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.

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, and credit market conditions should not impact real investment and subsequent economic growth. For a so-called credit cycle to drive recessions, 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. Previous research has used the predictability of bond returns to validate various measures as reliable indicators of credit market conditions, while forecasting power for economic aggregates suggests that credit market conditions have real consequences.

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. 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

[1] See, for example, Baron and Xiong (2016), Gilchrist and Zakrajšek (2012), Greenwood and Hanson (2013), Muir (2016).

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 their credit worthiness declines. These firms optimally repay their debts at the fastest 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 regressions results found in the data.

Our paper relates to an empirical literature that examines credit market variables as leading indicators of the business cycle. The empirical findings of Greenwood and Hanson (2013) motivate our focus on the role of time variation in the cross sectional dispersion in credit quality. However, they use the finding that increases in their measure of dispersion in credit quality forecasts low future bond returns to conjecture that dispersion is mostly driven by the low quality of bond issuers, not repayers, and thus that bond issuer quality deteriorates over the credit cycle. Unlike us, Greenwood and Hanson also do not demonstrate the ability of their measure of credit dispersion to predict core macro-aggregates like GDP and investment growth. Although we focus on somewhat different empirical evidence, our model is also consistent with their main findings.

Similarly, Gilchrist and Zakrajšek (2012) show that credit spreads, constructed using proprietary bond data, forecast recessions. Our measure, though constructed using only Compustat data, has similar predictive power. While Gilchrist and Zakrajšek focus on credit market limitations as an explanation of their findings, our results show how risk premia measures, based on bond data, can forecast macro-aggregates even in a frictionless model. [2]

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 variation in buyout activity.

The rest of the paper proceeds as follows. Section 2 describes our empirical results. Section 3 describes the model, and Section 4 discusses the model's main implications. Section 5 provides additional evidence, motivated by the model, concerning investment, payout, and predictability. The final section summarizes and concludes.

[2] Bordalo, Gennaioli, and Shleifer (2016) and Lopez-Salido, Stein, and Zakrajšek (2015) also use the Greenwood and Hanson measure in making the case for credit cycles. Atkeson, Eisfeldt, and Weill (2014) use a distance-to-default based measure to forecast recessions.

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 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, assets, and book value of equity. 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.

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:

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

where 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: 0.7% per quarter for repayers versus 0.2% for issuers.[3] Repayers have a strikingly lower investment rate than issuers: 4% versus 8.5%. Leverage for repayers is slightly higher than for issuers (32% versus 26%). On the other hand, repayers and issuers are of similar size (logarithm of 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. However, as we report in the Online Appendix, the default probability measure of Campbell, Hilscher, and Szilagyi (2008) leads to very similar findings.

[3] EDF is highly positively skewed. Most firms exhibit an EDF that is equal to zero; the averages are driven by the right tails in both portfolios.

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 the 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 each 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 6% 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:

$$Dispersion_t = \frac{1}{N} \sum_{j \in \text{Repayers}} EDF_{jt} - \frac{1}{N} \sum_{i \in \text{Issuers}} EDF_{it}, \quad (2)$$

where N is the number of firms in each quintile. Panel B of Figure 1 shows the time series of *Dispersion*. Consistent with the discussion above, *Dispersion* is positive throughout the sample, and reflects mainly time-series variation in the EDFs for repayers.

Our measure recalls the credit quality proxy of Greenwood and Hanson (2013). One key difference, however, is that Greenwood and Hanson substitute the EDF actual *value* for each firm with the NYSE *decile* of the EDF. Replacing actual EDFs with NYSE deciles obscures important features of the series; for example, the sign.[4] As we show in Figure 1, the difference between the average EDF of repayers and that of issuers is almost always positive. Firms that repay debt are closer to default, as one might expect from a rational model. A decile-based measure also obscures asymmetry: namely that it is the EDF of repayers during recessions that drives the difference in default frequencies.

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 credit worthiness 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 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

$$\overline{\Delta y}_{t\rightarrow t+k} = \beta_0 + \beta_1 Dispersion_t + \epsilon_{t,t+k}, \tag{3}$$

[4] 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.

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 GDP growth with a R^2 of around 10% and 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 1.74 percentage point increase in the future quarterly growth rate in investment and a 0.41 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

$$\overline{rx}_{t \to t+k} = \beta_0 + \beta_1 Dispersion_t + \epsilon_{t,t+k} \tag{4}$$

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.

