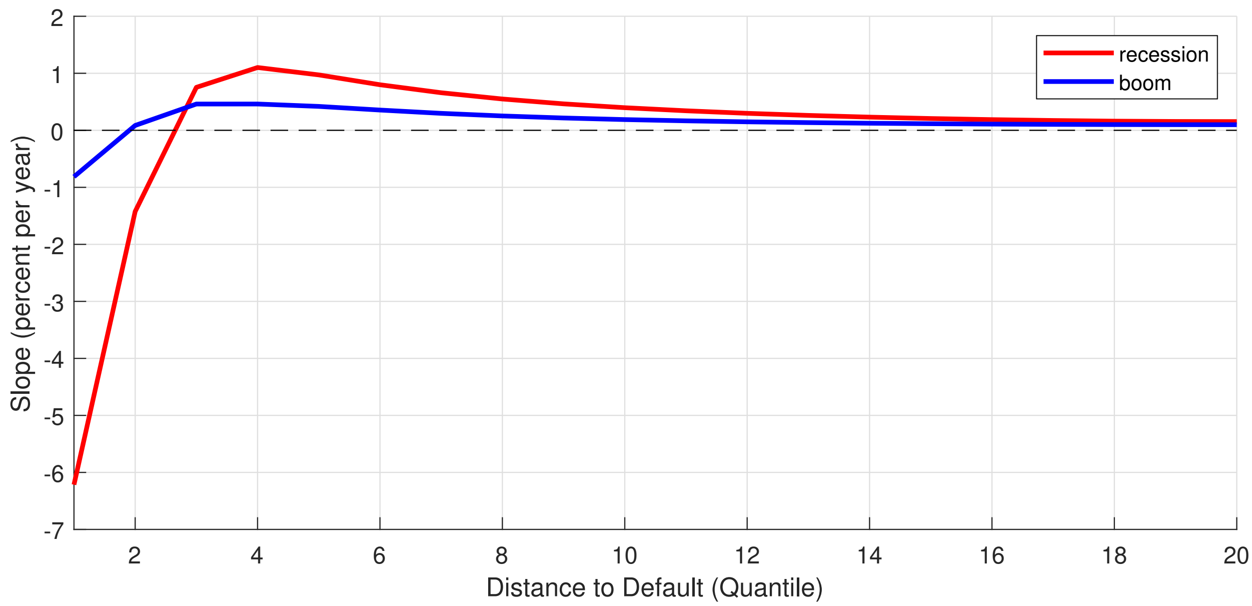


We simulate the model for 1000 firms and 1000 quarters. Then, we sort firms into 20 quantiles according to their rank in the net worth (n) and long-term debt (b_L) distribution, and compute the mean of each variable within each joint quantile. Colors range from blue to yellow, increasing in value of the policy.

Figure 8: **Credit Spreads over the Business Cycle**



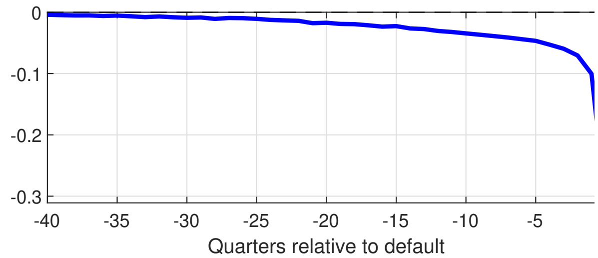
(a) Levels



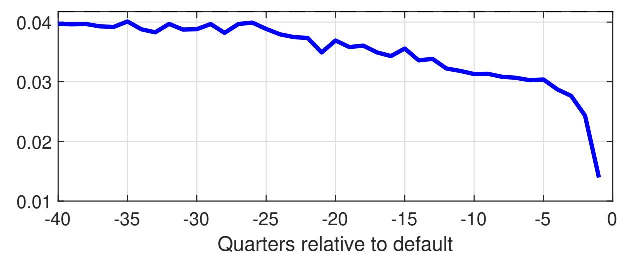
(b) Slope of the Term Structure

Using simulated data across recession and boom states, we sort firms by their equity value (top panel) $v(n, b_L, Z = z)$. After sorting into 20 bins we compute the average short and long-term credit spreads within each bin.

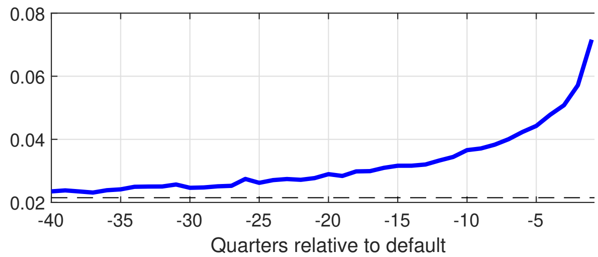
Figure 9: **Default Event Study**



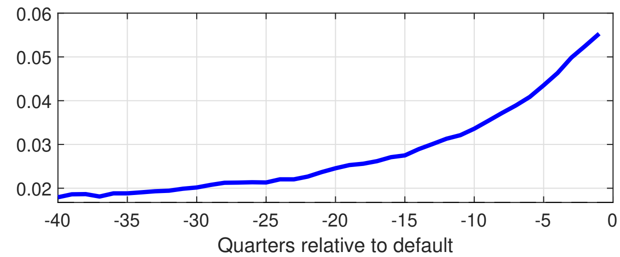
(a) Capital quality shock (ϵ)



