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Cyclical Dispersion in Expected Defaults*

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Abstract

A growing literature shows that credit indicators forecast aggregate real outcomes. While researchers have proposed various explanations, the economic mechanism behind these results remains an open question. In this paper, we show that a simple, frictionless, model explains empirical findings commonly attributed to credit cycles. Our key assumption is that firms have heterogeneous exposures to underlying economy-wide shocks. This leads to endogenous dispersion in credit quality that varies over time and predicts future excess returns and real outcomes.

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Abstract

A growing literature shows that credit indicators forecast aggregate real outcomes. While researchers have proposed various explanations, the economic mechanism behind these results remains an open question. In this paper, we show that a simple, frictionless, model explains empirical findings commonly attributed to credit cycles. Our key assumption is that firms have heterogeneous exposures to underlying economy-wide shocks. This leads to endogenous dispersion in credit quality that varies over time and predicts future excess returns and real outcomes.

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1 Introduction

Are business cycles driven by fluctuations in credit supply? Recent work in macroeconomics and finance suggests that they are.[1] However, in a frictionless economy, funds should flow to the highest value projects. Credit market conditions should not impact real investment and subsequent economic growth, though they might reflect future investment opportunities. For a so-called credit cycle to trigger a recession, as the literature suggests, financial frictions need to be severe, or agents irrational.

In this paper, we show how credit cycles can appear to drive asset prices and real outcomes, when in fact it is only investment opportunities that matter. We build a frictionless model in which investment opportunities vary over time and differentially across firms. Taken together, these two plausible assumptions are enough to generate the observed co-movements between credit variables and macro aggregates, creating the appearance of a credit cycle.

Our first contribution is empirical and designed to sharpen the implications of earlier studies. We show that a measure of dispersion in credit quality across firms is a robust predictor of both asset prices and macroeconomic aggregates. Specifically, dispersion in credit quality forecasts excess returns on investment-grade and high-yield corporate bonds as well as output and investment growth. This joint predictability of bond returns and of economic outcomes is at the core of the idea of a credit cycle. Predictability of bond returns is often used to validate various indicator of credit market conditions, while forecasting power for economic aggregates is generally interpreted as evidence that credit market conditions impact real activity.

We base our measure of credit dispersion on the differential observed credit quality of firms that are repaying their debt versus those that are issuing debt.

[1] See, for example, Baron and Xiong (2017), Belo, Lin, and Yang (2017), Christiano, Motto, and Rostagno (2014), Gilchrist and Zakrajšek (2012), Greenwood and Hanson (2013), Jermann and Quadrini (2012), Muir (2016).

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Unlike previous studies, we show that this measure is driven almost entirely by variations in the credit quality of firms repaying debt. This finding plays an important role in our modeling choices.

Our second contribution is to develop a tractable quantitative model of optimal firm behavior that accounts for these findings. We assume a cross section of heterogeneous firms making investment decisions under uncertainty. Shocks that are large and rare impact firms' capital stocks and productivity levels. The degree of risk varies both cross-sectionally and in the time series. These simple assumptions have powerful implications. Periods of elevated risk co-occur with low investment rates and low valuations in the aggregate. Moreover, firms with greater risk exposure cut their investments even relative to the aggregate; when risk increases, their relative valuations and credit worthiness decline. These firms will find it optimal to repay their investors at higher rates.

We show that, in both model and data, recessions are associated with spikes in dispersion in credit quality, driven by firms that are repaying their debt. Moreover, because most firms optimally choose lower investment during recessions, changes in measured credit quality predict future adverse economic outcomes, even if a rare shock does not actually occur. When calibrated to match average investment rates and measures of cross-sectional dispersion, our model successfully replicates the sign and the magnitude of the predictive regression results found in the data.

Our paper relates to work by Greenwood and Hanson (2013), who show that a measure of bond issuer quality forecasts excess bond returns. Their findings motivate our focus on cross-sectional dispersion of credit quality. They interpret their results in terms of the importance of bond issuer quality, and argue that this quality deteriorates over the credit cycle. Unlike us, Greenwood and Hanson do not demonstrate predictability of macro-aggregates.[2] Our

[2]Subsequent work uses the Greenwood and Hanson (2013) measure as a proxy for credit

empirical findings also relate to those of Gilchrist and Zakrajšek (2012). They show that credit spreads, constructed using proprietary bond data, forecast recessions. We show that our dispersion measure, though constructed using only Compustat data, has similar predictive power.[3]

Our model offers an explanation of both the predictability of bond excess returns and of macro-aggregates seen in the literature. By offering a parsimonious account of these diverse empirical findings, we show that evidence taken as pointing toward the importance of credit frictions readily admits an alternative interpretation. However, it is not the purpose of our study to show that credit market frictions are necessarily unimportant, nor do we rule out credit frictions as an alternative interpretation for this evidence.[4] Differentiating between these hypotheses remains an objective for future research.

The model developed in the paper is related to a now vast literature on corporate investment, asset prices, and the business cycle, and perhaps more specifically to recent papers by Gourio (2012) and Kuehn and Schmid (2014). We deploy the same neoclassical investment approach to address a substantively different set of questions relating to the credit cycle. Finally, our paper is in similar spirit to recent work by Santos and Veronesi (2016) who show that stylized facts about the movements in leverage and asset prices during "credit booms" arise naturally in a frictionless endowment economy and by Haddad, Loualiche, and Plosser (2017) who use a reduced-form model to argue that it is risk premia, combined with optimal decision making of firms, that drive

market conditions (Bordalo, Gennaioli, and Shleifer, 2016; Lopez-Salido, Stein, and Zakrajšek, 2015).

[3]The link between credit indicators and future economic activity is also present in studies such as Atkeson, Eisfeldt, and Weill (2014), Bernanke, Gertler, and Gilchrist (1999), Carlstrom and Fuerst (1997), Rampini (2005), Gertler and Kiyotaki (2015) and Gomes and Schmid (2017).

[4]A related recent paper is Elenev, Landvoigt, and Van Nieuwerburgh (2017) that shows how credit supply impacts recessions even in the absence of explicit credit supply shocks. In their model, cross-sectional dispersion in investment opportunities can deepen a downturn caused by a productivity shock, through a channel of constrained intermediaries.

variation in buyout activity.

2 Empirical Findings

In this section we develop a new indicator of credit market conditions that is a robust predictor of both macro aggregates and bond excess returns. Our basic measure shares several similarities with that of Greenwood and Hanson (2013) but differs in some key respects discussed below. Crucially, it also suggests a very different interpretation of the evidence and the role that credit supply shocks play in business cycle fluctuations. We then show that our measure is a good predictor of changes in macroeconomic activity and returns on financial assets at multiple horizons.

The main source of data for firm and portfolio level statistics is the CRSP/Compustat merged database. We limit the analysis to nonfinancial firms, excluding regulated and public service firms. To be included in our study, a firm must have positive sales, and assets. Data for the relevant macroeconomic aggregates comes from FRED, while our bond indices are from Barclays. We use quarterly data covering the period between 1976 and 2013. Appendix A provides further details on the definitions and construction of variables used in the study. We provide several additional empirical results in an Online Appendix.

2.1 Characteristics of debt repayers and issuers

To document time-variation in credit market conditions we start by sorting firms into quintiles each quarter according to their net debt repayment. We define net debt repayment as the change in book value of equity minus the change in book value of assets, which we normalize by the book value of assets in the previous quarter. By definition, firms with negative net debt repayment have issued debt during the quarter.[5]

Table 1 summarizes the cross-sectional distribution of repayment activity over the sample period. The table shows that there are about as many debt issuers as repayers during a typical quarter. Debt issuance is especially concentrated in quintile 1, while repayments are concentrated in quintile 5. Henceforth we concentrate on the properties of these extremes and refer to them as the portfolios of *issuers* and *repayers*, respectively.

Table 2 reports statistics for the two extreme portfolios. Beyond their descriptive value, these results establish an early basis for our subsequent analysis. We first compute the Expected Default Frequency (EDF) using the Merton (1974) model. That is, for firm i, we compute:

$$EDF_{it} = \mathcal{N}\left(\frac{-\log\frac{V_{it}}{B_{it}} - \left(\mu_{V_{it}} - \frac{\sigma^2_{V_{it}}}{2}\right)}{\sigma_{V_{it}}}\right), \qquad (1)$$

where $\mathcal{N}(\cdot)$ denotes the standard normal cumulative density function, V_{it} is the market value of the firm i's assets, B_{it} is the book value of debt, $\mu_{V_{it}}$ is the expected asset return, and $\sigma_{V_{it}}$ its asset return volatility. Details on the computation of these values are included in Appendix A.

Table 2 highlights some important differences and similarities between the two extreme portfolios. First, net debt repayers have a higher average expected default frequency than issuers: 0.8% per quarter for repayers versus 0.3% for issuers.[6] Repayers have a strikingly lower investment rate than issuers: 3.5% versus 7.6%. Leverage for repayers is slightly higher than for issuers (33% versus 27%). On the other hand, repayers and issuers are of similar size (logarithm of

[5] Covas and Den Haan (2011) also document cyclical behavior of repayment/issuance. However they focus on repayment behavior across the size distribution instead of the characteristics of repayers and issuers themselves.

[6] EDF is highly positively skewed. Most firms have very small EDFs so the averages are driven by the right tails in both portfolios.

book assets is about 4.77 for both repayers and issuers).

Its popularity and wide acceptance make EDF a natural benchmark to measure credit quality. Still, as we report in the Online Appendix, the default probability measure of Campbell, Hilscher, and Szilagyi (2008) leads to very similar findings. We are, however, agnostic as to the best way to predict default. Our model explains why EDF, as measured, has the properties that it does.

2.2 *Dispersion in expected defaults*

The previous section shows that an important difference between repayers and issuers is their Merton (1974) default probability. When measured over the sample, average EDF for firms in the top debt repayment quintile (the repayers) is significantly higher than that for firms in the bottom quintile (the issuers). We now examine time-series properties of these default probabilities.

In each period, we construct a cross-sectional average of EDFs for repayers and for issuers. Panel A of Figure 1 shows the time series of these cross-sectional averages. Notably, the average EDF for repayers lies above that for issuers in nearly every period. That is, the findings in Table 2 hold not only on average but at almost every point in time. The average EDF for repayers is also far more volatile than that for issuers, taking on especially high values during recessions. For instance, while the average EDF for repayers is below 2% (per quarter) for most of the sample, it spikes to 7% during the financial crisis.

Motivated by these findings, we define dispersion in credit quality as the difference between average EDF of repayers and average EDF of issuers:

$$Dispersion_t = \frac{1}{N_{\text{repayers}}} \sum_{j \in \text{Repayers}} EDF_{jt} - \frac{1}{N_{\text{issuers}}} \sum_{i \in \text{Issuers}} EDF_{it}, \qquad (2)$$

where N_{repayers} and N_{issuers} are the number of firms in top and bottom quintile respectively. Panel B of Figure 1 shows the time series of *Dispersion*. Consistent with the discussion above, *Dispersion* is almost always positive throughout the sample, and reflects mainly time-series variation in the EDFs of repayers.

Our measure recalls the credit quality proxy of Greenwood and Hanson (2013). One key difference, however, is that Greenwood and Hanson replace the actual *value* of EDF for each firm with the NYSE *decile* of the EDF. This obscures important features of the underlying series; for example, the sign.[7] As we show in Figure 1, the difference between the average EDF of repayers and that of issuers is nearly always positive. Firms that repay debt are closer to default, as one might expect from a rational model. In addition, a decile-based measure also obscures asymmetry: namely the fact that it is the EDF of repayers that drives the difference in default frequencies during recessions .

Significantly, Greenwood and Hanson's interpretation of variation in credit dispersion focuses on the behavior of issuers, rather than repayers (they call their measure "Issuer EDF"). They argue that times when issuers have relatively high EDFs are times when markets inefficiently oversupply credit. However, our portfolio EDFs show clearly how the cross-sectional distribution is driven by repayers that are close to default. While repayers and issuers EDFs are not dramatically different during booms, the creditworthiness of repayers deteriorates sharply in recessions. It is this sharply countercyclical behavior of repayers' default frequencies that drives the variation in EDF spreads over time. This evidence is not an easy fit with a narrative based on inefficient credit booms.