Our measure significantly forecasts excess returns on investment-grade and high-yield bond at horizons ranging from 6 months to 2 years. R^2-statistics are economically significant, for example 14% at the one-year horizon and 11% at the 2-year horizon. For high-yield bonds, results are also strong, with R^2-statistics rising as high as 32% at the 2-year horizon. We find that a 1 percentage-point increase in *Dispersion* is associated with a 2.3 percentage-point increase in the quarterly high-yield bond return.

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 time series behavior of *Dispersion* suggests an alternative interpretation, which we pursue below.

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 simple to highlight the key mechanisms.[5]

We assume a continuum of 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, 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 the role of real production and investment decisions in generating the main empirical findings. Importantly, it also makes it clear how credit market frictions are not essential to replicate the empirical evidence. Methodologically,

[5] 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 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.

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 agent 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. We assume $\xi_{t+1} \overset{iid}{\sim} N(\mu_\xi - \frac{\sigma_\xi^2}{2}, \sigma_\xi^2)$, and independent of $\epsilon_{c,t+1}$. 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. 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 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.[6] Under these assumptions, the price of the government bill is

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

while the yield is the inverse of (10). The realized return is

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

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

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

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 $\omega_{i,t+1} \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_\omega^2)$, 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 $\phi_i \xi_{t+1} x_{t+1}$. The term ϕ_i captures heterogeneous exposure to these shocks. We set firm-specific normal-times growth at

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

so that firms grow, on average, at the same rate. For simplicity, we assume firms have the same exposure to $\epsilon_{c,t+1}$. Note that this structure implies that firms are subject to common and idiosyncratic productivity shocks, as well as to a shock that is independent of these, common across firms, and 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. It also, following the approach of Gourio (2012), captures destruction of capital that occurs during disasters. This can proxy for either literal capital destruction (in the case of war), or misallocation of capital due to economic disruption.

Firms face costs when adjusting capital (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 payout to investors is thus

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

3.2.3 Firm Value, Optimal Investment and Payout

To solve the firm's problem, it is helpful to define the planned capital stock, $\widetilde{K}_{it} = \frac{K_{it}}{e^{\phi_i \xi_t x_t}}$, namely what K_t would be if there were no disaster. Equation 15 implies that planned capital obeys the law of motion

$$\widetilde{K}_{i,t+1} = (1-\delta)\widetilde{K}_{it} e^{\phi_i \xi_t x_t} + I_{it}. \tag{18}$$

Firm i therefore solves the following fixed-point problem:

$$V_i(\widetilde{K}_{it}e^{\phi_i \xi_t x_t}, z_{it}, p_t) = \max_{I_{it}, \widetilde{K}_{i,t+1}} \Bigg[z_{it}^{1-\alpha} \left(\widetilde{K}_{it} e^{\phi_i \xi_t x_t} \right)^{\alpha} - I_{it} - \lambda \left(I_{it} \, , \, \widetilde{K}_{it} e^{\phi_i \xi_t x_t} \right) + \mathrm{E}_t[M_{t+1} V_i(\widetilde{K}_{i,t+1} e^{\phi_i \xi_{t+1} x_{t+1}}, z_{i,t+1}, p_{t+1})] \Bigg],$$

subject to (18), 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

$$\mathrm{E}_t \left[M_{t+1} R^I_{i,t+1} \right] = 1, \tag{19}$$

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

$$R^I_{i,t+1} = \frac{e^{\phi_i \xi_{t+1} x_{t+1}}}{1 + \lambda_I \left(I_{it}, K_{it} \right)} \left(\alpha \frac{Y_{i,t+1}}{K_{i,t+1}} - \lambda_K \left(I_{i,t+1}, K_{i,t+1} \right) + (1-\delta) \Big(1 + \lambda_I \left(I_{i,t+1}, K_{i,t+1} \right) \Big) \right). \tag{20}$$

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

$$\frac{\Pi_{it}}{K_{it}} = \left(\frac{z_{it}}{K_{it}} \right)^{1-\alpha} - \frac{I_{it}}{K_{it}} - \frac{\lambda \left(I_{it}, K_{it} \right)}{K_{it}}. \tag{21}$$

The quantity Π_{it}/K_{it} is the analogue of repayment in the model. Equation (21) directly links investment and payout choices. In particular, issuers are firms with negative payout, and thus relatively high investment rates, a feature evident in the summary statistics reported in Table 2.

3.2.4 Debt Claims

Separating total investor payout between exact debt and equity claims requires specific assumptions about capital structure. However, virtually all existing capital structure models will preserve the strong positive relation between investment rates and security issuance. We thus choose to abstract from any specific form of financing frictions driving the choice of leverage and debt repayments and impose an exogenous capital structure under the classic Modigliani-Miller paradigm. Abstracting from financing frictions has the advantage of better highlighting the key role of investment and profitability in generating the type of phenomena often perceived as an "credit cycle".