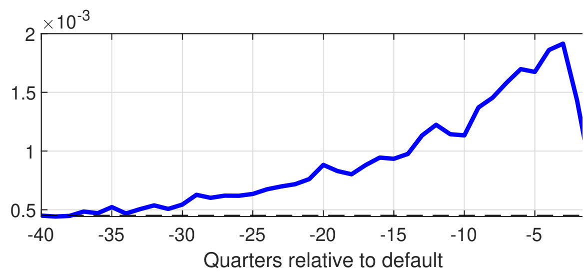
(b) Investment



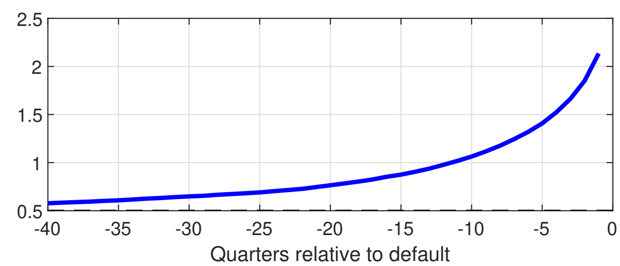
(c) Equity issuance



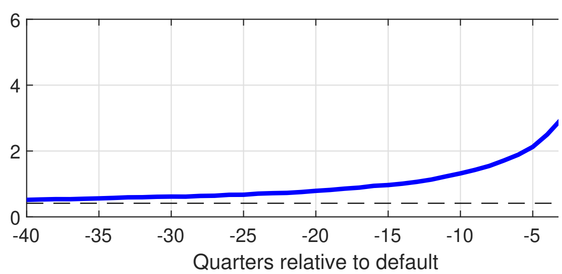
(d) LT debt issuance



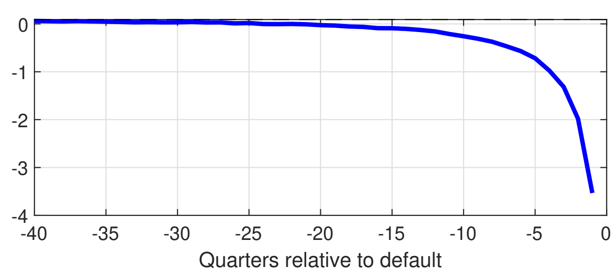
(e) ST debt issuance



(f) LT credit spread



(g) ST credit spread



(h) Credit spread slope

Using simulated data, we collect all firms that eventually default, and then plot the average of the respective variables of these firms in the 40 quarters prior to default. The blue line is the resulting average. The dashed, black line is the unconditional average of the respective variable.

Tables

Table 1: **CDS Summary Statistics**

	Full Sample			Positive States			Negative States		
	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
Full Sample									
mean	1.426	2.211	2.438	1.232	2.004	2.232	1.968	2.672	2.835
xsstddev	3.614	3.611	3.289	3.326	3.322	3.008	4.469	4.353	3.912
skew	7.828	5.360	4.644	8.077	5.700	4.870	6.327	4.696	4.190
kurt	85.564	43.102	33.088	86.353	48.472	35.949	56.186	31.681	25.572
CDS-Compustat Merged Sample									
mean	1.146	1.893	2.140	1.012	1.741	1.990	1.560	2.262	2.459
xsstddev	2.857	3.036	2.805	2.577	2.782	2.565	3.611	3.675	3.341
skew	7.244	5.120	4.382	7.274	5.281	4.400	6.195	4.532	3.954
kurt	75.296	40.849	30.943	75.388	44.096	31.485	55.357	30.304	23.469
CDS-Compustat-EDF Merged Sample									
mean	1.181	1.942	2.189	1.043	1.794	2.043	1.594	2.308	2.504
xsstddev	2.987	3.136	2.877	2.650	2.868	2.633	3.712	3.731	3.370
skew	6.963	5.071	4.410	6.583	4.974	4.233	6.080	4.500	3.979
kurt	68.144	39.480	30.998	60.907	38.458	28.704	54.176	30.771	24.504

This table provides cross-sectional moments of the CDS data, across different maturities and samples. For each sample and maturity, the time series average of the cross-sectional mean, std. deviation, skewness, and kurtosis are reported. The middle panel focuses on dates where quarterly industrial production growth is in the top 25% of realizations. The right-most panel focuses on when industrial production growth is in the bottom 25% of realizations. All data are winsorized at the .5% level, by maturity.