2.3 Predicting macro aggregates

A recent influential line of works shows that measures of credit conditions forecast the business cycle (e.g., Gilchrist and Zakrajšek, 2012). We now show

[7]Another difference, which at first glance seems trivial but also obscures interpretation, is that they subtract the average decile for repayers from the average decile for issuers rather than the other way around.

that this is also the case for our measure.

Table 3 presents results from fitting an ordinary least squares (OLS) regression of the average k-quarter GDP and investment growth on *Dispersion*. Specifically, we estimate the following regression

$$\overline{\Delta y}_{t\to t+k} = \alpha + \beta_1\, Dispersion_t + \beta_2\, \Delta y_{t-1\to t} + \epsilon_{t,t+k}. \tag{3}$$

where $\overline{\Delta y}_{t\to t+k}$ denotes the average GDP or investment growth between period t and $t+k$. Panel A shows that *Dispersion* predicts 1-quarter ahead with a highly statistically significant coefficient. Predictability remains statistically significant at horizons up to about one year.

Panel B shows that *Dispersion* is an even more powerful predictor of investment growth. At the 1-quarter horizon, a decrease of 1 percentage point in *Dispersion*, i.e. a lower spread in cross sectional default risk, is associated with a 1.17 percentage point increase in the future quarterly growth rate in investment and a 0.29 percentage point quarterly increase in GDP. We conclude that the cross-sectional dispersion in portfolio EDFs captures important information about future economic conditions.

2.4 Forecasting bond excess returns

Dispersion also strongly forecasts excess bond returns. Table 4 reports results from an OLS regression of continuously-compounded realized bond returns for investment-grade and high-yield bonds, less the continously-compounded government bond return of comparable maturity. That is, we estimate

$$\overline{rx}_{t\to t+k} = \alpha + \beta_1\, Dispersion_t + \beta_2\, \Delta y_{t-1\to t} + \epsilon_{t,t+k}. \tag{4}$$

where $rx_{t\to t+k}$ denotes the continuously compounded excess return measured from period t to $t+k$ and $\overline{rx}_{t\to t+k}$ is the average, namely this quantity scaled by k. In this regression we also control for lagged GDP growth, $\Delta y_{t-1\to t}$.

Table 4 shows that high *Dispersion* forecasts high excess returns on investment-grade and high-yield bonds at horizons ranging from 6 months to 2 years. R^2-statistics are economically significant: 15% at the one-year horizon and 11% at the 2-year horizon for investment grade bonds. The results appear even stronger for high-yield bonds, with R^2-statistics rising as high as 33% at the 2-year horizon.

Researchers often interpret the predictability of excess bond returns as evidence for periods in which investors over-supply credit (e.g. Greenwood and Hanson (2013)). However, the documented time series behavior of *Dispersion* suggests an alternative interpretation, which we now pursue.

3 Model

In this section we show how we can interpret the empirical findings above through the lens of a representative agent asset pricing model with heterogeneous firms. The model's structure is purposefully kept simple to highlight its key mechanisms.[8]

We assume a continuum of heterogenous firms that produce a common final good and maximize the value of their assets by making optimal production, investment and payout decisions. Firms differ in their productivities and in their exposures to aggregate shocks. They own and accumulate capital by taking advantage of stochastic investment opportunities while responding to unexpected changes in the economic environment. In our model, these changes are characterized as shifts in the probability of an extreme, economy-wide,

[8]In particular we do not link consumption to output of firms through a market clearing condition, but rather we value the firms using no-arbitrage. Given that our model has a detailed cross-section of long-lived firms, imposing market clearing would significantly complicate the model without affecting the main economic results. Kuehn and Schmid (2014) adopt a similar approach.

adverse event.

Perhaps the most striking assumption is that we do not characterize the firm's choice of capital structure, relying instead on a setting in which Modigliani and Miller (1958) holds. While this is an extreme view, it allows us to highlight the exact role of real production and investment decisions in generating the main empirical findings. Importantly, this makes it clear that credit market frictions are not required to replicate the empirical evidence. Methodologically, this approach resembles that in Philippon (2009) who shows how bond prices are informative about a firm's investment decisions even in a frictionless setting.

3.1 The stochastic discount factor

We assume all financial claims are owned and priced by an infinitely-lived representative investor with an Epstein and Zin (1989) utility function. Let $\beta \in (0,1)$ be the time-preference rate, γ relative risk aversion and ψ the elasticity of intertemporal substitution, so that the stochastic discount factor (SDF) equals

$$M_{t+1} = \beta^{\theta} \left(\frac{C_{t+1}}{C_t} \right)^{-\gamma} \left(\frac{S_{t+1} + 1}{S_t} \right)^{-1+\theta}, \tag{5}$$

where S_t is the ex-dividend wealth-consumption ratio at time t and $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$.

The representative agent consumes the endowment C_t. The log of the endowment follows the stochastic process

$$\log C_{t+1} - \log C_t = \mu_c + \epsilon_{c,t+1} + \xi_{t+1} x_{t+1}, \tag{6}$$

where $\epsilon_{c,t+1} \overset{iid}{\sim} N(0, \sigma_c^2)$ is the normal-times shock, and μ_c is the normal-times growth rate. Conditional on time-t information, x_{t+1} is a Bernoulli random variable which takes on the value 1 with probability p_t and 0 otherwise. The probability p_t follows a first-order Markov process:

$$\log p_{t+1} = (1-\rho_p)\log\tilde{p} + \rho_p \log p_t + \epsilon_{p,t+1}, \tag{7}$$

where $\epsilon_{p,t+1} \overset{iid}{\sim} \mathcal{N}\left(0, \sigma_p^2\right)$ and independent of $(\epsilon_{t+1}, \xi_{t+1}, x_{t+1})$. Equation (7) implies that the unconditional expectation of p_t equals:

$$\bar{p} = \exp\left\{\log\tilde{p} + \frac{\sigma_p^2}{2(1-\rho_p^2)}\right\}. \tag{8}$$

In what follows, we refer to the event $x_t = 1$ as a disaster at time t, and p_t as the disaster probability. We assume that the disaster size $\xi_{t+1} \overset{iid}{\sim} N(\mu_\xi - \frac{\sigma_\xi^2}{2}, \sigma_\xi^2)$, and independent of $\epsilon_{c,t+1}$. Wachter (2013) assumes a similar structure in continuous time.

Under assumptions (5)-(7), the wealth-consumption ratio depends on p_t alone and solves the fixed-point problem

$$\mathrm{E}_t\left[\beta^\theta\left(\frac{C_{t+1}}{C_t}\right)^{1-\gamma}\Big(S(p_{t+1})+1\Big)^\theta\right] = S(p_t)^\theta. \tag{9}$$

Note that (9) is a first-order condition for the representative investor.

Following Barro (2006), we use as a reference asset the short term government bill, which may default in the case of disaster. Formally, define a random variable $\xi_{g,t}$ such that $\xi_{g,t} = \xi_t$ with probability q and 0 otherwise. That is, if a disaster occurs ($x_t = 1$), the government partially defaults with probability q, and the resulting loss in face value is the same, in percentage terms, as the decline in consumption.[9] Under these assumptions, the price of the government

[9]Conditional on a disaster, the default event is independent of the disaster size.

bill is

$$P_{gt} = \mathrm{E}_t[M_{t+1}(1 - x_{t+1} + e^{\xi_{g,t+1}} x_{t+1})]$$
$$= \mathrm{E}_t[M_{t+1}(1 - x_{t+1} + (1 - q + qe^{\xi_{t+1}})x_{t+1})], \tag{10}$$

The yield is then equal to $1/P_{gt}$ while realized return is given by

$$R_{g,t+1} = \frac{1 - x_{t+1} + e^{\xi_{g,t+1}} x_{t+1}}{P_{gt}}. \tag{11}$$

While outright government default is possible, this assumption mainly captures the likelihood of inflation and currency devaluation to lower the real values of debt in the event of a disaster.

3.2 Firms

The production sector comprises a continuum of heterogeneous firms. Firms maximize the present value of their distributions, taking the investors' stochastic discount factor as given.

3.2.1 Technology

Firm i uses capital K_{it} to produce output Y_{it} according to the Cobb-Douglas production function

$$Y_{it} = z_{it}^{1-\alpha} K_{it}^{\alpha}, \tag{12}$$

where α determines the returns to scale of production and z_{it} is the firm-specific productivity level. We assume z_{it} follows the process

$$\log z_{i,t+1} - \log z_{it} = \mu_i + \epsilon_{c,t+1} + \phi_i \xi_{t+1} x_{t+1} + \omega_{i,t+1}. \tag{13}$$

During normal-times, firm-i productivity grows at rate μ_i and is subject to the same shocks as consumption ($\epsilon_{c,t+1}$). Idiosyncratic shocks also hit each firm:

we let $\omega_{i,t+1} \overset{iid}{\sim} \mathcal{N}(0, \sigma_\omega^2)$, and assume $\omega_{i,t+1}$ and $\omega_{j,t+1}$ are independent for $i \neq j$, and that $\omega_{i,t+1}$ is independent of other $t+1$ shocks for all i. Importantly, firms are exposed to the same Bernoulli shocks as consumption through the term $\phi_i \xi_{t+1} x_{t+1}$, where ϕ_i captures heterogeneous exposure to these shocks.

To ensure firms grow, on average, at the same rate, we normalize firm-specific normal-times growth to

$$\mu_i = \mu_c + \log\left(E[e^{\xi_{t+1}x_{t+1}}]\right) - \log\left(E[e^{\phi_i \xi_{t+1}x_{t+1}}]\right), \tag{14}$$

For simplicity, we assume firms have the same exposure to $\epsilon_{c,t+1}$. Hence, this structure implies that firms are subject to common and idiosyncratic shocks to current productivity, plus an additional independent shock that affects the distribution of future productivity.

3.2.2 Investment opportunities

The law of motion for firm i's capital stock is:

$$K_{i,t+1} = \Big[(1-\delta)K_{it} + I_{it}\Big] e^{\phi_i \xi_{t+1} x_{t+1}}, \tag{15}$$

where δ is depreciation and I_{it} is firm i's investment at time t. Equation (15) captures the depreciation cost necessary to maintain existing capital stock. Following Gourio (2012), it also captures destruction of capital that occurs during disasters. This can proxy for either a literal capital destruction (in the case of war) or a large misallocation in capital due to economic disruption.

Firms face further costs when adjusting capital. Following Hayashi (1982) we assume that each dollar of added productive capacity requires $1 + \lambda(I_{it}, K_{it})$ dollars of expenditures, where

$$\lambda(I_{it}, K_{it}) = \eta \left(\frac{I_{it}}{K_{it}}\right)^2 K_{it}, \tag{16}$$

and where $\eta > 0$ determines the severity of the adjustment cost. Firm i's net total payout to its investors is thus

$$\Pi_{it} = z_{it}^{1-\alpha} K_{it}^{\alpha} - I_{it} - \lambda \left(I_{it}, K_{it} \right). \tag{17}$$

3.2.3 Firm value, optimal investment and payout

Given production and investment decisions, the total value of firm i obeys the following Bellman equation:

$$V_i(K_{it}, z_{it}, p_t) = \max_{I_{it}} \Bigg[z_{it}^{1-\alpha} \left(K_{it} \right)^{\alpha} - I_{it} - \lambda \left(I_{it}, K_{it} \right) + \\ \mathrm{E}_t [M_{t+1} V_i(K_{i,t+1}, z_{i,t+1}, p_{t+1})] \Bigg],$$

subject to (15), where V_i is cum-dividend value for firm i.

Appendix B characterizes the full model solution. Optimal investment for each firm i satisfies the Euler equation

$$\mathrm{E}_t \left[M_{t+1} R^I_{i,t+1} \right] = 1, \tag{18}$$

where the endogenous return to capital accumulation, $R^I_{i,t+1}$, equals

$$R^I_{i,t+1} = \frac{e^{\phi_i \xi_{t+1} x_{t+1}}}{1 + \lambda_I \left(I_{it}, K_{it} \right)} \left(\alpha \frac{Y_{i,t+1}}{K_{i,t+1}} - \lambda_K \left(I_{i,t+1}, K_{i,t+1} \right) + (1-\delta) \Big(1 + \lambda_I \left(I_{i,t+1}, K_{i,t+1} \right) \Big) \right). \tag{19}$$

and $\lambda_j(\cdot)$ denotes the derivative of $\lambda(\cdot)$ with respect to variable j.