Under the classic Modigliani-Miller irrelevance conditions, financial decisions do not affect a firm's real decisions and can be constructed independently from them. We assume that each firm is endowed with an exogenous amount of debt with face value of B_{it} and specify the following partial adjustment model of leverage

$$b_{i,t+1} - b_{it} = \kappa_i^1 (v_{it} - v_{i,t-1}). \tag{22}$$

where $b_{it} = B_{it}/z_{it}$ and $v_{it} = V_{it}/z_{it}$ and we calibrate the value κ_i^0 to match observed leverage ratios for each portfolio of firms.

Given the series for B_{it} and V_{it} as well as asset returns $V_{i,t+1}/(V_{it} - \Pi_{it})$ we can compute the value of EDF_{it} for each firm i at time t using equation (1). To compute the return on debt we assume that, at time t, firm i repays the face value B_{it} unless it defaults, in which case it repays a proportion ν of value V_{it}. Default occurs when $V_{i,t+1} < B_{it}$. We also assume that, if disaster occurs without default, corporate debt suffers the same loss as government debt (see Section 3.1). Under these conditions, the price of the debt claim equals:

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

while the return is

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

Importantly, 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}.

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 averaging 400 independent samples with 38 years (152 quarters) of firm-level data. Each sample path contains 2500 firms. Appendix C provides more computational details.

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.

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 choose parameters 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.[7]

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 2.13. 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 calculate population moments in simulated data. 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 3.7, 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

[7]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).

yield and the consumption claim.[8]

For firms, we set the returns-to-scale parameter $\alpha = 0.7$ (e.g. Cooper and Ejarque, 2003). We set depreciation $\delta = 4\%$ per quarter to match the average investment-to-capital ratio in the data, and we 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 a normal component 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. The value of these sensitivities are assumed to be uniformly distributed between 1 and 1.5. Because our results are based on the highest and lowest quintiles, they are not particularly sensitive to the form of this distribution.[9]

We assume a debt recovery rate of 60%, which equals the value-weighted recovery rate for senior unsecured debt estimated by Moody's Investor Services (Ou, Chlu, and Metz, 2011). Finally, the parameters characterizing the exogenous process for debt, κ_i^0 and κ_i^1, are set to match the average portfolio leverage ratios. Given this and the different shock sensitivities above, the volatility of the idiosyncratic shocks is set to match portfolio expected default frequencies.

4.2 Cross-section of Firms

Table 8 shows the characteristics of firms in the two extreme repayment and issuance portfolios on our simulated data, and compares these with historical data. Our results are all based on averages across 400 artificial economies with a long burn-in sample. In each artificial sample, we sort firms based on their debt repayment activity, defined as in (21). The table shows that, on average,

[8] We compute the return on the value-weighted CRSP index from 1951 to 2013. Following Barro and Ursua (2008), we adjust for leverage by dividing by 1.5.

[9] The average value for ϕ is chosen so that the firm with this ϕ has an unlevered equity premium equal to the consumption claim. Because of the implied dividend policy, this ϕ is greater than one.

repayers have higher default probabilities (EDF) than issuers, with magnitudes similar to those in the data. Specifically, we find that repayers (firms in the top repayment quintile) have an average EDF of 0.008, compared with 0.007 in the data, while issuers (firms in the bottom repayment quintile) have an EDF of 0.001, compared with 0.002 in the data. Repayers have lower rates of investment — 0.02 versus 0.07 for issuers – and higher (prior) leverage ratios.

These patterns match well with what we found earlier in the data. While we chose parameters so that firm types would have the correct average leverage, it is reassuring that this implies the correct relation between repayment characteristics, leverage, EDF, and investment.

4.3 Dynamics of Investment, Value, and Credit Quality

To understand the joint dynamics of quantities, firm values, EDF, and risk premia, we calculate the response of these quantities to an shift in the main state variable, the probability of a disaster, p.

Figure 2 shows the response of firm value, investment, output, and EDF to an increase in the probability of a disaster. Specifically, we consider the effects of a shift in disaster probability from its initial average level to 2.3% per quarter. Along these simulated paths, we set productivity shocks to zero.[10] The figure reports the results for a firm with exposure $\phi_i = 1$, although the patterns are identical for all values of ϕ_i.

The first 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. At the same

[10] To compute EDF values in these figures we set $\mu_{V_i} = \mu_1$ and $\sigma_{V_i} = 0.34$.

time, greater risk leads agents to invest more for precautionary reasons. At our parameter values, the first two effects dominate the second, and the firm reduces investment. Because of adjustment costs, investment remains depressed over several years.