Table 2: **Summary Statistics, by Risk Group**

	Overall	1	2	3	4	5
Full Sample						
1Y CDS Spread	1.411	0.131	0.229	0.439	1.001	5.202
5Y CDS Spread	2.208	0.366	0.641	1.129	2.229	6.633
10Y CDS Spread	2.437	0.577	0.920	1.475	2.636	6.536
5Y - 1Y Spread	0.789	0.235	0.412	0.689	1.228	1.392
Average Firm Count	482.445	96.894	96.676	96.717	96.689	96.653
CDS-Compustat Merged Sample						
1Y CDS Spread	1.148	0.116	0.207	0.355	0.806	4.237
5Y CDS Spread	1.895	0.346	0.596	0.974	1.845	5.695
10Y CDS Spread	2.142	0.553	0.869	1.312	2.249	5.713
5Y - 1Y Spread	0.739	0.230	0.388	0.619	1.039	1.426
Leverage	0.331	0.280	0.287	0.309	0.345	0.433
Long-Term Debt Ratio	0.875	0.839	0.861	0.880	0.891	0.907
Log Book Assets	23.096	23.821	23.362	23.005	22.802	22.474
Log Market Equity	22.925	24.203	23.467	22.919	22.445	21.502
Market-Book Ratio	1.478	2.004	1.606	1.436	1.262	1.054
Cash-Assets Ratio	0.096	0.100	0.090	0.093	0.097	0.100
Investment Growth	0.006	0.010	0.010	0.010	0.006	-0.005
Average Firm Count	263.951	53.230	52.578	53.224	52.578	52.996
CDS-Compustat-EDF Merged Sample						
1Y CDS Spread	1.184	0.126	0.207	0.373	0.823	4.352
5Y CDS Spread	1.944	0.362	0.613	1.006	1.909	5.806
10Y CDS Spread	2.192	0.574	0.898	1.351	2.327	5.796
5Y - 1Y Spread	0.753	0.234	0.405	0.633	1.086	1.419
1Y EDF	1.219	0.088	0.155	0.330	0.803	4.693
5Y EDF	1.042	0.194	0.300	0.485	0.954	3.268
10Y EDF	1.037	0.310	0.445	0.637	1.093	2.694
5Y - 1Y Spread	-0.177	0.107	0.145	0.155	0.152	-1.425
Average Firm Count	201.008	40.594	40.519	39.992	40.519	40.381

This table provides cross-sectional means of the Markit CDS, Compustat, and Moody's EDF data, across different risk groups. For each statistic of interest and risk group, the time series average of the cross-sectional mean is reported. The risk groups are identified by a cross-sectional sort based on lagged average CDS values. All data are winsorized at the .5% level, by maturity.

Table 3: **Credit Spreads in the Tails of the Distribution**

	Overall	25	10	5	2	1
Full Sample						
1Y CDS Spread	1.411	4.428	8.168	12.101	19.183	25.073
5Y CDS Spread	2.208	5.870	9.437	12.976	19.157	23.692
10Y CDS Spread	2.437	5.875	8.963	11.995	17.258	21.056
5Y - 1Y Spread	0.789	1.410	1.192	0.735	-0.215	-1.597
Average Firm Count	482.445	121.016	48.710	24.604	10.131	5.331
CDS-Compustat Merged Sample						
1Y CDS Spread	1.148	3.606	6.553	9.527	14.644	19.469
5Y CDS Spread	1.895	5.028	7.961	10.726	15.405	19.319
10Y CDS Spread	2.142	5.129	7.682	10.051	14.068	17.355
5Y - 1Y Spread	0.739	1.396	1.344	1.086	0.556	-0.388
Leverage	0.331	0.420	0.472	0.509	0.537	0.549
Long-Term Debt Ratio	0.875	0.906	0.910	0.907	0.881	0.851
Log Book Assets	23.096	22.523	22.404	22.408	22.614	22.659
Log Market Equity	22.925	21.641	21.132	20.791	20.468	20.206
Market-Book Ratio	1.478	1.075	0.974	0.886	0.830	0.789
Cash-Assets Ratio	0.096	0.099	0.098	0.098	0.099	0.095
Investment Growth	0.006	-0.003	-0.009	-0.014	-0.020	-0.026
Average Firm Count	263.951	66.373	26.881	13.684	5.791	3.115
CDS-Compustat-EDF Merged Sample						
1Y CDS Spread	1.184	3.703	6.797	10.005	15.368	19.495
5Y CDS Spread	1.944	5.132	8.205	11.178	16.004	19.419
10Y CDS Spread	2.192	5.206	7.870	10.399	14.556	17.374
5Y - 1Y Spread	0.753	1.400	1.339	1.053	0.425	-0.281
1Y EDF	1.219	3.961	7.405	10.925	15.544	19.058
5Y EDF	1.042	2.851	4.677	6.463	8.815	10.517
10Y EDF	1.037	2.414	3.579	4.682	6.072	7.050
5Y - 1Y Spread	-0.177	-1.110	-2.728	-4.462	-6.729	-8.541
Average Firm Count	201.008	50.648	20.508	10.512	4.516	2.639

This table provides cross-sectional means of the Markit CDS, Compustat, and Moody's EDF data, focusing on the tail of the distribution. For each statistic of interest we focus on a small percentage of firms identified through the highest X% of lagged 1Y CDS. Within each group, the time series average of the cross-sectional mean is reported. All data are winsorized at the .5% level, by maturity.