Given this optimal investment choice, investor total payout relative to the book value of assets equals

$$\frac{\Pi_{it}}{K_{it}} = \left(\frac{z_{it}}{K_{it}} \right)^{1-\alpha} - \frac{I_{it}}{K_{it}} - \frac{\lambda \left(I_{it}, K_{it} \right)}{K_{it}}. \tag{20}$$

The quantity Π_{it}/K_{it} is the analogue of repayment in the model. Equation (20) highlights the direct link between optimal investment and payout choices. In particular, it becomes apparent that firms with negative payouts (issuers), are also those with relatively high investment rates, a feature that is evident in the summary statistics reported in Table 2.

3.2.4 Debt claims

In this Modigliani-Miller setting, optimal capital structure is not defined. We must therefore assume an exogenous capital structure. As we will show, our results are quite robust to this choice.

Let B_{it} equal the face value of the debt issued by firm i at time t. For simplicity, we assume this debt is due in full in the next period. The firm thus defaults if its value cannot cover the face value of debt: that is $V_{i,t+1} < B_{it}$. If default occurs, bondholders receive a portion ν of the value. To ensure corporate debt remains riskier than government debt, we assume corporate debt suffers the same loss as government debt when disasters occur. The pricing of debt is consistent with the pricing of firm cash flows. That is, the price at time t of the debt claim for firm i is

$$\begin{aligned} D_{it} = \mathrm{E}_t \Big[M_{t+1}(B_{it} \mathbb{1}_{V_{i,t+1} > B_{it}} [(1 - x_{t+1}) + (1 - q + q e^{\xi_{t+1}}) x_{t+1}] \\ + \nu V_{i,t+1} \mathbb{1}_{V_{i,t+1} < B_{it}}) \Big], \end{aligned} \tag{21}$$

while the return is

$$R_{it} = (B_{it} \mathbb{1}_{V_{i,t+1} > B_{it}} [(1 - x_{t+1}) + e^{\xi_{g,t+1}} x_{t+1}] + \nu V_{i,t+1} \mathbb{1}_{V_{i,t+1} < B_{it}}) \frac{1}{D_{it}}. \tag{22}$$

Although bondholders may experience losses on their claims, we assume that there is no deadweight loss and the value of the firm remains unchanged and equal to V_{it}.[10]

[10]Effectively, corporate bonds equal a zero-coupon government bill, short a put option with the face value of debt as the exercise price. Culp, Nozawa, and Veronesi (2018) use

3.2.5 Aggregation and the cross section of firms

Given an exogenous distribution of firms $f(\phi_i)$, it is straightforward to construct any relevant economy-wide aggregates. Specifically, we compute aggregate output and investment as

$$Y_t = \int Y_{it} df \ , \qquad I_t = \int I_{it} df, \tag{23}$$

where I_{it} is the optimal investment for firm i and Y_{it} is the resulting output.

4 Model Implications

We now describe the quantitative implications of our model and compare them with the empirical results in Section 2. We solve the model using standard numerical methods and simulate the resulting artificial economy to investigate its properties. Section 4.1 describes our parameter choices. Section 4.2 compares summary statistics from the model to those in the data. Section 4.3 describes the model solution and illustrates its dynamics using impulse-response functions. We then directly compare regressions in data simulated from the model to those in the historical data in Section 4.4. Our quantitative results are based on 400 independent samples of length 38 years (152 quarters) of firm-level data. Each sample path contains 2500 firms. Appendix C provides additional details on the computation.

4.1 Calibration

To match the sampling frequency in the data, we calibrate the model at a quarterly frequency. Tables 5 and 7 report the values of our key parameters.

similar reasoning to show, empirically, that pseudo-bond spreads constructed using options have predictive power for macroeconomic aggregates. Like our work, their results suggest that bond-market specific frictions do not account for the predictive power of bond spreads.

We choose the normal-times growth rate and volatility, μ_c and σ_c to match post-war U.S. consumption data. Due to their nature as rare events, precise calculations of the probability and distributions of rare events are not possible. We generally choose parameter values that are conservative given prior studies. We set the average probability of a disaster $\bar{p}$ to be 2% per annum (Barro and Ursua (2008) estimates 2.9% based on OECD countries and 3.7% based on all countries). We assume the average consumption lost in a disaster state is 30% with a volatility of 15% (Backus, Chernov, and Martin, 2011). These values are also conservative given that 30% is close to the average disaster size, and that the distribution of disasters appears to have a tail that is much fatter than that implied by the normal distribution.[11]

The process for p_t is latent to the econometrician. We assume values that give a reasonable amount of volatility and persistence, while implying stability of the numerical solution. We set the autoregressive coefficient to be 0.94 (quarterly) with an unconditional standard deviation of 1.93. We solve for the equilibrium wealth-consumption ratio using (9), assuming a seven-node Markov chain for p_t.

Given the wealth-consumption ratio, the SDF follows from (5). We then compute yields and returns on the government bill rate from (10) and (11). We follow Barro (2006) and many subsequent studies, and choose the probability of government default conditional on disaster to be 40%. We calibrate the model so that average yield on government debt in the model matches the average government bill rate, and so that the average premium on the consumption claim, $E\left[\frac{S(p_{t+1})+1}{S(p_t)}\frac{C_{t+1}}{C_t} - R_{g,t+1}\right]$, matches the unlevered equity premium. We match the latter with a value of γ of 3.9, while the former implies a value of β equal to 0.99. Following Gourio (2012), we set ψ to equal 2. Table 6 reports moments for the government bill yield and the consumption claim.[12]

[11] We use per-capita annualized data on personal consumption expenditures from the BEA. We compute quarterly values from annual data by dividing by 4 (μ_c) and by 2 (σ_c).

[12] We compute the return on the value-weighted CRSP index from 1951 to 2013. Following

For firms, we follow Cooper and Ejarque (2003) and set the returns-to-scale parameter $\alpha = 0.7$. We set depreciation $\delta = 4\%$ per quarter to match the average investment-to-capital ratio in the data, and then choose η to match the volatility of investment growth relative to the volatility of output growth in the data.

The process for firm-specific productivity (13) combines two normal components with differential sensitivities, ϕ_i, to disaster realizations. As a result, firm-level investment and repayment decisions reflect a mixture of temporary variation in individual investment opportunities and differential exposure to aggregate shocks. We choose the average value for ϕ so that a firm with this sensitivity has an unlevered equity premium equal to the consumption claim. Because of the implied dividend policy, this ϕ is around 1.25. The value of the other sensitivities are then assumed to be uniformly distributed between 1 and 1.5. Because our results are essentially based on the highest and lowest quintiles, they are not particularly sensitive to the exact form of this distribution. We assume a debt recovery rate in default of 60%, which equals the value-weighted recovery rate for senior unsecured debt estimated by Moody's Investor Services (Ou, Chlu, and Metz, 2011).

It remains to characterize the exogenous process for the face value of debt. Firms are endowed with face value equal to B_{i1}. In order that debt scales with productivity, we define a process for $b_{it} = B_{it}/z_{it}$. Define $v_{it} = V_{it}/z_{it}$ and assume that leverage partially adjusts with firm value:

$$b_{i,t} - b_{i,t-1} = \kappa_i(v_{i,t-1} - v_{i,t-2}), \tag{24}$$

Thus when firm value rises, the firm takes on more debt. Moreover, the adjustment is partial, so that $0 \leq \kappa_i < 1$. The parameters characterizing the exogenous process for debt are set to match the average portfolio leverage

Barro and Ursua (2008), we adjust for leverage by dividing by 1.5.

ratios.[13] We discuss the role of our leverage assumption and the impact of possible alternatives in Section 5.2.

Given simulated series for $b_{it} = B_{it}/z_{it}$ and $v_{it} = V_{it}/z_{it}$, as well as asset returns $V_{i,t+1}/(V_{it} - \Pi_{it})$, we now compute the value of EDF_{it} for each firm i at time t by applying equation (1) in artificial data. The volatility of the idiosyncratic shocks, which has a second-order effect on firm value, but a first-order effect on σ_V, is set to match the average EDFs on the portfolios.

4.2 Portfolio characteristics in simulated data

For each time point in each artificial sample, we sort the cross-section of firms based on repayment, defined by (20). Table 8 reports average characteristics of repayers (the top repayment quintile) and issuers (the bottom quintile), and compares them with their counterparts in historical data.

Our model implies the correct relation between repayment and EDF. Table 8 shows that, on average, repayers have higher default probabilities (EDF) than issuers, and that magnitudes of both are similar to those in the data. Repayers have an average EDF of 0.6%, compared with 0.8% in the data, while issuers have an average EDF of 0.1%, compared with 0.3% in the data. Repayers also exhibit lower average rates of investment — 0.02 versus 0.07 for issuers – and higher (beginning of period) average leverage ratios. These moments also match, qualitatively and quantitatively, their counterparts in the data. These results show that our calibration is plausible, and that the model captures the basic cross-sectional relation between repayment, leverage, investment, and EDF.

[13] This implies values of κ_i that are increasing in ϕ_i and range between 0.2 and 0.3.

4.3 Dynamics of investment, value, and credit quality

To understand the joint dynamics of macroeconomic quantities, firm values, and credit quality, we calculate how these respond to a shift in the probability of a disaster (our main state variable).

Figure 2 shows impulse responses for an increase in p_t from its unconditional average to 2.3% per quarter.[14] The left panel shows the path of the disaster probability: it increases, and then mean-reverts to its average level over the subsequent periods. The middle panel shows the response of the key corporate policies. When the disaster probability increases, firms reduce their investment immediately. The reason is that future cash flows produced by investment are now riskier: they have a lower mean, and are discounted at a higher risk premium. Increased risk also incentivize firms to invest more for precautionary reasons, but, at least given our parameter values, the first two effects dominate. Adjustment costs ensure that investment remains depressed for several years.

Because cash flows from productive activities are now both riskier and lower in expectation, firm values decline, as the middle panel also shows. Over the subsequent years, firm value drifts upward, representing the required compensation to investors for bearing the risk of a disaster which, in this sample, has not occurred. Because the firm's decisions at $t-1$ determine capital at time t (in the absence of a disaster), and because productivity is itself not affected, output responds only with a lag. Eventually, however, lower levels of investment reduce the stock of capital and, with it, firm output. We see both of these responses in the middle panel.

The right panel shows the response of EDF. Because firm value falls when p_t rises, EDF increases on impact. The magnitude of the increase in EDF is much greater, in percentage terms, than the decline in firm value because of the nonlinearity embedded in the calculation of EDF. Usually, EDF is close to

[14] We set productivity shocks to zero. EDF values are computed using $\mu_V = \mu_1$ and $\sigma_V = 0.34$. We consider a firm with $\phi_i = 1$; however, these patterns hold for all firms.

zero. A substantial decline in firm value relative to debt outstanding leads the probability that value crosses the default boundary (according to the Merton model) to be revised sharply upward. This result does not depend on our specification of B_{it}. As we discuss in Section 5.2, EDF will rise as firm values fall, unless firms implausibly reduce debt at a rate faster than the decline in value.[15]

Figure 3 focuses on our measure of dispersion (credit quality of repayers minus credit quality of issuers) and its relation to macro-aggregates. As we have seen, when the probability of disaster rises, the typical firm's value falls. Firms do not suffer this effect equally, however, with those that more exposed to disaster risk, through high ϕ_i, suffering the largest drops in value, and moving closer to default. At the same time, these firms will also experience the largest reduction in investment opportunities making them much more likely to repay their debt. This endogenous behavior of firms naturally produces a cross section where debt repayers exhibit especially high values of EDF.

Putting these facts together, we then find that cross-sectional dispersion in credit quality will increase following an increase in the probability of disaster. Moreover, because all firms face lower investment opportunities, investment falls throughout the economy, and, eventually, so does output. Figure 3 shows how lower levels of investment, and a slow decline in output, follow a spike in *Dispersion*.

Importantly, although the model implies that repayers are high EDF firms, they are not *always* high ϕ_i firms. Improvements in p_t, as well as firm heterogeneity arising from idiosyncratic shocks, can lead high-sensitivity firms to experience increases in value and declines in EDF. At these times, high sensitivity firms become net issuers. However, the relation between EDF and economic conditions is strongly asymmetric. While almost all firms are far

[15] As firms adjust their leverage over time, EDF reverts back to its mean. In our benchmark calibration, the process occurs quickly. We discuss alternative calibrations in Section 5.2.

from their default boundary in good times, recessions produce a sharp rise in EDFs for a subset of firms.