For the same set of reasons, namely cash flows from investment are riskier and lower in expectation, firm value declines. 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 third 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 than the decline in firm value. This is because EDF represents how close the firm is to default. This will be true unless firms implausibly reduce debt at a faster rate than the decline in total firm value. Over time firm value rise, debt levels adjust and the probability of default starts to fall.

Figure 3 focuses on our measure of dispersion, and its relation to macro-aggregates. We calculate *Dispersion* in the model as in the data: by simulating a cross-section of firms and sorting them into repayers and issuers. As we have seen, when the probability of disaster rises, the typical firm's value falls. Firms do not suffer this effect equally, however. The values of those that are more exposed to disaster risk, through high ϕ_i, will fall by more, moving these firms closer to default. However, these firms also suffer from reduced investment opportunities. As a result these same firms are then much more likely to repay their debt. This endogenous response of firms leads to a cross section where debt repayers exhibit especially high values of EDF.

Putting these facts together, we find that cross sectional dispersion in credit quality will increase following an increase in the probability of disaster. In addition, 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*.

Although the model implies that repayers are high EDF firms, they are not necessarily high ϕ_i firms. Improvements in p_t, as well as idiosyncratic shocks, can lead high-sensitivity firms to invest and become net issuers. At these times, these firms' value increases and EDF falls. Moreover, the relation between EDF and economic conditions is asymmetric because EDF cannot go below zero. In good economic times, all firms are far from their default boundary, whereas recessions naturally produce a rise in the cross-sectional dispersion of EDF.

4.4 Predictive Regressions in Model and Data

We now use the intuition developed in Section 4.3 to interpret the predictability findings in model and data.

4.4.1 Predictability of Macro Aggregates

Table 9 shows not only that the intuition in the model directionally matches the data, but that the model produces many similar quantitative findings. Specifically, Table 9 shows how our quantitative model replicates the empirical finding that an increase in *Dispersion* predicts a sizable decline in both aggregate output and investment growth. While R^2 coefficients are smaller in the model at some horizons as compared with the data, the coefficients on *Dispersion* are also of a similar magnitude, and the predictability is economically meaningful in both.

The reasons for this predictability are already 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. This response of output and investment 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). Because *Dispersion* predicts excess bond returns, it can be interpreted as risk premium measure. Hence, by linking a risk premium to future movements in aggregate output, our model also rationalizes the findings in Gilchrist and Zakrajšek (2012) and others.

Table 10 shows the model's implications for the predictability of bond returns. To construct theoretical counterparts to the 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.

Table 10 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. In the model, bonds are priced by the same economic agents who make real investment decisions. When the probability of a disaster rises, bonds are more likely to default. Moreover, the world has also gotten riskier; 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 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 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 for a substantial number of samples. This is because the relation between the disaster probability, default dispersion, and expected returns is quite non-linear. Hence, fitted excess returns will sometimes be negative, even without assuming investors are irrational.

5 Additional Results

Our model raises the question of whether we should distinguish between debt repayments and total repayments (debt plus equity) to all 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 create portfolios of firms based not on just their net debt repayment, but instead according to their total security repayments or, equivalently, (the negative of) asset growth. Asset growth is defined as the change in book assets, divided by the value of assets in the previous period; by the firm's accounting identity. In our model asset growth is simply equal to the firm's investment rate. The economic mechanism proposed in Section 3 then implies that sorts based on asset growth should also identify risky firms.

Figure 4 displays a reconstructed empirical dispersion measure, but now computed using the spread in EDF values between the bottom asset growth quintile and the top one. It is immediately apparent that this time series behaves very much like our benchmark series that was based on debt repayments alone. Moreover, as we report in our Online Appendix, the key predictability regressions for returns and for economic growth obtained using a broader repayment measure also produce very similar results.

This supports 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.[11]

6 Conclusions

This paper makes three contributions. First, we show that firms who are on average repayers of securities have an Expected Default Frequency (EDF)

[11] 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, which implies that firms that are growing more are less exposed to disaster risk and have a lower required rate of return.