Table 4: **Risk Exposures of CDS, Across Different Measures**

Panel A – Industrial Production

	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
ipgrowth_q	-0.50***	-0.44***	-0.37***	-0.46***	-0.40***	-0.33***	-0.31***	-0.25***	-0.20***
	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
Industry FE	Y	Y	Y	N	N	N	N	N	N
Firm FE	N	N	N	Y	Y	Y	Y	Y	Y
Compustat Controls	N	N	N	N	N	N	Y	Y	Y
R2	0.02	0.03	0.03	0.42	0.53	0.56	0.47	0.61	0.64
N	119447	119447	119447	119447	119447	119447	62536	62536	62536

Panel B – Nonfarm Payroll Employment

	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
nonfarmgrowth_q	-0.36***	-0.30***	-0.24***	-0.34***	-0.27***	-0.22***	-0.18***	-0.12***	-0.08***
	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Industry FE	Y	Y	Y	N	N	N	N	N	N
Firm FE	N	N	N	Y	Y	Y	Y	Y	Y
Compustat Controls	N	N	N	N	N	N	Y	Y	Y
R2	0.02	0.03	0.03	0.42	0.52	0.56	0.46	0.61	0.64
N	119447	119447	119447	119447	119447	119447	62536	62536	62536

Panel C – VIX

	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
VIX_q	0.92***	0.80***	0.63***	0.91***	0.80***	0.63***	0.53***	0.41***	0.30***
	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.04)	(0.07)	(0.06)	(0.05)
Industry FE	Y	Y	Y	N	N	N	N	N	N
Firm FE	N	N	N	Y	Y	Y	Y	Y	Y
Compustat Controls	N	N	N	N	N	N	Y	Y	Y
R2	0.06	0.06	0.05	0.45	0.56	0.58	0.48	0.62	0.65
N	119447	119447	119447	119447	119447	119447	62536	62536	62536

Panel D – Market Returns

	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
sp500ret_q	-0.48***	-0.45***	-0.38***	-0.42***	-0.39***	-0.32***	-0.39***	-0.36***	-0.30***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)	(0.04)	(0.03)
Industry FE	Y	Y	Y	N	N	N	N	N	N
Firm FE	N	N	N	Y	Y	Y	Y	Y	Y
Compustat Controls	N	N	N	N	N	N	Y	Y	Y
R2	0.02	0.03	0.03	0.42	0.53	0.56	0.47	0.62	0.65
N	119447	119447	119447	119447	119447	119447	62536	62536	62536

In this table, each column represents a pooled regression of the form:

$$s_{it}^m = \beta_M M_t + \beta_X' X_{it} + \varepsilon_{it}^m$$

broken out by maturity $m \in (1Y, 5Y, 10Y)$ and an aggregate risk measure M_t that is one of quarterly industrial production growth, nonfarm payroll growth, average VIX (over the quarter), and the S&P 500 quarterly return. The dependent variable represents the CDS spread for firm i at time t. Each panel, top to bottom, uses a different aggregate risk measure. From left to right, each panel uses no fixed effects, industry fixed effects, and firm-level effects. All standard errors are clustered at the firm-level.

Table 5: **Credit Spread Risk Exposures in the XS**

Industrial Production

	Risk Group 1			Risk Group 3			Risk Group 5		
	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
ipgrowth_q	-0.02***	-0.02***	-0.02***	-0.08***	-0.09***	-0.07***	-1.26***	-1.00***	-0.83***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.18)	(0.14)	(0.12)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Compustat Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.28	0.46	0.54	0.33	0.45	0.49	0.49	0.58	0.60
N	12927	12927	12927	12512	12512	12512	12000	12000	12000

Nonfarm Payroll Employment

	Risk Group 1			Risk Group 3			Risk Group 5		
	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
nonfarmgrowth_q	-0.01***	-0.01***	-0.00*	-0.05***	-0.04***	-0.03***	-0.78***	-0.58***	-0.47***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.14)	(0.10)	(0.09)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Compustat Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.27	0.45	0.54	0.30	0.43	0.48	0.47	0.57	0.58
N	12927	12927	12927	12512	12512	12512	12000	12000	12000

VIX

	Risk Group 1			Risk Group 3			Risk Group 5		
	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
VIX_q	0.07***	0.08***	0.06***	0.24***	0.22***	0.14***	2.40***	1.87***	1.47***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)	(0.29)	(0.22)	(0.19)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Compustat Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.46	0.56	0.57	0.61	0.53	0.51	0.54	0.62	0.63
N	12927	12927	12927	12512	12512	12512	12000	12000	12000