4.4 Predictive regressions in model and data

We now discuss how the qualitative results in Section 4.3 translate into quantitative findings that match the data.

4.4.1 Predictability of macro aggregates

Table 3 shows median betas and R^2-statistics in simulated data, along with these statistics from historical data. We repeat the exact same predictive regressions in the model as discussed previously in the paper. The table shows that the model can replicate the forecastability of both GDP and investment growth. While R^2 statistics are smaller at some horizons in the model, the coefficients on *Dispersion* are of a similar magnitude and the predictability is economically meaningful as in the data.[16]

The reasons for this predictability are apparent in Figure 3. In the model, a rise in *Dispersion* indicates an increase in the probability of economic disaster. This is because some firms are affected more strongly by this probability than others, and EDF is very sensitive to fluctuations in overall firm value. Importantly, because firms that are most affected are also those repaying debt, a sort based on repayment behavior can have much predictive value for macro aggregates.

Although the declines in investment and output growth follow a deterioration in credit quality and create what might appear to an econometrician as a tightening of credit, this is clearly not the case here. The response of output

[16] In the Online Appendix, we report predictability of macro-aggregates by the credit spread and bond premia in the data, replicating the results of Gilchrist and Zakrajšek (2012). After controlling for lagged macro aggregates, these results are less strong than what we find for *Dispersion*. Because credit spreads and risk premia increase with risk, our model also explains credit spread and bond premia predictability, as the Online Appendix shows.

and investment in the model is driven solely by variation in risk premia and associated investment opportunities.

4.4.2 Predictability of bond returns

Besides capturing the predictive power of *Dispersion* for macro-aggregates, our model also explains why *Dispersion* predicts excess returns on corporate bonds, the key empirical finding of Greenwood and Hanson (2013).

Table 4 shows the model's implications for the predictability of bond returns. To construct theoretical counterparts to investment-grade and high-yield portfolios we first sort firms in the model, in every period, according to their EDF and construct five credit quality portfolios. We label the firms in the lowest credit quality portfolio as High Yield and the remaining quintiles as Investment Grade. We then construct bond return indices for both types by weighting individual firm returns by the face value of their debt.[17]

Table 4 shows that the model can also replicate the economically significant R^2 and coefficients found in the data. In the model, *Dispersion* predicts excess bond returns precisely because it proxies for changes in the probability of a disaster. Bonds are priced by the same economic agents who make real investment decisions. When the probability of a disaster rises, firms are more likely to default. Moreover, risk overall increases; the marginal utility of investors rises, leading investors to demand a greater risk premium on bonds. These effects cause bond prices to fall, and their required rates of return to rise. Note that Table 4 does not indicate higher rates of return due to a Peso problem (namely, investors are simply receiving payments in states without disasters). Rather, a high disaster probability leads to a higher population risk

[17] Average (annualized) default rates on investment grade and high yield bonds in the model are 0.3% and 3.9% respectively. This compares with 0.2% and 2.8% default rates in Moody's data on BBB and B bonds respectively (data from 1920 to 2010). Credit spreads are 0.5% for investment grade bonds and 7% for high-yield bonds, compared with 1.6% and 5.7% in the data (from Bank of America, 1997 to 2010).

premium.

Thus, while Greenwood and Hanson (2013) interpret low values of *Dispersion* as a sign of irrational exuberance in credit markets (which is then followed by low subsequent bond returns), our findings suggest that such low values should instead be viewed as indicators of a period of low aggregate risk. When *Dispersion* is low, even firms with poor investment opportunities (repayers) remain unlikely to default. Periods of low excess returns naturally follow from this drop in required premia.

Finally, even though true risk premia in our model are always positive, the OLS regressions predict, at a 1-quarter horizon, negative excess returns on investment-grade debt in some samples. This is because the relation between the disaster probability, default dispersion, and expected returns is nonlinear. Hence, fitted excess returns will sometimes be negative, even without assuming investors are irrational.

5 Robustness

Although we have made a number of important assumptions and simplifications in our analysis above, our results are generally robust to many alternative choices. In this section, we consider two types of robustness analysis. In Section 5.1 we examine the robustness of our empirical results to the measure of repayment. In Section 5.2 we discuss the robustness of our theoretical results to the firm's leverage policy.

5.1 Alternative measures of repayment

In the data, we identify repayment as the negative of the change in book value of debt as a fraction of the previous period's assets.[18] That is, we consider change

[18] We can also identify repayment as actual cash flows to debtholders. However these data are only available annually. In the Online Appendix, we show that *Dispersion* based on

in book equity (BE) minus change in assets, divided by assets in the previous period. In this, we follow the prior literature (Greenwood and Hanson, 2013). Our model, however, raises the question of whether we should distinguish at all between debt repayments and total (debt plus equity) repayments to investors. It is interesting to ask whether the predictive power of *Dispersion* in the data hinges on this distinction.

To answer this question, we now form portfolios on the basis of total repayments. By the balance sheet identity, total repayments equal the amount the firm earns, less the growth in its balance sheet. We therefore compute earnings before interest and taxes ($EBIT$), minus change in assets, divided by assets in the previous period. If A_t represents assets at time t,

$$\text{Total repayments}_{it} = \frac{EBIT_{it} - \Delta A_{it}}{A_{i,t-1}}. \tag{25}$$

This is precisely the sorting variable that the model suggests. The analogue to $EBIT$ in the model is operating earnings minus depreciation and adjustment costs:

$$EBIT_{it} = Y_{it} - \lambda(I_{it}, K_{it}) - \delta K_{it}.$$

Then, (25) equals the definition of payout in (20).[19]

Figure 4 shows that the resulting series for *Dispersion* is very similar to our original series. Moreover, the regression results, shown in Tables 9 and 10

this sort has comparable properties, namely the EDF for repayers is more higher and more cyclical. Its predictive power remains equally high.

[19]It follows from (17) and the evolution of capital K_t in (15) that

$$\begin{aligned}
\Pi_{it} &= Y_{it} - \lambda_{it} - I_{it} \\
&= \underbrace{Y_{it} - \lambda_{it} - \delta K_{it}}_{EBIT} - \underbrace{\left(\hat{K}_{i,t+1} - K_{it}\right)}_{\Delta A_{t+1}}
\end{aligned}$$

where $\hat{K}_{i,t+1}$ is the capital that prevails if there is no disaster, and $\lambda_{it} - \lambda(I_{it}, K_{it})$. Along no-disaster simulation paths, $\hat{K}_t = K_t$. If there were a disaster, presumably it would be represented, in accounting, as a charge against earnings.

are also nearly identical. Sorting firms based on total repayments identifies the same information as sorting on debt repayments.[20]

Finally, our model also suggests that we can ignore repayment entirely and simply sort firms directly based on their investment behavior.[21] Figure 4 shows when we construct portfolios based on disinvestment, or $-\Delta A_{it}$, the resulting series for *Dispersion* is virtually identical to that obtained when we use total repayments. Tables 9 and 10 confirm that the regression results are again very similar.

These results support our view that the main driver of fluctuations in credit quality in the data is the optimal investment response of firms to underlying shocks. As implied by our model, the behavior of debt repayment, per se, does not hold any unique predictive power.[22]

5.2 Alternative leverage models

The previous evidence also serves to illustrate how dispersion in debt behavior is strongly correlated with variation in investment and total repayments. For the same reason we expect that departures from the partial adjustment model for debt (see Eq. (24)) will not play a crucial role in our theoretical results. In this section we investigate this issue and ask what characteristics does the leverage rule need to have for the model to match the data, and whether those characteristics are realistic features of leverage in the data.

First, we consider two very simple, though unrealistic, leverage rules. The

[20]Total repayments are also closely related to free cash flow. Note that the net change in total firm assets is

$$\Delta A = \underbrace{I + \Delta \text{NWC}}_{\text{Non-cash investment}} + \Delta \text{Cash},$$

where NWC is net working capital. Thus free cash flow equals total repayment plus change in cash. However change in cash has no predictive power for macro variables or returns.

[21]Again, see (20).

[22]Cooper, Gulen, and Schill (2008) show that, in the cross-section, firms that grow their assets more earn lower subsequent returns. This finding is in the spirit of our model, where growing firms are less exposed to disaster risk and have a lower required rate of return.

first is that debt simply scales with productivity so $B_{it} = B_i z_{it}$. The second is that leverage is constant, so that $B_{it} = \kappa_i V_{it}$. Our benchmark rule can be thought of as in between these extremes. Note that a perhaps even simpler rule, namely constant debt, would clearly not work in our model, because the fraction of debt to value would become negligible as the firms, and the economy, grow.

Tables 11 and 12 repeat the key predictive regressions for these two simple rules. Nearly all of our results hold, qualitatively, in these two extreme cases. Again, high credit dispersion forecasts both low growth in macroeconomic aggregates and high excess returns on corporate bonds, so that our results are robust to even very wide variations on the leverage rule.

To understand why even these extreme cases can capture our main findings, consider the formula for EDF in (1) where EDF depends negatively on the value-to-debt ratio. When debt scales with productivity, as well as in our benchmark case, the value-to-debt ratio encodes investment opportunities. Thus repayers, which have low investment opportunities in times of economic stress, will also have high EDFs during this time. This reasoning holds as long as debt adjusts only partially to firm value, and is quite robust to the form that this adjustment takes.[23]

How is it then that our results hold even when the leverage ratio remains a constant? The answer is that, even though the value-to-debt ratio is the most important source of variation in EDF, it is not the only source. Another source is asset volatility. Even when value-to-debt is constant, in times of economic stress, repayers are those that have high σ_V^2. This leads them to have

[23]There is one notable difference between the benchmark case and the case when debt scales with productivity, and has to with investment growth regressions at a longer horizon. To capture the forecastability of investment growth, EDF must depend to some extent on changes in investment opportunities. As Figure 2 shows, when the disaster probability changes, investment changes immediate, and so there is an immediate change in the growth rate. Investment level continues to change, slowly, due to adjustment costs. However, investment growth (either positive or negative), converges toward zero.

higher EDFs than issuers, even in the constant leverage case. Because this effect is small, however, EDF variation is unrealistically low, and the regression coefficients are not empirically reasonable.

As a final exercise, we also consider the case of a leverage rule that is directly estimated from the data. We consider a leverage rule that is based on firm characteristics and evolves slowly over time (e.g. Lemmon, Roberts, and Zender (2008)).[24] Applying this detailed empirical leverage rule to the model confirms the key findings that high EDF dispersion forecasts downturns, and high bond risk premia.

6 Additional implications: expected equity returns

Our model rests on a dispersion of loadings on aggregate risk. Firms that are more exposed to risk become repayers when aggregate risk is greater. That means that, while unconditionally firms that are riskier might be either repayers or issuers, sorting on a repayment variable will find firms whose exposure to the risk is greater when the risk itself is greater. As a result, we expect that these firms, because they have greater exposure during the worst times, will command a higher risk premium for equities as well as bonds. In the baseline model, the expected return on total assets for repayers exceeds that of issuers by about 1.3% per annum.

We now ask whether this difference is identifiable in the data. Table 13 shows expected returns and αs relative to the 4-factor model on the repayment quintile portfolios. The difference in expected returns between repayers and issuers is 3% per annum, which is similar to the model in the sense that the model reports returns on total assets. The α relative to the 4-factor model

[24] Specifically, leverage now responds to past book leverage, profitability, and Tobin's Q.

is smaller but still statistically significant. Interestingly, the repayer-minus-issuer portfolio (RMI) loads positively on the HML factor and negatively on the momentum factor, suggesting that these firms share some of the risks of value firms, and that they are "anti-momentum." These findings are intuitive. The higher expected returns on repayers suggests again a narrative based on fundamental properties of these firms, rather than excessive optimism in the bond market per se.

7 Conclusions

This paper makes three contributions. First, we show that firms who are on average repayers of securities have an Expected Default Frequency (EDF) that is both higher and more sensitive to cyclical fluctuations than those who are issuers of securities. Moreover, we observe that repayers exhibit lower investment rates and a higher leverage before rebalancing their debt.

Second, the spread between the EDF of repayers and issuers forecasts movements in key macroeconomic aggregates and bond returns. As a result, this measure appears as a strong leading indicator for the economic cycle and for bond returns. Those facts provide the basis for the theoretical analysis which is perhaps our major contribution.