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. 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 model 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 if their primary SIC code is between 4900 and 4999, between 6,000 and 6,999, or greater than 9,000, 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*). For each year, 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 the EDF equation (1) where V_{it} is the market value of the firm's equity plus debt, B_{it} is the face value of the firm i's debt computed as one-fourth of its short-term debt (*dlcq*) plus one-eight of its long-term debt (*dlttq*), μ_{V_i} is the firm's asset drift and σ_{iV} the asset volatility. Consistent with Merton (1974) model, μ_{V_i} is the logarithm of the firm's average stock (gross) return over the prior 12 months. $\sigma_{V_i} = \frac{E_{it}}{E_{it}+B^{\sigma}_{it}}\sigma_{E_i} + \frac{B^{\sigma}_{it}}{E_{it}+B^{\sigma}_{it}}(0.05+0.25\sigma_{E_i})$ where E_{it} refers to the market capitalization of firm i at time t, σ_{E_i} is estimated using the last 12 months and B^{σ}_{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.

Appendix B Firm's Problem

We define firm value recursively, using the Bellman equation. The main issue with the Bellman equation in this setting is that capital at time $t+1$ ($K_{j,t+1}$), which is usually chosen at time t subject to the budget constraint, is stochastic as of time t on account of the disasters. We therefore define a concept which we refer to as planned capital, namely the capital that the firm would have in the absence of disasters. Planned capital is

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

The value function for firm i then solves

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

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

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

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

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

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 $k \in [\underline{\mathrm{k}}, \bar{k}]$ 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)	−0.311	−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	0.160	0.080

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	$7.08e^{-07}$	0.007	0.062
EDF - Issuers$_t$	0.000	0.000	$5.10e^{-09}$	0.002	0.035
Investment - Repayers$_t$	0.000	0.024	0.098	0.038	0.067
Investment - Issuers$_t$	0.006	0.044	0.188	0.082	0.137
Leverage - Repayers$_{t-1}$	0.030	0.275	0.697	0.322	0.248
Leverage - Issuers$_{t-1}$	0.018	0.211	0.606	0.265	0.224
Size - Repayers$_{t-1}$	2.224	4.609	7.534	4.766	2.038
Size - Issuers$_{t-1}$	2.181	4.622	7.565	4.768	2.059

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: Data

	Horizon k				
	1	2	3	4	8
			Panel A: GDP		
β	-0.41^{***}	-0.32^{***}	-0.25^{***}	-0.21^{***}	-0.09^{*}
	[−6.42]	[−4.69]	[−3.85]	[−3.30]	[−1.59]
R^2	0.1128	0.0999	0.0774	0.0622	0.0186
			Panel B: Investment		
β	-1.74^{***}	-1.34^{***}	-0.94^{***}	-0.64^{**}	-0.13
	[−6.53]	[−4.45]	[−3.45]	[−2.78]	[−0.67]
R^2	0.1548	0.1262	0.0762	0.0429	0.0030

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

Notes: Estimation of

$$\overline{\Delta y}_{t \to t+k} = \alpha + \beta\, Dispersion_t + \epsilon_{t+k}.$$

The table reports 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*). We define dispersion as average EDF of repayers minus average EDF of issuers. 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 5% and 1% are denoted by ** and ***, respectively.

Table 4. Forecasting Excess Returns on Bonds: Data

	Horizon k				
	1	2	3	4	8
		Panel A: Investment Grade			
β	0.73	0.96***	0.91***	0.81***	0.50***
	[1.24]	[2.87]	[3.06]	[3.35]	[3.04]
R^2	0.0323	0.1054	0.1292	0.1363	0.1101
		Panel B: High Yield			
β	2.28**	2.50***	2.30***	2.06***	1.56***
	[2.05]	[3.21]	[3.48]	[3.63]	[6.62]
R^2	0.0806	0.1589	0.2180	0.2435	0.3221

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

Notes: Estimation of

$$\overline{rx}_{t\to t+k} = \alpha + \beta\, Dispersion_t + \epsilon_{t+k}.$$

The table reports coefficients and R^2 statistics from predictive regressions of average excess log returns on bonds over various horizons onto dispersion in credit quality ($Dispersion$). 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 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 5% and 1% are denoted by ** and ***, respectively.

Table 5. Parameter Values for the Aggregate Economy

Description	Parameter	Value
Relative risk aversion	γ	3.67
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	0.73
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	0.0101
Government bill yield volatility	0.0222	0.0243
Average premium on the consumption claim	0.0532	0.0598
Volatility of the consumption claim return	0.1226	0.0903

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 Net Repayers and Issuers

Variable	Data	Model
EDF - Repayers$_t$	0.007	0.008
EDF - Issuers$_t$	0.002	0.001
Investment - Repayers$_t$	0.038	0.020
Investment - Issuers$_t$	0.082	0.070
Leverage - Repayers$_{t-1}$	0.322	0.359
Leverage - Issuers$_{t-1}$	0.265	0.314