Market Returns

	Risk Group 1			Risk Group 3			Risk Group 5		
	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
sp500ret_q	-0.03***	-0.04***	-0.05***	-0.11***	-0.14***	-0.12***	-1.45***	-1.24***	-1.04***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.14)	(0.12)	(0.11)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Compustat Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.30	0.49	0.56	0.37	0.48	0.50	0.50	0.60	0.61
N	12927	12927	12927	12512	12512	12512	12000	12000	12000

In this table, each column represents a pooled regression of the form:

$$s_{it}^m = \beta_M M_t + \beta_X' X_{it} + \varepsilon_{it}^m$$

broken out by maturity $m \in (1Y, 5Y, 10Y)$ and an aggregate risk measure M_t that is one of quarterly industrial production growth, nonfarm payroll growth, average VIX (over the quarter), and the S&P 500 quarterly return. For a specific risk measure, from left to right, we focus on ex-ante risk groups 1, 3, and 5 determined by lagged 1Y CDS spreads. The dependent variable represents the CDS spread for firm i at time t. All standard errors are clustered at the firm-level.

Table 6: **Cross-Sectional Risk Exposures in Recession States**

Overall Cyclicality

	Risk Group 1			Risk Group 3			Risk Group 5		
	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
ipgrowth_q	-0.02***	-0.02***	-0.02***	-0.08***	-0.09***	-0.07***	-1.26***	-1.00***	-0.83***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.18)	(0.14)	(0.12)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Compustat Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.28	0.46	0.54	0.33	0.45	0.49	0.49	0.58	0.60
N	12927	12927	12927	12512	12512	12512	12000	12000	12000

Cyclicality in Recessions

	Risk Group 1			Risk Group 3			Risk Group 5		
	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
ipgrowth_q	-0.03***	-0.02***	-0.01	-0.12***	-0.12***	-0.10***	-1.58***	-1.19***	-1.01***
	(0.00)	(0.00)	(0.01)	(0.02)	(0.02)	(0.02)	(0.29)	(0.22)	(0.18)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Compustat Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.35	0.51	0.56	0.50	0.55	0.53	0.57	0.65	0.66
N	3821	3821	3821	3703	3703	3703	3560	3560	3560

Cyclicality in Non-Recessions

	Risk Group 1			Risk Group 3			Risk Group 5		
	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
ipgrowth_q	0.00***	-0.01***	-0.02***	0.02***	-0.01**	-0.02***	0.10	0.03	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.09)	(0.08)	(0.06)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Compustat Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.28	0.50	0.59	0.26	0.45	0.51	0.54	0.63	0.65
N	9106	9106	9106	8809	8809	8809	8440	8440	8440

In this table, each column represents a pooled regression of the form:

$$s_{it}^m = \beta_{ip}\Delta IP_t + \beta_X' X_{it} + \varepsilon_{it}^m$$

broken out by maturity $m \in (1Y, 5Y, 10Y)$ where the aggregate risk measure is given by quarterly industrial production growth. For a set of states, from left to right, we focus on ex-ante risk groups 1, 3, and 5 determined by lagged 1Y CDS spreads. From top to bottom, we vary the time period of focus (full-sample, recession states, non-recessions). Recession states are determined by the bottom 25% of industrial production growth movements. The dependent variable represents the CDS spread for firm i at time t. All standard errors are clustered at the firm-level.

Table 7: **Cross-Sectional Risk Exposures in Recession States, Robustness**

Cyclicality in Recessions, Payroll Employment

	Risk Group 1			Risk Group 3			Risk Group 5		
	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
nonfarmgrowth_q	-0.01***	-0.00	0.01*	-0.05***	-0.04***	-0.04**	-0.77***	-0.52**	-0.47***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.28)	(0.21)	(0.17)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Compustat Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.34	0.50	0.56	0.46	0.53	0.53	0.55	0.64	0.65
N	3821	3821	3821	3703	3703	3703	3560	3560	3560

Cyclicality in Non-Recessions, Payroll Employment

	Risk Group 1			Risk Group 3			Risk Group 5		
	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
nonfarmgrowth_q	-0.01***	-0.02***	-0.02***	-0.03***	-0.02**	0.00	-0.04	-0.05	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.10)	(0.09)	(0.07)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Compustat Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.29	0.51	0.58	0.27	0.46	0.51	0.54	0.63	0.65
N	9106	9106	9106	8809	8809	8809	8440	8440	8440

Cyclicality in Recessions, Market Returns

	Risk Group 1			Risk Group 3			Risk Group 5		
	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
sp500ret_q	-0.05***	-0.07***	-0.07***	-0.19***	-0.23***	-0.21***	-2.15***	-1.83***	-1.52***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.27)	(0.22)	(0.19)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Compustat Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.38	0.56	0.60	0.56	0.61	0.58	0.59	0.68	0.69
N	3821	3821	3821	3703	3703	3703	3560	3560	3560

Cyclicality in Non-Recessions, Market Returns

	Risk Group 1			Risk Group 3			Risk Group 5		
	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
sp500ret_q	-0.01***	-0.02***	-0.03***	-0.03***	-0.04***	-0.04***	-0.44***	-0.40***	-0.36***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.09)	(0.07)	(0.07)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Compustat Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.30	0.51	0.59	0.27	0.46	0.51	0.54	0.64	0.65
N	9106	9106	9106	8809	8809	8809	8440	8440	8440