Finally, we build a rational framework where heterogeneous firms make optimal investment decisions while facing differential exposures to a rare economic disaster. We show that our model is capable of matching the key empirical facts even though our firms face no independent stochastic variation in financial conditions, as would be suggested, by a model with credit frictions.

What allows us to explain a complicated, and seemingly unrelated set of facts with a simple model, is that the same mechanism causing credit quality to fall for repayers also causes lower investment in the aggregate. Lower investment naturally leads to lower output. This result occurs not only when a higher disaster probability predicts an actual disaster, but even in the absence of a disaster. Thus our paper provides a basis for fear-driven business cycles that are predictable, correlated with risk premia, and fully rational.

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Appendix A Variable Definitions and Data

This appendix offers a detailed description of the data sources, and variable construction.

A.1 U.S. Economic Data

Real GDP per Capita: The data are from FRED and are in chained 2009 dollars. The series is taken from the US. Bureau of Economic Analysis and the series ID is A939RX0Q048SBEA.

Real Investment per Capita: To compute Investment growth we use the following data from FRED:

1. Gross private domestic investment, fixed investment, nonresidential and residential, BEA, NIPA table 1.1.5, line 8, billions of USD, seasonally adjusted at annual rates.

2. Personal consumption expenditures on durable goods, BEA, NIPA table 1.1.5, line 4, billions of USD, seasonally adjusted at annual rates.

3. Civilian non-institutional population over 16, BLSLNU00000000Q.

4. Gross Domestic Product, BEA, NIPA table 1.1.5, line 1, billions of USD, seasonally adjusted at annual rates.

5. Real Gross Domestic Product, BEA, NIPA table 1.1.6, line 1, billions of USD, in 2009 chained dollars.

6. GDP deflator equals to the ratio of 4 to 5

A.2 Financial Data

US Corporate High Yield Index: The Barclays US Corporate High Yield Bond Index measures the USD-denominated, high yield, fixed-rate corporate bond market. Securities are classified as high yield if the middle rating of Moody's, Fitch and S&P is Ba1/BB+/BB+ or below. Bonds from issuers with an emerging markets country of risk, based on Barclays EM country definition, are excluded. The data range from 1987 to 2013. We use continuously compounded returns.

US Credit Index (Investment Grade): The Barclays US Credit Index measures the investment grade, US dollar-denominated, fixed-rate, taxable corporate and government-related bond markets. It is composed of the US Corporate Index and a non-corporate component that includes foreign agencies, sovereigns, supranationals and local authorities. The data range from 1976 to 2013. We use continuously compounded returns.

Intermediate Treasuries - 10 yr constant maturity: Returns for the 10 year constant maturity treasury bonds are from GFD. We use continuously compounded returns.

Bond Excess Returns: Barclays' High Yield or Credit Index net of 10 yr constant maturity Treasury.

Equity returns: Firm level equity returns come from CRSP.

A.3 Firm Characteristics: Definitions and Data

Firm-level data are from CRSP/Compustat merged. We exclude companies in the following 2- or 3-digits NAICS sectors: 22 (Utilities); 491 (Postal Service); 52 (Finance & Insurance); 61 (Educational Services); 92 (Public Administration); and 99 (Unclassified), as the model is inappropriate for regulated, financial, or public service firms. Our sample starts from 1976. As regards market-based firm-level variables, we use only common ordinary shares to compute the market capitalization.

Debt Repayment: Debt repayment is the change in equity minus the change in assets, scaled by lagged assets. Book equity is stockholder's equity, plus deferred taxes and investment tax credits (*txditcq*) when available, minus preferred stock (*pstkq*). For stockholder's equity we use *seqq*; if *seqq* is missing we use the book value of common equity (*ceqq*) plus the book value of preferred stock (*pstkq*); finally, if still both of those are missing, we use assets (*atq*) minus total liabilities (*ltq*) minus minority interest (*mibq*). We replace negative stockholder's equity with small positive values of 1$, following a recent literature concerned with possible mis-measurement in those negative book value of equity firms (Campbell et al., 2008). For each quarter, we compute debt repayment in the top and in the bottom NYSE quintile and split all the firms accordingly.

EDF: EDF is computed using the procedure in Bharath and Shumway (2008). For each firm i and year t, we use compute the EDF in (1). In this equation, V_{it} is the market value of the firm's equity plus debt, B_{it}. The debt B_{it}, is a proxy for the debt coming due that quarter (Campbell et al., 2008), namely one fourth of short-term debt (*dlcq*) plus one-eighth of its long-term debt (*dlttq*).

To compute μ_{V_i} and σ_{V_i}, we use monthly returns. μ_{V_i} equals the log average (gross) equity return. $\sigma_{V_i} = \frac{E_{it}}{E_{it}+B_{it}}\sigma_{E_i} + \frac{B_{it}}{E_{it}+B_{it}}(0.05/\sqrt{12} + 0.25\sigma_{E_i})$, where σ_{E_i} is the monthly volatility of the equity return (Bharath and Shumway, 2008). The mean and volatility of equity returns are computed using 12-month rolling windows. B_{it} equals the short-term debt (dlcq) plus half of long-term debt (dlttq), an estimate commonly used by scholars for the market value of debt. When using these quantities in (1), we multiply μ_{V_i} by 3 and σ_{V_i} by $\sqrt{3}$ to express in quarterly terms.

Appendix B Firm's Problem

We define firm value recursively, using the Bellman equation. Unlike in the standard investment problem, capital at time $t+1$ is stochastic given information at time t. We therefore define planned capital, namely the capital that the firm would have in the absence a disasters:

$$\widetilde{K}_{j,t+1} = \frac{K_{j,t+1}}{e^{\phi_j \xi_{t+1} x_{t+1}}}.$$

The value function for firm i then solves

$$\begin{aligned} V_j(\widetilde{K}_{jt} e^{\phi_j \xi_t x_t}, z_{jt}, p_t) = \max_{I_{jt}, \widetilde{K}_{i,t+1}} \Bigg[z_{jt}^{1-\alpha} \left(\widetilde{K}_{jt} e^{\phi_j \xi_t x_t} \right)^{\alpha} - I_{jt} - \lambda \left(I_{jt} \, , \, \widetilde{K}_{jt} e^{\phi_j \xi_t x_t} \right) + \\ + \mathrm{E}_t \left[M_{t+1} V_j(\widetilde{K}_{j,t+1} e^{\phi_j \xi_{t+1} x_{t+1}}, z_{j,t+1}, p_{t+1}) \right] \Bigg] \quad \text{(B.1)} \end{aligned}$$

$$\text{s.t.} \qquad \widetilde{K}_{j,t+1} = (1-\delta) \widetilde{K}_{jt} e^{\phi_j \xi_t x_t} + I_{jt}. \qquad \text{(B.2)}$$

Let q_{jt} be the Lagrange multiplier on (B.2). The first-order conditions with respect to the level of investment and next-period planned capital are

$$[I_{jt}] \qquad q_{jt} = 1 + \lambda_I \left(I_{jt}, \widetilde{K}_{jt} e^{\phi_j \xi_t x_t} \right) \qquad \text{(B.3)}$$

$$[\widetilde{K}_{j,t+1}] \qquad q_{jt} = \mathrm{E}_t \left[M_{t+1} e^{\phi_j \xi_{t+1} x_{t+1}} \frac{\partial V_{j,t+1}}{\partial \widetilde{K}_{j,t+1}} \right]. \qquad \text{(B.4)}$$

Taking the derivative on both sides of (B.1), we obtain

$$e^{\phi_j \xi_t x_t} \frac{\partial V_{jt}}{\partial \widetilde{K}_{jt}} = \alpha z_{jt}^{1-\alpha} \widetilde{K}_{jt}^{\alpha-1} e^{\alpha \phi_j \xi_t x_t} - \lambda_{\widetilde{K}} \left(I_{jt}, \widetilde{K}_{jt} e^{\phi_j \xi_t x_t} \right) + q_{jt}(1-\delta) e^{\phi_j \xi_t x_t}. \quad \text{(B.5)}$$

The derivatives of the adjustment cost function with respect to investment and capital are

$$\lambda_I\left(I_{jt}, \widetilde{K}_{jt}e^{\phi_j\xi_t x_t}\right) = 2\eta\left(\frac{I_{jt}}{\widetilde{K}_{jt}e^{\phi_j\xi_t x_t}}\right) \tag{B.6}$$

$$\lambda_{\widetilde{K}}\left(I_{jt}, \widetilde{K}_{jt}e^{\phi_j\xi_t x_t}\right) = -\eta\left(\frac{I_{jt}}{\widetilde{K}_{jt}}\right)^2 e^{-\phi_j\xi_t x_t}. \tag{B.7}$$

Substituting (B.5) and (B.7) into (B.4), yields

$$\begin{aligned} q_{jt} = \mathrm{E}_t\Bigg[M_{t+1}e^{\phi_j\xi_{t+1}x_{t+1}}\Bigg(&\alpha z_{j,t+1}^{1-\alpha}\left(\widetilde{K}_{j,t+1}e^{\phi_j\xi_{t+1}x_{t+1}}\right)^{\alpha-1} \\ &+\eta\left(\frac{I_{j,t+1}}{\widetilde{K}_{j,t+1}}\right)^2 e^{-2\phi_j\xi_{t+1}x_{t+1}} + q_{j,t+1}(1-\delta)\Bigg)\Bigg]. \end{aligned} \tag{B.8}$$

Linking actual to planned capital, we rewrite (B.8) in terms of the original state variables:

$$q_{jt} = \mathrm{E}_t\left[M_{t+1}e^{\phi_j\xi_{t+1}x_{t+1}}\left(\alpha\frac{Y_{j,t+1}}{K_{j,t+1}} + \eta\left(\frac{I_{j,t+1}}{K_{j,t+1}}\right)^2 + q_{j,t+1}(1-\delta)\right)\right]. \tag{B.9}$$

We use (B.3) and (B.6) to find the Euler equation in the text:

$$\mathrm{E}_t\left[M_{t+1}\underbrace{\frac{e^{\phi_j\xi_{t+1}x_{t+1}}}{1+2\eta\frac{I_{jt}}{K_{jt}}}\left(\alpha\frac{Y_{j,t+1}}{K_{j,t+1}} + \eta\left(\frac{I_{j,t+1}}{K_{j,t+1}}\right)^2 + (1-\delta)\left(1+2\eta\frac{I_{i,t+1}}{K_{j,t+1}}\right)\right)}_{R^I_{j,t+1}}\right] = 1. \tag{B.10}$$

With no adjustment costs, equation (B.10) simplifies to

$$\mathrm{E}_t\left[M_{t+1}\underbrace{e^{\phi_j\xi_{t+1}x_{t+1}}\left(\alpha\frac{Y_{j,t+1}}{K_{j,t+1}} + 1 - \delta\right)}_{R^I_{j,t+1}}\right] = 1. \tag{B.11}$$

Appendix C Model Solution

We use numerical dynamic programming to obtain approximations of the Value function $V(\cdot)$ and Investment policy function $I(\cdot)$ which solve the firm's optimization problem. However, because our firm-specific productivity is a random walk, it is useful to scale individual variables so that we work with a stationary model. Hence, we define the following stationary variables for firm j:

$$y_{jt} = \frac{Y_{jt}}{z_{jt}}, \qquad k_{jt} = \frac{K_{jt}}{z_{jt}}, \qquad i_{jt} = \frac{I_{jt}}{z_{jt}}, \qquad v_{jt} = \frac{V_{jt}}{z_{jt}}$$

The stationary output and the firm's capital law of motion now become:

$$y_{jt} = k_{jt}^{\alpha} \tag{C.1}$$

$$k_{j,t+1} = \frac{(1-\delta)k_{jt} + i_{jt}}{e^{\mu_j + \epsilon_{c,t+1} + \omega_{j,t+1}}} \tag{C.2}$$

The problem is complicated by the fact that the agent does not choose k_{t+1}, because this object is stochastic. So, we define $\widetilde{k}_{j,t+1} = \frac{\widetilde{K}_{j,t+1}}{z_{jt}}$ to be the level of capital next period that the firm chooses so as to maximize its value. $\widetilde{k}_{j,t+1} = k_{j,t+1} e^{\mu_j + \epsilon_{c,t+1} + \sigma_\omega \omega_{j,t+1}} = (1-\delta)k_{jt} + i_{jt}$ is known at time t.