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

	Horizon k				
	1	2	3	4	8
Panel A: Δ GDP $_{t\to t+k}$					
β					
Data	-0.41^{***}	-0.32^{***}	-0.25^{***}	-0.21^{***}	-0.09^{*}
Model	-0.52	-0.54	-0.44	-0.42	-0.21
R^2					
Data	0.1128	0.0999	0.0774	0.0622	0.0186
Model	0.0130	0.0158	0.0172	0.0200	0.0215
Panel B: Δ Investment $_{t\to t+k}$					
β					
Data	-1.74^{***}	-1.34^{***}	-0.94^{***}	-0.64^{**}	-0.13
Model	-6.06	-2.33	-0.89	-0.12	1.87
R^2					
Data	0.1548	0.1262	0.0762	0.0429	0.0030
Model	0.0920	0.0208	0.0074	0.0071	0.0084

Notes: Estimation of

$$\overline{\Delta y}_{t\to t+k} = \alpha + \beta\, Dispersion_t + \epsilon_{t+k}$$

The table reports the OLS coefficients and R^2 from the predictive regressions of macroeconomic aggregates onto *Dispersion* both in the data and (the median values) within the model. The empirical results were already presented in table 3. The quarterly empirical sample spans from January 1976 to September 2013. For the model, simulations are run on $N = 400$ time-series paths of the same length as the empirical sample.

Table 10.

Forecasting Excess Returns on Bonds

	Horizon k				
	1	2	3	4	8
Panel A: Investment Grade					
β					
Data	0.73	0.96***	0.91***	0.81***	0.50***
Model	0.20	0.11	0.10	0.08	0.05
R^2					
Data	0.0323	0.1054	0.1292	0.1363	0.1101
Model	0.5517	0.2511	0.2025	0.1682	0.0937
Panel B: High Yields					
β					
Data	2.28**	2.50***	2.30***	2.06***	1.56***
Model	2.16	1.55	1.11	0.97	0.68
R^2					
Data	0.0806	0.1589	0.2180	0.2435	0.3221
Model	0.4835	0.2194	0.1808	0.1577	0.1021

Notes: Estimation of

$$\overline{rx}_{t\to t+k} = \alpha + \beta\, Dispersion_t + \epsilon_{t+k}$$

The table reports the OLS coefficients and R^2 from predictive regressions for the average returns on investment grade and high yield bonds in excess of the government bond rate both in the data and (the median values) within the model. The empirical results were already presented in table 4. 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.