In this table, each column represents a pooled regression of the form:

$$s_{it}^m = \beta_M M_t + \beta_X' X_{it} + \varepsilon_{it}^m$$

broken out by maturity $m \in (1Y, 5Y, 10Y)$ where the aggregate risk measure is given by either payroll employment growth or market returns. For a set of states, from left to right, we focus on ex-ante risk groups 1, 3, and 5 determined by lagged 1Y CDS spreads. From top to bottom, for a given aggregate risk measure, we vary the time period of focus (recession states vs. non-recessions). Recession states are determined by the bottom 25% of that measure's movements. The dependent variable represents the CDS spread for firm i at time t. All standard errors are clustered at the firm-level.

Table 8: **Cross-Sectional Risk Exposures, by Liquidity**

Full Sample

	Risk Group 1			Risk Group 3			Risk Group 5		
	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
ipgrowth_q	-0.02***	-0.02***	-0.02***	-0.08***	-0.09***	-0.07***	-1.26***	-1.00***	-0.83***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.18)	(0.14)	(0.12)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Compustat Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.28	0.46	0.54	0.33	0.45	0.49	0.49	0.58	0.60
N	12927	12927	12927	12512	12512	12512	12000	12000	12000

Medium Liquidity ($\geq$ 5 Quotes)

	Risk Group 1			Risk Group 3			Risk Group 5		
	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
ipgrowth_q	-0.02***	-0.02***	-0.02***	-0.09***	-0.10***	-0.07***	-1.46***	-1.14***	-0.92***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.30)	(0.23)	(0.19)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Compustat Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.26	0.42	0.56	0.28	0.41	0.47	0.38	0.48	0.50
N	9157	9157	9157	7866	7866	7866	4365	4365	4365

High Liquidity ($\geq$ 7 Quotes)

	Risk Group 1			Risk Group 3			Risk Group 5		
	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
ipgrowth_q	-0.02***	-0.02***	-0.02***	-0.10***	-0.10***	-0.07***	-1.50***	-1.19***	-0.96***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.36)	(0.28)	(0.22)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Compustat Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.22	0.44	0.62	0.28	0.40	0.47	0.41	0.48	0.51
N	5277	5277	5277	4844	4844	4844	2385	2385	2385

In this table, each column represents a pooled regression of the form:

$$s_{it}^m = \beta_{ip}\Delta IP_t + \beta_X' X_{it} + \varepsilon_{it}^m$$

broken out by maturity $m \in (1Y, 5Y, 10Y)$ where the aggregate risk measure is given by quarterly industrial production growth. For a set of states, from left to right, we focus on ex-ante risk groups 1, 3, and 5 determined by lagged 1Y CDS spreads. From top to bottom, we vary the set of observations based on liquidity grouping (full-sample, medium (or higher) liquidity, and high liquidity). The liquidity measure used to sort observations is based on the number of dealer quotes for a contract at a point in time. The dependent variable represents the CDS spread for firm i at time t. All standard errors are clustered at the firm-level.

Table 9: **Decomposition of CDS Spreads**

	Overall	25	10	5	2	1
			Decomposition of 1Y Spreads			
1Y CDS Spread	1.179	3.664	6.720	9.808	15.021	19.115
1Y Exp. Loss Component	0.837	2.773	5.355	8.045	11.667	14.448
1Y Credit Risk Premium	0.362	0.964	1.490	1.987	3.529	4.552
			Decomposition of 5Y Spreads			
5Y CDS Spread	1.940	5.095	8.127	11.020	15.800	19.175
5Y Exp. Loss Component	0.707	2.023	3.508	5.018	7.053	8.527
5Y Credit Risk Premium	1.227	3.042	4.510	5.786	8.114	9.443
			Decomposition of 10Y Spreads			
10Y CDS Spread	2.189	5.173	7.803	10.284	14.342	17.143
10Y Exp. Loss Componenet	0.690	1.733	2.785	3.839	5.227	6.220
10Y Credit Risk Premium	1.486	3.386	4.861	6.135	8.344	9.609
			Slope by Component			
5Y - 1Y CDS Spread	0.753	1.400	1.330	1.076	0.527	-0.173
5Y - 1Y Exp. Loss Component	-0.116	-0.692	-1.706	-2.772	-4.175	-5.316
5Y - 1Y Credit Risk Premium	0.863	2.068	2.987	3.750	4.510	4.755
Average Firm Count	200.283	50.467	20.447	10.492	4.516	2.639

This table provides cross-sectional moments of the CDS data, decomposed by maturity into expected loss and credit risk premium components. The decomposition methodology from Berndt et al. (2018) is explained in greater detail, in the main text. For each panel, from top to bottom, average moments of a tail portion of the distribution are displayed. All data are winsorized at the .5% level, by maturity.