The stationary value function then solves:

$$\begin{aligned} v_j(k_{jt}, p_t) = \max_{i_{jt}, \tilde{k}_{j,t+1}} \Bigg[& k_{jt}^{\alpha} - i_{jt} - \lambda\left(i_{jt}, k_{jt}\right) \\ & + \mathrm{E}_t \left[M_{t+1}\, e^{\mu + \epsilon_{c,t+1} + \omega_{j,t+1} + \phi_j \xi_{t+1} x_{t+1}}\; v_j(k_{j,t+1}, p_{t+1}) \right] \Bigg] \end{aligned} \tag{C.3}$$

where $\lambda\left(i_{jt}, k_{jt}\right) = \eta \left(\frac{i_{jt}}{k_{jt}}\right)^2 k_{jt}$.

We discretize the distributions of the i.i.d. shocks $\epsilon_{c,t+1}$ and $\omega_{j,t+1}$ using the method of Tauchen (1986). We discretize the process for p_t using a 7-

node Markov chain based on the method of Rouwenhorst (1995), which better captures persistent processes (Kopecky and Suen, 2010).

For each firm j, we use an iterative procedure to jointly approximate the value function and the investment policy function on discrete grids for capital $k \in [\underline{k}, \bar{k}]$ and disaster probability p. For each firm j, we start with an initial guess for the value function $v_j^0(k_{j,0}, p)$ and iterate over the Bellman equation recursively so that after l iterations, firm j solves:

$$\begin{aligned} v_j^{l+1}(k_{jt}, p_t) = \max_{i_{jt}, \tilde{k}_{j,t+1}} \; & k_{jt}^{\alpha} - i_{jt}(k_{jt}, p_t) - \lambda\left(i_{jt}(k_{jt}, p_t), k_{jt}\right) \\ & + \mathrm{E}_t\left[M_{t+1}\, e^{\mu_j + \epsilon_{c,t+1} + \omega_{j,t+1} + \phi_j \xi_{t+1} x_{t+1}}\; v_j^l(k_{j,t+1}, p_{t+1})\right] \end{aligned}$$

$$s.t. \qquad k_{j,t+1} = \frac{(1-\delta)k_{jt} + i_{jt}(k_{jt}, p_t)}{e^{\mu_j + \epsilon_{c,t+1} + \omega_{j,t+1}}}$$

After solving the problem of each individual firm j we obtain model-implied moments by taking the averages across 400 simulated economies of 38 years each. Each economy consists of 2500 companies equally distributed across 5 equidistant values of the disaster sensitivity $\phi_j \in [1, 1.5]$. The burn-out sample for each simulation consists of the first 1000 periods.

Table 1. Debt Repayment by Portfolios

Portfolio	10%	50%	90%	Average
1 (Issuers)	−0.313	−0.092	−0.048	−0.178
2	−0.043	−0.027	−0.015	−0.028
3	−0.015	−0.006	0.001	−0.007
4	0.002	0.010	0.021	0.011
5 (Repayers)	0.024	0.050	0.156	0.078

Source: CRSP/Compustat merged

Notes: Each quarter, we sort firms into quintiles based on debt repayment. We define debt repayment as the change in book value of equity minus change in book value of assets over the quarter divided by lagged book value of assets. The table shows the average debt repayment in each portfolio, as well as the 10th, 50th, and 90th percentile. Negative values imply issuance of debt during the quarter. Data are from 1976 to 2013.

Table 2. Characteristics of Repayers and Issuers: Data

Variable	10%	Median	90%	Average	Standard Dev.
EDF - Repayers$_t$	0.000	0.000	$5.32e^{-08}$	0.008	0.070
EDF - Issuers$_t$	0.000	0.000	$8.51e^{-11}$	0.003	0.039
Investment - Repayers$_t$	0.000	0.023	0.091	0.035	0.062
Investment - Issuers$_t$	0.006	0.042	0.178	0.076	0.120
Leverage - Repayers$_{t-1}$	0.030	0.283	0.721	0.332	0.256
Leverage - Issuers$_{t-1}$	0.018	0.215	0.629	0.273	0.232
Size - Repayers$_{t-1}$	2.212	4.613	7.549	4.768	2.046
Size - Issuers$_{t-1}$	2.162	4.623	7.580	4.769	2.072

Source: CRSP/Compustat merged, CRSP

Notes: Each quarter, we sort firms into quintiles based on debt repayment. We define debt repayment as the change in book value of equity minus change in book value of assets over the quarter divided by lagged book value of assets. Repayers are the firms in quintile five, while issuers are the firms in quintile one. EDF is the quarterly expected default frequency from the Merton (1974) model. Investment is quarterly capital expenditures minus sale of property divided by the book value of property plant and equipment. Leverage is financial debt in current liabilities plus long-term debt divided by market value of assets (market value of equity plus book value of debt). Size is the logarithm of book value of assets in millions of dollars. We restrict the analysis to companies whose assets are greater than $1 Mln. Investment is Winsorized at the 1 percent level. Data are from 1976 to 2013.

Table 3.
Forecasting Macroeconomic Quantities

		Horizon k				
		1	2	3	4	8
		Panel A: Δ GDP $_{t\to t+k}$				
β_1	Data	-0.29^{***}	-0.22^{***}	-0.18^{**}	-0.13^{*}	-0.039
		[-3.79]	[-2.77]	[-2.45]	[-1.92]	[-0.56]
	Model	-1.21	-0.76	-0.70	-0.58	-0.32
R^2	Data	0.186	0.172	0.143	0.117	0.035
	Model	0.099	0.257	0.277	0.276	0.199
		Panel B: Δ Investment $_{t\to t+k}$				
β_1	Data	-1.17^{***}	-0.99^{***}	-0.72^{***}	-0.46^{*}	-0.001
		[-4.40]	[-3.47]	[-2.69]	[-1.85]	[-0.01]
	Model	-9.09	-3.20	-1.20	-022	2.52
R^2	Data	0.277	0.227	0.169	0.110	0.023
	Model	0.185	0.062	0.035	0.033	0.036

Source: Bureau of Economic Analysis, CRSP/Compustat merged, CRSP

Notes: Estimation of

$$\overline{\Delta y}_{t\to t+k} = \alpha + \beta_1 \, Dispersion_t + \beta_2 \, \Delta y_{t-1\to t} + \epsilon_{t,t+k}.$$

The table reports the slope coefficients and R^2 statistics from predictive regressions of average GDP (Panel A) and average investment growth (Panel B) over various horizons onto dispersion in credit quality (*Dispersion*) and growth in GDP between time $t-1$ and t both in the data and (the median values) within the model. We define dispersion as average EDF of repayers minus average EDF of issuers. We present t-statistics from Newey and West (1987) standard errors, with $k-1$ lags, where k is the regression horizon, in squared parentheses. Data are quarterly from January 1976 until September 2013. Statistical significance levels at 5% and 1% are denoted by ** and ***, respectively. For the model, simulations are run on $N = 400$ time-series paths of the same length as the empirical sample.

Table 4.
Forecasting Excess Returns on Bonds

		Horizon k				
		1	2	3	4	8
		Panel A: Investment Grade				
β_1	Data	0.36	0.71***	0.75***	0.77***	0.46**
		[0.84]	[2.81]	[3.13]	[3.28]	[2.46]
	Model	0.24	0.13	0.10	0.08	0.06
R^2	Data	0.008	0.089	0.126	0.149	0.112
	Model	0.582	0.324	0.271	0.249	0.180
		Panel B: High Yield				
β_1	Data	0.67	1.26**	1.66***	1.61***	0.86**
		[0.90]	[2.22]	[3.40]	[3.46]	[2.38]
	Model	2.51	1.48	1.15	0.88	0.69
R^2	Data	0.048	0.144	0.198	0.243	0.334
	Model	0.524	0.288	0.254	0.240	0.184

Source: Barclays Capital, Global Financial Data, CRSP/Compustat merged, CRSP

Notes: Estimation of

$$\overline{rx}_{t\to t+k} = \alpha + \beta_1 \, Dispersion_t + \beta_2 \, \Delta y_{t-1\to t} + \epsilon_{t,t+k}.$$

The table reports the slope coefficients and R^2 statistics from predictive regressions of average excess log returns on bonds over various horizons onto dispersion in credit quality (*Dispersion*) and growth in GDP between time $t-1$ and t. Panel A reports results for investment grade bonds; panel B reports results for high yield bonds. We define dispersion as average EDF of repayers minus average EDF of issuers. We present t-statistics from Newey and West (1987) standard errors, with $k-1$ lags, where k is the regression horizon, in squared parentheses. Investment-grade bond data are quarterly from January 1976 until September 2013. High-yield bond data are quarterly from January 1987 to June 2013. Statistical significance levels at 5% and 1% are denoted by ** and ***, respectively. To construct the investment grade and high-yield indices within the model, each period we sort companies based on their expected default frequency. High yield bonds are bonds issued by firms in the top quintile of EDF. Investment grade bonds are bonds issued by firms in the first quintile of EDF. Simulations are run on N = 400 time-series paths of the same length as the sample for January 1976 to September 2013 at the quarterly frequency.

Table 5. Parameter Values for the Aggregate Economy

Description	Parameter	Value
Relative risk aversion	γ	3.88
Rate of time preference	β	0.99
Elasticity of intertemporal substitution	ψ	2
Persistence of probability of disaster	ρ_p	0.94
Volatility of log probability of disaster	σ_p	0.66
Average probability of disaster	$\overline{p}$	0.0052
Mean of the disaster distribution	μ_ξ	$\log(1-0.30)$
Volatility of the disaster distribution	σ_ξ	0.15
Average growth in log consumption (normal times)	μ_c	0.00495
Volatility of log consumption growth (normal times)	σ_c	0.0089
Probability of government default given disaster	q	0.40

Notes: The representative agent has Epstein and Zin (1989) utility with risk aversion γ, elasticity of intertemporal substitution ψ, and time discount factor β. The aggregate endowment is given by

$$C_{t+1} = C_t e^{\mu_c + \epsilon_{c,t+1} + \xi_{t+1} x_{t+1}}$$

where x_{t+1} is a disaster indicator that takes the value 1 with probability p_t. The variable ξ_{t+1} is normally distributed with mean $\mu_\xi - \frac{\sigma_\xi^2}{2}$ and standard deviation σ_ξ. We assume that the logarithm of p_t follows a Markov process with persistence ρ_p and volatility σ_p. In the model, we assume that the government bill experiences a loss, conditional on a disaster, with probability q; in this case the percentage loss is equal to the percent decline in consumption.
We calibrate the model at a quarterly frequency.

Table 6. The Consumption Claim and the Government Bill Rate

Moment	Data	Model
Average government bill yield	0.0101	0.0100
Government bill yield volatility	0.0222	0.0233
Average premium on the consumption claim	0.0532	0.0598
Volatility of the consumption claim return	0.1226	0.0893

Notes: This table reports aggregate moments in the data and in simulations from the model. All data and model moments are in annualized terms. In the data we compute the average premium and volatility on the consumption claim using the CRSP value-weighted return, divided by 1.5 to adjust for leverage. Data are from 1951-2013. Model moments are from a quarterly simulation of length 250,000 years.

Table 7. Parameter Values for Individual Firms

Description	Parameter	Value
Returns to scale	α	0.70
Depreciation rate	δ	0.04
Adjustment cost on capital	η	7.5
Volatility of idiosyncratic TFP shock (normal times)	σ_ω	0.13
Minimum sensitivity to disasters	$\min_i(\phi_i)$	1.00
Maximum sensitivity to disasters	$\max_i(\phi_i)$	1.50
Recovery value given default	ν	0.60

Notes: The table shows parameter values for the firm's problem. We assume that each firm i has a Cobb-Douglas production function of the form

$$Y_{it} = z_{it}^{1-\alpha} K_{it}^{\alpha}$$

where the logarithm of the firm-specific productivity level, z_{it}, follows a random walk process given by:

$$\log z_{i,t+1} = \log z_{it} + \mu_i + \epsilon_{c,t+1} + \phi_i \xi_{t+1} x_{t+1} + \omega_{i,t+1}$$

Firms net cash flows to its investors are given by

$$\Pi(K_{it}, z_{it}) = z_{it}^{1-\alpha} K_{it}^{\alpha} - I_{it} - \eta \left(\frac{I_{it}}{K_{it}} \right)^2 K_{it}$$

and the law of motion for each firm's capital stock is:

$$K_{i,t+1} = \Big[(1-\delta) K_{it} + I_{it} \Big] e^{\phi_i \xi_{t+1} x_{t+1}}$$

We calibrate the model at a quarterly frequency. Values for the sensitivity of disaster are in equal increments starting from the minimum and going to the maximum.