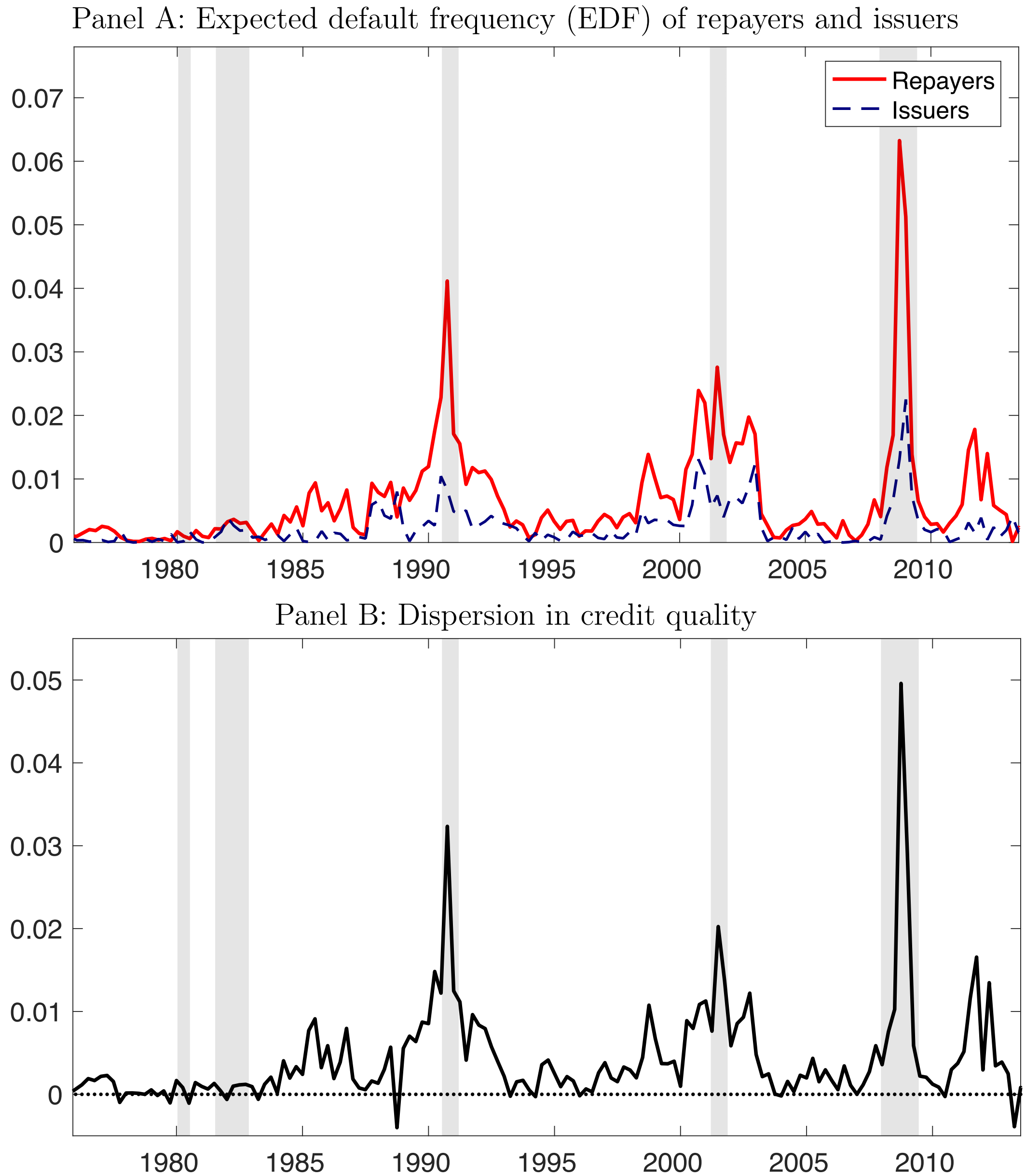

Fig. 1. Expected default frequency and its dispersion. Each quarter, we sort firms in the data into quintiles based on debt repayment. We define debt repayment as the change in book value of equity minus change in book value of assets over the quarter divided by lagged book value of assets. Repayers 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.

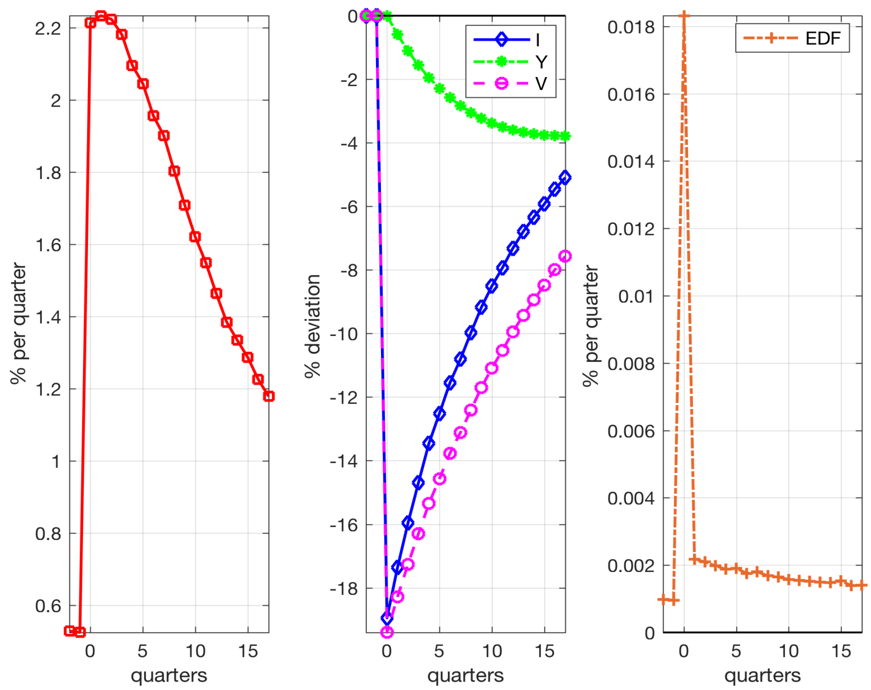

Fig. 2. Impulse response function of investment, output and firm value (middle) and EDF (right) to an increase in disaster probability (left). The figure shows the response to a temporary increase in the quarterly disaster probability. We simulate 20,000 series for the economy. In each series, we enforce 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 $\phi_i = 1$.