Table 10: **Cross-Sectional Risk Exposures, by CDS Component**

Total Spread

	Overall			Risk Group 1			Risk Group 3			Risk Group 5		
	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
ipgrowth_q	-0.28***	-0.22***	-0.17***	-0.02***	-0.03***	-0.02***	-0.09***	-0.09***	-0.08***	-1.07***	-0.83***	-0.69***
	(0.04)	(0.03)	(0.03)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.16)	(0.12)	(0.11)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Compustat Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.53	0.67	0.69	0.31	0.48	0.55	0.37	0.46	0.49	0.57	0.66	0.67
N	48062	48062	48062	9829	9829	9829	9545	9545	9545	9561	9561	9561

Expected Loss Component

	Overall			Risk Group 1			Risk Group 3			Risk Group 5		
	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
ipgrowth_q	-0.15***	-0.03**	-0.01	-0.01**	-0.00	0.00	-0.05***	-0.01	0.00	-0.55***	-0.16**	-0.08*
	(0.03)	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.14)	(0.06)	(0.04)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Compustat Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.59	0.69	0.74	0.58	0.83	0.91	0.67	0.78	0.83	0.66	0.73	0.75
N	48062	48062	48062	9829	9829	9829	9545	9545	9545	9561	9561	9561

Risk Premium Component

	Overall			Risk Group 1			Risk Group 3			Risk Group 5		
	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y	1Y	5Y	10Y
ipgrowth_q	-0.13***	-0.18***	-0.15***	-0.01***	-0.03***	-0.02***	-0.04***	-0.09***	-0.08***	-0.51***	-0.62***	-0.54***
	(0.02)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.11)	(0.08)	(0.07)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Compustat Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.38	0.56	0.62	0.45	0.47	0.55	0.55	0.43	0.46	0.43	0.53	0.58
N	48062	48062	48062	9829	9829	9829	9545	9545	9545	9561	9561	9561

In this table, each column represents a pooled regression of the form:

$$y_{it}^m = \beta_{ip}\Delta IP_t + \beta_X' X_{it} + \varepsilon_{it}^m$$

broken out by maturity $m \in (1Y, 5Y, 10Y)$ where the aggregate risk measure is given by quarterly industrial production growth. From top to bottom, the dependent variable is either the total CDS spread, the expected loss component, or the risk premium component. Within a panel, from left to right, we focus on overall sensitivities by maturity, or ex-ante risk groups 1, 3, and 5 determined by lagged 1Y CDS spreads. All standard errors are clustered at the firm-level.

Table 11: **Calibration**

(a) Externally calibrated parameters

	Value	Role	Target
δ	0.037	depreciation rate	Compustat deprecation rate
α	0.65	returns to scale	Hennessy & Whited (2007)
τ	0.35	corporate tax rate	US corporate tax rate
ρ	0.95	persistence, aggregate shock	Zhang (2005)
σ	0.007	volatility, aggregate shock	Zhang (2005)
β	0.9902	discount rate	mean, risk-free rate

(b) Internally calibrated parameters

	Value	Role	Target
ϕ_1	0.175	equity issuance cost	equity issuance, frequency
ξ_S	0.01	ST debt issuance cost	debt issuance, frequency
ξ_L	0.02	LT debt issuance cost	leverage, mean
ψ	36	fixed cost	long-term debt share, mean
σ^{ε}	0.125	volatility, capital quality shock	default rate (1 year)
χ_0	0.5	recovery in default	recovery rate, mean
χ_1	3.75		recovery rate, volatility
χ_2	-75		corr. btw. recovery & default
γ_0	4	household sdf	equity risk premium
γ_1	-20		Sharpe ratio

(c) Targeted moments

	Model	Data
equity issuance, frequency	6.30	5.25
debt issuance, frequency	29.43	24.14
leverage, mean	28.50	32.68
long-term debt share, mean	97.39	87.11
default rate (1 year)	1.26	1.00
recovery rate, mean	0.51	0.40
recovery rate, volatility	0.22	0.10
corr. btw. recovery & default	-0.49	-0.82
equity risk premium	1.24	6.00
Sharpe ratio	0.21	0.20

This table presents parameters used to calibrate the model. The top panel focuses on external parameters that are set outside of model output while the middle panel displays parameters that target data moments. The final panel examines the performance of the targeted moments, based on a simulated panel of 1000 firms for 2000 quarters, where we discard the first 1000 quarters.

Table 12: **Cross-sectional moments**

(a) Means

	Data	Baseline
Leverage	32.68	28.50
Long-Term Debt Share	87.11	97.39
Investment/Capital	2.35	3.87
Debt Issuance/Capital	6.42	1.88
Equity Issuance/Capital	3.57	2.13
Cash Flow/Capital	3.55	1.29
Debt Issuance, Frequency	24.14	29.43
Equity Issuance, Frequency	5.25	6.30

(b) Standard deviations

	Data	Baseline
Leverage	19.88	19.91
Long-Term Debt Share	18.08	14.09
Investment/Capital	1.98	11.56
Debt Issuance/Capital	8.82	3.71
Equity Issuance/Capital	3.19	4.56
Cash Flow/Capital	2.40	0.55
Debt Issuance, Frequency	-	45.57
Equity Issuance, Frequency	-	24.30

(c) Cross-sectional leverage regression

	Data	Baseline
Size (log(K))	0.01	-0.60
Market-to-book	-0.08	-0.24
Profitability	-0.29	-1.12

All model moments are based on a panel simulation of 1000 firms and 2000 periods, discarding the first 1000 periods. We compute cross-sectional moments across firms and time.