Table 8. Characteristics of Repayers and Issuers

Variable	Data	Model
EDF - Repayers$_t$	0.008	0.006
EDF - Issuers$_t$	0.003	0.001
Investment - Repayers$_t$	0.035	0.020
Investment - Issuers$_t$	0.076	0.070
Leverage - Repayers$_{t-1}$	0.332	0.357
Leverage - Issuers$_{t-1}$	0.273	0.312

Notes: We simulate 400 paths at a quarterly frequency of length equal to the 1976–2013 sample. Each sample path contains 2500 firms. Along each sample path we follow the procedure for forming repayment-based portfolios described in Table 2. We report averages for the portfolios over the sample paths and compare them with averages from the data. EDF, Investment, and Leverage are computed in a method comparable to the data. For example, investment is I_{it} in the model divided by capital K_{it}. Leverage is defined using the book value B_{it} of debt divided by the market value of assets V_{it}.

Table 9. Forecasting Macroeconomic Quantities: Alternative Sorting Variables

Sorting variable		Horizon k (quarters) 1	2	3	4	8
		Panel A: Δ GDP $_{t\to t+k}$				
Total repayments	β_1	-0.27^{***}	-0.20^{***}	-0.17^{**}	-0.12^{**}	-0.04
		[−3.85]	[−2.75]	[−2.47]	[−2.16]	[−0.79]
	R^2	0.195	0.176	0.146	0.119	0.037
Disinvestment	β_1	-0.22^{***}	-0.16^{***}	-0.13^{**}	-0.09^{*}	-0.032
		[−3.79]	[−2.77]	[−2.19]	[−1.74]	[−0.62]
	R^2	0.188	0.173	0.140	0.113	0.035
		Panel B: Δ Investment $_{t\to t+k}$				
Total repayments	β_1	-1.08^{***}	-0.93^{***}	-0.68^{***}	-0.46^{**}	-0.03
		[−4.55]	[−3.63]	[−2.81]	[−2.17]	[−0.15]
	R^2	0.282	0.234	0.174	0.115	0.023
Disinvestment	β_1	-0.93^{***}	-0.77^{***}	-0.53^{**}	-0.32^{*}	-0.003
		[−4.65]	[−3.72]	[−2.52]	[−1.66]	[−0.01]
	R^2	0.285	0.231	0.166	0.107	0.023

Source: Bureau of Economic Analysis, CRSP/Compustat merged, CRSP

Notes: Estimation of

$$\overline{\Delta y}_{t\to t+k} = \alpha + \beta_1\, \mathit{Dispersion}_t + \beta_2\, \Delta y_{t-1\to t} + \epsilon_{t+k}.$$

The table reports the slope coefficients and R^2 statistics from predictive regressions of average GDP growth (Panel A) and investment growth (Panel B) over various horizons onto dispersion in credit quality (*Dispersion*) and the dependent variable between time $t-1$ and t. We define dispersion in two different ways. Dispersion is the average EDF of firms in the highest quintile of total repayments (EBIT- change in assets) minus firms in the lowest. We also sort on disinvestment only ($-\Delta A_t$). Total repayments and disinvestment are both relative to the lagged value of assets. We construct t-statistics from Newey and West (1987) standard errors, with $k-1$ lags, where k is the regression horizon. Data are quarterly from January 1976 until September 2013. Statistical significance levels at 10%, 5% and 1% are denoted by *, ** and ***, respectively.

Table 10. Forecasting Excess Returns on Bonds: Alternative Sorting Variables

Sorting variable		Horizon k (quarters) 1	2	3	4	8
Panel A: Investment Grade						
Total repayments	β_1	0.19	0.52**	0.57**	0.61***	0.38**
		[0.49]	[2.07]	[2.44]	[2.87]	[2.35]
	R^2	0.003	0.071	0.101	0.124	0.102
Disinvestment	β_1	0.45	0.58**	0.55**	0.54**	0.34**
		[1.17]	[2.42]	[2.41]	[2.59]	[2.12]
	R^2	0.023	0.101	0.120	0.135	0.113
Panel B: High Yield						
Total repayments	β_1	0.20	0.77	1.11**	1.23***	0.72**
		[0.27]	[1.19]	[2.42]	[2.81]	[2.22]
	R^2	0.043	0.127	0.158	0.209	0.328
Disinvestment	β_1	0.84	1.07**	1.24***	1.19***	0.65**
		[1.30]	[2.02]	[2.73]	[2.87]	[1.97]
	R^2	0.058	0.153	0.194	0.235	0.335

Source: Bureau of Economic Analysis, CRSP/Compustat merged, CRSP

Notes: Estimation of

$$\overline{rx}_{t\rightarrow t+k} = \alpha + \beta_1\, \mathit{Dispersion}_t + \beta_2\, \Delta y_{t-1\rightarrow t} + \epsilon_{t+k}.$$

The table reports the slope coefficients and R^2 statistics from predictive regressions of average excess log returns on investment grade bonds (Panel A) and high yield bonds (Panel B) over various horizons onto dispersion in credit quality (*Dispersion*) and growth in GDP between time $t-1$ and t. We define dispersion in two different ways. Dispersion is the average EDF of firms in the highest quintile of total repayments (EBIT- change in assets) minus firms in the lowest. We also sort on disinvestment only ($-\Delta A_t$). Total repayments and disinvestment are both relative to the lagged value of assets. We construct t-statistics from Newey and West (1987) standard errors, with $k-1$ lags, where k is the regression horizon. Investment-grade bond data are quarterly from January 1976 until September 2013. High-yield bond data are quarterly from January 1987 to June 2013. Statistical significance levels at 10%, 5% and 1% are denoted by *, ** and ***, respectively.

Table 11.
Forecasting Macroeconomic Quantities: Alternative Leverage Models

		Horizon k				
		1	2	3	4	8
Panel A: Δ GDP $_{t\to t+k}$						
β_1	$\frac{B_t}{V_t}=\chi$	-7.11×10^5	-7.17×10^5	-5.01×10^5	-4.46×10^5	-2.40×10^5
	$b_t=\chi$	-0.08	-0.06	-0.05	-0.05	-0.03
	Estimated	-2.19	-1.68	-1.57	-1.48	-1.03
R^2	$\frac{B_t}{V_t}=\chi$	0.053	0.195	0.210	0.217	0.184
	$b_t=\chi$	0.133	0.308	0.323	0.314	0.237
	Estimated	0.089	0.238	0.254	0.270	0.214
Panel B: Δ Investment $_{t\to t+k}$						
β_1	$\frac{B_t}{V_t}=\chi$	-3.66×10^6	-3.94×10^5	-2.77×10^4	-6.82×10^3	-1.61×10^3
	$b_t=\chi$	-0.34	-0.02	0.21	0.37	0.91
	Estimated	-22.86	-13.97	-8.81	-5.85	4.51
R^2	$\frac{B_t}{V_t}=\chi$	0.012	0.012	0.015	0.019	0.023
	$b_t=\chi$	0.050	0.018	0.035	0.049	0.096
	Estimated	0.084	0.035	0.031	0.033	0.039

Notes: Estimation of

$$\overline{\Delta y}_{t\to t+k}=\alpha+\beta_1\,Dispersion_t+\beta_2\,\Delta y_{t-1\to t}+\epsilon_{t+k}.$$

The table reports the β_1 coefficients and R^2 statistics computed from alternative models of leverage. In the first case ($\frac{B_t}{V_t}=\chi$), we fix market leverage to a constant value dependent on the level of sensitivity ϕ_i. In the second scenario we keep the scaled book value of debt constant and variations in market leverage will come only through variation in the market value of assets. In the final case, firms choose the book value of debt according to the following rule (which was estimated in our empirical sample)

$$\frac{B_t}{K_t}-\kappa_0=0.886\left(\frac{B_{t-1}}{K_{t-1}}-\kappa_0\right)-0.0077\frac{\Pi_{t-1}}{K_{t-1}}-0.0013\frac{V_{t-1}}{K_{t-1}}$$

Simulations are run on N = 400 time-series paths of the same length as the sample for January 1976 to September 2013 at the quarterly frequency.

Table 12.
Forecasting Excess Returns on Bonds: Alternative Leverage Models

		Horizon k				
		1	2	3	4	8
Panel A: Investment Grade						
β_1	$\frac{B_t}{V_t} = \chi$	1.90×10^4	1.72×10^4	1.11×10^4	1.09×10^4	0.49×10^4
	$b_t = \chi$	0.04	0.03	0.02	0.02	0.01
	Estimated	1.01	0.76	0.62	0.53	0.32
R^2	$\frac{B_t}{V_t} = \chi$	0.154	0.156	0.153	0.152	0.130
	$b_t = \chi$	0.810	0.680	0.608	0.518	0.339
	Estimated	0.376	0.327	0.309	0.276	0.182
Panel B: High Yield						
β_1	$\frac{B_t}{V_t} = \chi$	1.01×10^5	1.05×10^5	0.83×10^5	0.61×10^5	0.29×10^5
	$b_t = \chi$	0.34	0.25	0.20	0.17	0.12
	Estimated	7.84	5.43	4.43	3.73	2.09
R^2	$\frac{B_t}{V_t} = \chi$	0.150	0.156	0.153	0.148	0.125
	$b_t = \chi$	0.411	0.391	0.415	0.394	0.298
	Estimated	0.418	0.354	0.326	0.293	0.205

Notes: Estimation of

$$\overline{rx}_{t\to t+k} = \alpha + \beta_1\, \mathit{Dispersion}_t + \beta_2\, \Delta y_{t-1\to t} + \epsilon_{t+k}.$$

The table reports the β_1 coefficients and R^2 statistics computed from alternative models of leverage. In the first case ($\frac{B_t}{V_t} = \chi$), we fix market leverage to a constant value dependent on the level of sensitivity ϕ_i. In the second scenario we keep the scaled book value of debt constant and variations in market leverage will come only through variation in the market value of assets. In the final case, firms choose the book value of debt according to the following rule (which was estimated in our empirical sample)

$$\frac{B_t}{K_t} - \kappa_0 = 0.886\left(\frac{B_{t-1}}{K_{t-1}} - \kappa_0\right) - 0.0077\frac{\Pi_{t-1}}{K_{t-1}} - 0.0013\frac{V_{t-1}}{K_{t-1}}$$

To construct the investment grade and high-yield indices within the model, each period we sort companies based on their expected default frequency. High yield bonds are bonds issued by firms in the top quintile of EDF. Investment grade bonds are bonds issued by firms in the first quintile of EDF. Simulations are run on N = 400 time-series paths of the same length as the sample for January 1976 to September 2013 at the quarterly frequency.

Table 13. Expected Returns on Debt Repayment Portfolios

	Issuers	R2	R3	R4	Repayers	RMI
$\overline{R}$	11.71***	10.93***	13.00***	14.27***	14.63***	2.91**
	(2.87)	(2.62)	(2.50)	(2.53)	(2.66)	(1.32)
α	−0.10	−0.08	0.09	0.15**	0.14*	0.24**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.10)
β_{Mkt}	1.07***	1.01***	0.98***	1.00***	1.02***	−0.05
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
β_{SMB}	0.13***	−0.02	0.01	0.02	0.13***	−0.01
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.06)
β_{HML}	−0.25***	−0.20***	-0.06*	0.04	0.05	0.30***
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.06)
β_{Mom}	0.05**	0.01	−0.04**	−0.04**	−0.05**	−0.09 ***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)

Source: CRSP/Compustat merged, CRSP

Notes: This table reports time-series averages of annualized value-weighted portfolio returns with standard errors in parentheses (Panel A), and results from the time-series estimation for the CAPM (Panel B). Each quarter, we sort firms into quintiles based on debt repayment. We define debt repayment as the change in book value of equity minus change in book value of assets over the quarter divided by lagged book value of assets. Repayers are the firms in the top quintile; issuers are the firms in the bottom. RMI is repayers minus issuers. For each repayment portfolio (i), we estimate the 4-factor model

$$R^e_{it} = \alpha_i + \beta_i^{Mkt} R^e_{mt} + \beta_i^{SMB} R_t^{SMB} + \beta_i^{HML} R_t^{HML} + \beta_i^{Mom} R_t^{Mom} + \epsilon_{it}.$$

where R^i, R^M, R^{SMB}, R^{HML}, and R^{Mom} are respectively the excess returns for portfolio i, the market excess return, the size, the value and the momentum factor. The sample period spans from January 1975 to March 2016. Statistical significance levels at 10%, 5% and 1% are denoted by $*$, $**$ and $***$, respectively.