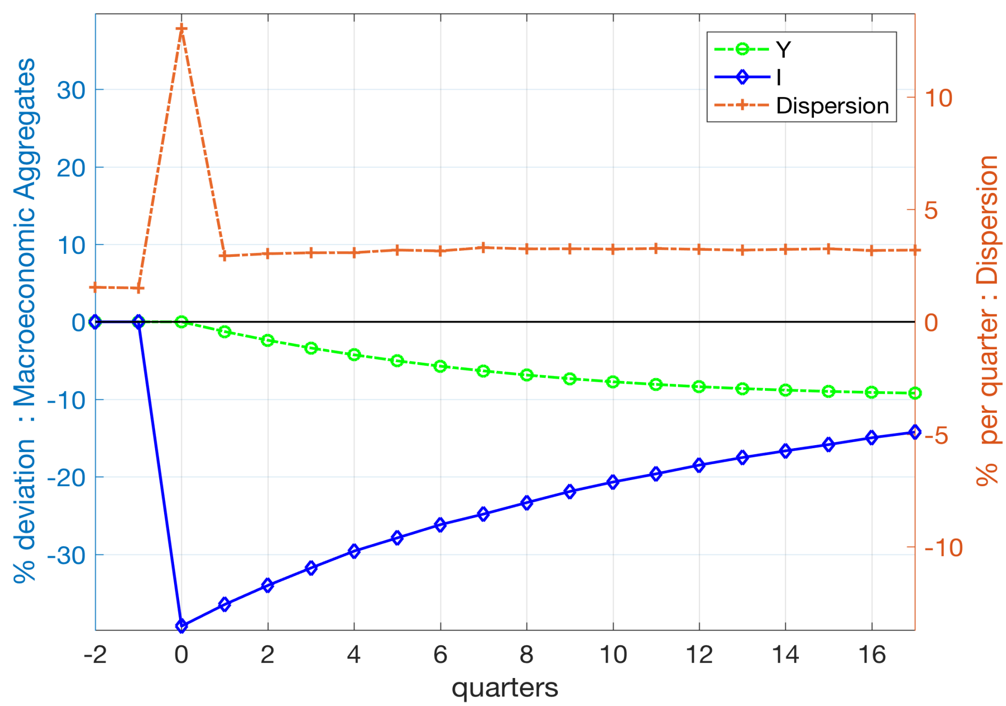

Fig. 3. Impulse response function of dispersion (right axis), and investment and output (left axis) to an increase in disaster probability. The figure shows the response to a temporary increase in the quarterly disaster probability from 0.52% to 2.23%. To calculate impulse responses, we repeat the procedure 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.

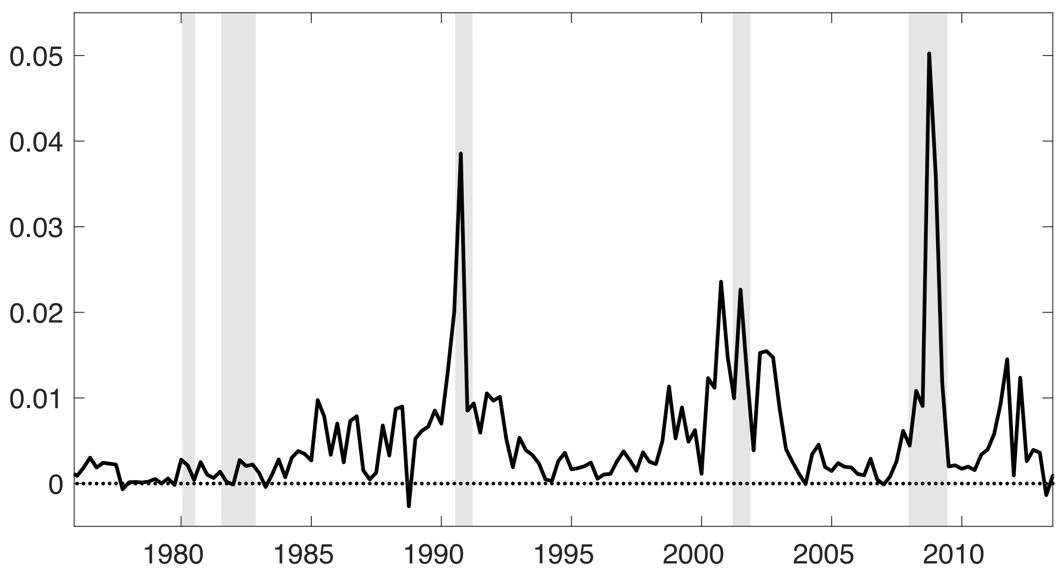

Fig. 4. Dispersion based on asset growth. Each quarter we sort firms in the data into quintiles based on change in book value of assets divided by total assets. The figure shows the average EDF of the bottom asset growth quintile minus the average EDF of the top asset growth quintile. The shaded areas correspond to NBER recessions.