Table 13: **Correlations of Average Moments with GDP**

	Data	Baseline
Investment/Assets	0.32	0.35
Debt Issuance/Assets	0.42	-0.01
Equity Issuance/Assets	0.22	-0.23
Cash Flow/Assets	0.36	0.99
LT Share	0.35	0.68
Leverage	-0.23	0.93
Default Rate	-0.55	-0.78
Credit Spread, Long	-0.66	-0.99
Credit Spread, Short	-	-0.96
Recovery rate	-	0.58

All model moments are based on a panel simulation of 1000 firms and 2000 periods, discarding the first 1000 periods. We compute correlations between cross-sectional averages of firm-level variables and model-based GDP.

Table 14: **Credit Spread Moments – Model vs. Data**

(a) All states

	data, 1 qtr	model, 1 qtr	data, 5 yrs	model, 5 yrs
mean	1.44	0.42	2.22	0.51
stddev	3.61	1.49	3.62	0.54
skew	7.74	4.67	5.29	2.04
kurt	83.93	27.21	42.04	7.19

(b) Positive states

	data, 1 qtr	model, 1 qtr	data, 5 yrs	model, 5 yrs
mean	1.24	0.16	2.03	0.31
stddev	3.31	0.55	3.32	0.28
skew	7.99	4.78	5.53	1.71
kurt	84.98	29.35	46.15	5.40

(c) Negative states

	data, 1 qtr	model, 1 qtr	data, 5 yrs	model, 5 yrs
mean	2.06	0.60	2.73	0.66
stddev	4.42	1.96	4.32	0.66
skew	6.14	3.94	4.47	1.68
kurt	55.10	18.74	29.30	5.13

All model moments are based on a panel simulation of 1000 firms and 2000 periods, discarding the first 1000 periods. We compute cross-sectional moments across firms and time. Data moments are from Markit.

Table 15: **Cyclicality of Credit Spreads – Model vs. Data**

(a) All firms

	data, 1 qtr	model, 1 qtr	data, 5 yrs	model, 5 yrs
beta	-0.51	-0.18	-0.45	-0.14
se	0.04	0.00	0.03	0.00

(b) Risk group 1

	data, 1 qtr	model, 1 qtr	data, 5 yrs	model, 5 yrs
beta	-0.02	-0.00	-0.02	-0.03
se	0.00	0.00	0.00	0.00

(c) Risk group 3

	data, 1 qtr	model, 1 qtr	data, 5 yrs	model, 5 yrs
beta	-0.13	-0.00	-0.14	-0.07
se	0.01	0.00	0.01	0.00

(d) Risk group 5

	data, 1 qtr	model, 1 qtr	data, 5 yrs	model, 5 yrs
beta	-1.76	-0.89	-1.47	-0.42
se	0.15	0.01	0.13	0.00

All model moments are based on a panel simulation of 1000 firms and 2000 periods, discarding the first 1000 periods. Each period, we split firms into 5 bins according to their equity value. Within each bin, we then regress credit spreads on the aggregate state Z. The model regressions do not contain firm fixed effects. Data moments are from Markit.

Table 16: **Model Robustness**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
credit spread (1 year)	0.42	0.42	1.45	0.74	0.42	0.61	0.83
credit spread (5 years)	0.51	0.47	0.45	0.35	0.51	0.06	0.51
default rate	1.26	1.19	3.66	1.66	1.26	1.93	1.75
recovery in default	0.51	0.48	0.33	0.43	0.51	0.27	0.49
Leverage	28.50	30.04	77.59	44.64	28.53	81.91	28.01
Long-Term Debt Share	97.39	98.04	97.36	77.10	97.41	33.40	96.06
beta (1 year)	-0.18	-0.17	-1.46	-0.20	-0.18	-0.93	-0.48
beta, (5 years)	-0.14	-0.12	-0.22	-0.07	-0.14	-0.08	-0.16

In this table, we compare model solutions under different parameter sets. Model (1) is the baseline. Model (2) sets $\gamma_0 = 0$ and $\gamma_1 = 0$, such that investors are risk-neutral. Model (3) removes equity issuance costs ($\phi = 0$), model (4) debt issuance costs ($\xi_S = \xi_L = 0$). Model (5) sets $\gamma_1 = 0$, such that risk aversion is constant over the business cycle. Model (6) removes both debt and equity issuance costs, i.e. $\phi = \xi_S = \xi_L = 0$. Model (7) reduces the value of the equity financing constraint.