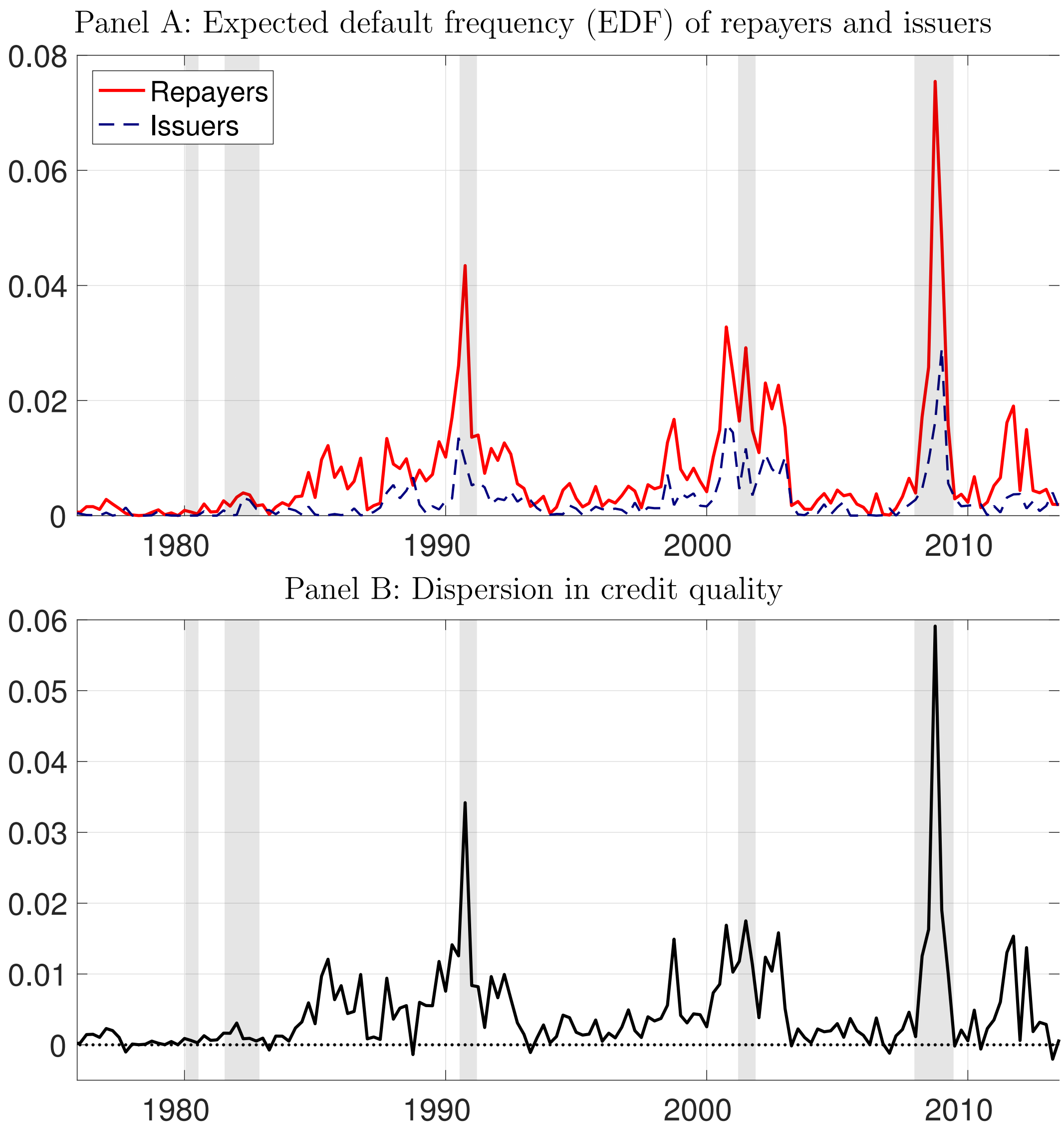

Fig. 1. **Expected default frequency and its dispersion.** Each quarter, we sort firms in the data into quintiles based on debt repayment. We define debt repayment as the change in book value of equity minus change in book value of assets over the quarter divided by lagged book value of assets. Repayers are the firms in the top quintile; issuers are the firms in the bottom. EDF is the quarterly expected default frequency from the Merton (1974) model. Panel A shows the EDF for repayers (solid line) and for issuers (dashed line). Panel B shows the difference: the EDF for repayers minus the EDF for issuers. Shaded areas correspond to NBER recessions.

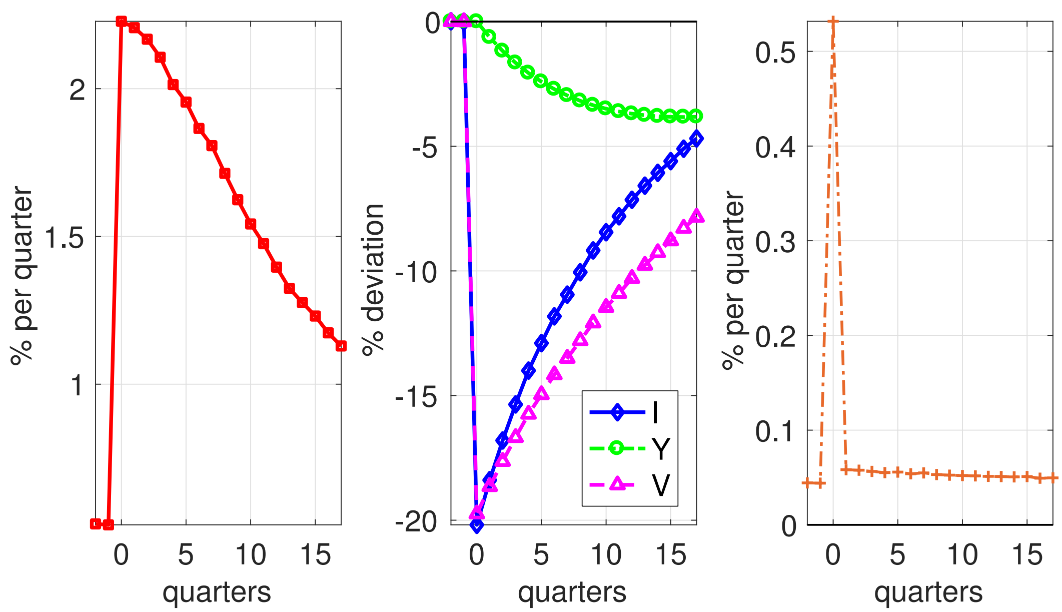

Fig. 2. **Impulse response function of investment, output and firm value (middle) and EDF (right) to an increase in disaster probability (left).** The figure shows the response to a temporary increase in the quarterly disaster probability. We simulate 20,000 series for the economy. In each series, we enforce the second observation on p_t following the burn-in sample, to equal 2.2%. We set productivity shocks to zero. We show investment, output, and firm value scaled by firm-specific productivity. All quantities are for $\phi_i = 1$.

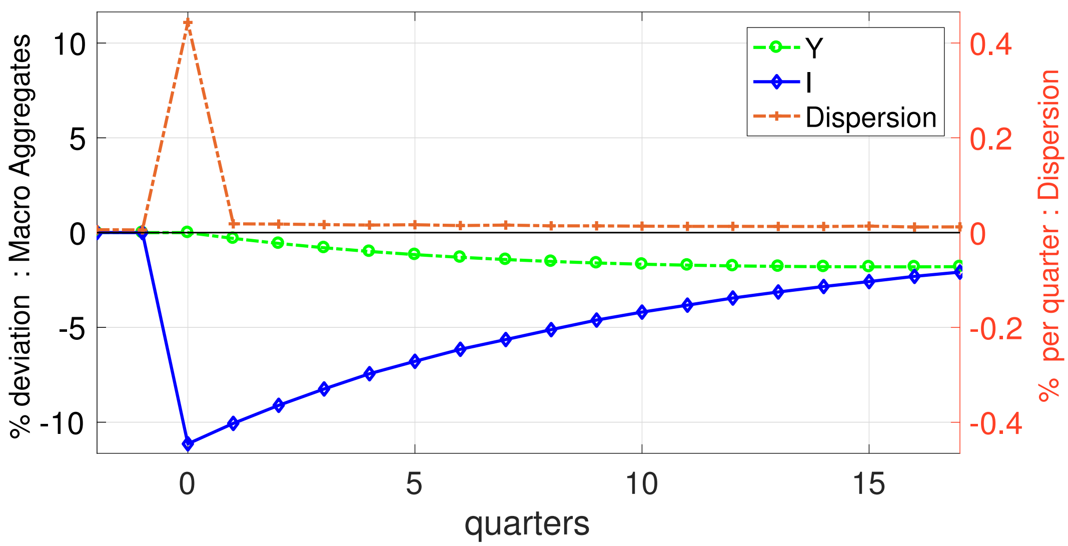

Fig. 3. **Impulse response function of dispersion (right axis), and investment and output (left axis) to an increase in disaster probability.** The figure shows the response to a temporary increase in the quarterly disaster probability from 0.52% to 2.23%. To calculate impulse responses, we repeat the procedure described in the caption of Figure 2. Given series for firm-level variables, we calculate debt repayment, EDF, and Dispersion. Dispersion is defined as the average EDF of repayers minus average EDF of issuers.

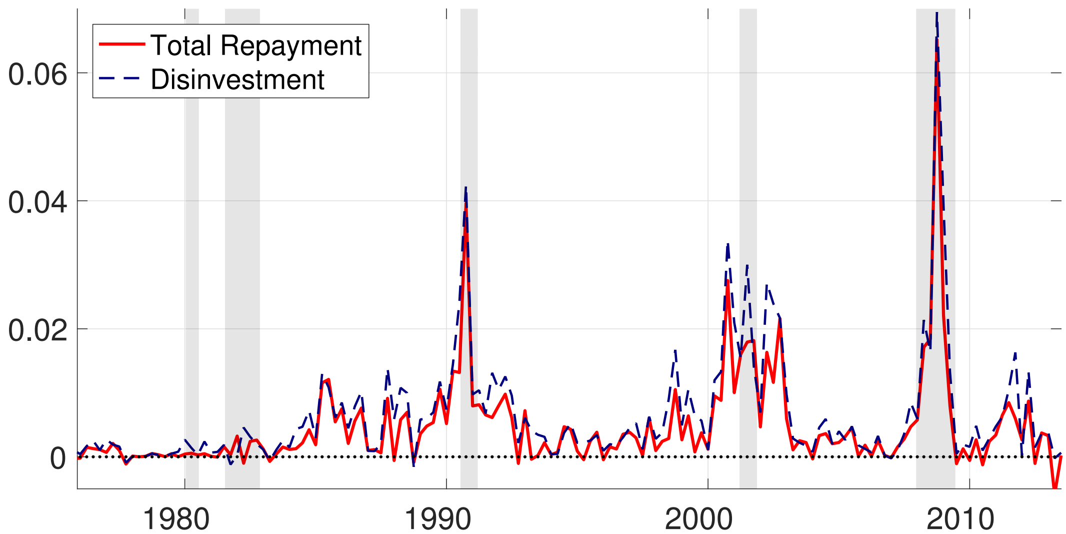

Fig. 4. **Dispersion in Expected default frequency: Total Repayments.** Each quarter, we sort firms in the data into quintiles based on total repayment. Total Repayments are defined as EBIT net of the change in assets (scaled by total assets). Repayers are the firms in the top quintile; issuers are the firms in the bottom. EDF is the quarterly expected default frequency from the Merton (1974) model. The solid line represents the difference in EDF between firms repaying the most and firms issuing the most. The dashed line instead shows the difference in EDF when the same exercise is repeated on disinvestment only ($-\Delta$Assets). Shaded areas correspond to NBER recessions.