Cyclical Dispersion in Expected Defaults

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Abstract

A growing empirical literature shows that proxies for credit market conditions forecast aggregate real outcomes. While researchers have proposed various explanations, the economic mechanism behind these results remains an open question. In this paper, we propose a simple mechanism and document that the same forecasting regressions results hold in our model as in the data. We base our mechanism on differential exposures of firms’ productivity and capital stocks to economy-wide risks. We show how these assumptions endogenously lead to a cross section in which firms sort on measures of credit quality, that this cross-sectional dispersion of credit quality varies over time, and that dispersion forecasts both excess bond returns and real outcomes as in the data. We also confirm other predictions of the model for the cross section and time series of prices and returns.

Keywords: Expected Default, Bond Issuance, Business Cycles, Disaster Risk

JEL codes: G12, G32, E32

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1 Introduction

A substantial literature in macroeconomics and finance implicates changing credit conditions in the fluctuations of asset prices and in shifts in real investment and economic growth. The reasons why credit conditions should have such large and diverse effects are poorly understood; in a frictionless economy, funds should flow to the highest value projects, and credit conditions should not be relevant. The underlying hypothesis of much of the credit literature, stated explicitly or implicitly, is that the observed co-movements of credit availability with macroeconomic variables and asset prices are inconsistent with a frictionless benchmark. As a result, these explanations often appeal to either market frictions or behavioral bias, not always modeled explicitly.¹

In this paper, we argue that asset returns and real outcomes can appear to be driven by a credit cycles, when in fact they may be driven solely by investment opportunities. The only key assumptions are that these investment opportunities vary over time, and also differentially across firms. We show formally how these simple assumptions can create the appearance of a credit cycle.

Our first contribution is empirical. We show that a measure of dispersion in credit quality is a robust predictor of both bond excess returns and economic growth. Our measure is based on using debt repayment and issuance as a sorting variable. We then compute a measure of the differential credit quality of firms that are repaying their debt versus those that are issuing debt. We show that this measure, which is mainly driven by the credit quality of firms repaying debt, forecasts excess returns on investment-grade and high-yield corporate bonds. Importantly, our measure also forecasts GDP 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

¹See, for example, Baron and Xiong (2016), Gilchrist and Zakrajšek (2012), Greenwood and Hanson (2013), Muir (2016).
suggests that our measure accurately captures credit market conditions while the forecasting power for economic aggregates shows that these credit market conditions have real consequences.

Our second contribution is to show how a tractable quantitative model can account for these key findings. We consider a model with heterogeneous firms in which their capital stock and the productivity are exposed to rare, large, disasters whose probabilities vary over time. Periods of high risk of a negative outcome (disaster) are associated with low valuations and, naturally, to endogenously lower rates of investment. These effects will be especially large for firms that have a high exposure to these risks. As a result, these firms will endogenously choose higher repayment rates while simultaneously moving closer to the estimated default boundary.

We show that, in both model and data, recessions are associated with spikes in dispersion in credit quality, that are driven by firms who are repaying their debt. Moreover, because most firms optimally choose lower investment during recessions, changes in measured credit quality will predict future adverse economic outcomes, even if no disasters actually occur. When calibrated to match average investment rates and measures of cross section 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 use of a distance-to-default measure with issuance as a sorting variable. They argue that low quality of bond issuers, as opposed to that of repayers, forecasts low future bond returns, and thus that bond issuer quality deteriorates over the credit cycle. Unlike us, Greenwood and Hanson do not demonstrate predictability of macro-aggregates. Though we focus on different empirical evidence, our model is also
consistent with their main findings as well.\footnote{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, but do not examine return forecastability or build a model to explain their 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.

Our paper is methodologically related to a vast literature on investment and the business cycle and specifically to recent papers by Gourio (2012) and Kuehn and Schmid (2014). We use the same real business cycle methodology to address a new and substantively different set of questions relating to the credit cycle.

The rest of the paper is organized as follows. Section 2 describes our empirical methodology and contains our main empirical results regarding the predictability of issuance measures for both macroeconomic activity and asset returns. Section 3 describes our theoretical framework, and Section 4 discusses the model’s main findings. Section 5 uses the model to provide additional evidence about the role of investment decisions in driving the main predictability results. The final section summarizes and concludes.

## 2 Empirical Findings

In this section we construct 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 in Greenwood and Hanson (2013) but differs in some key respects discussed below. More importantly, our mea-
sure 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 also 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.

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 debt repayment. This is defined as the change in the book value of equity minus the change in the book value of assets, normalized by the book value of assets in the previous quarter. A negative value for net debt repayment implies that the firm was a net issuer of debt during the quarter.

Table 1 summarizes the cross section distribution of repayment activity over the sample period. The table shows that there are about as many issuers as repayers during a typical quarter. Net 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 using the Merton (1974) model. That is, for firm \( i \), we compute:

\[
EDF_{it} = N \left( -\frac{\log \frac{V_{it}}{B_{it}} - \left( \mu_{V_{it}} - \frac{\sigma_{V_{it}}^2}{2} \right)}{\sigma_{V_{it}}} \right),
\]

where \( V_{it} \) is the market value of the firm’s assets, \( B_{it} \) is the book value of debt, \( \mu_{V_{it}} \) is firm \( i \)’s asset expected return, and \( \sigma_{V_{it}} \) its asset volatility. Details on the computation of these values are included in Appendix A.

First, repayers have a higher average expected default frequency than issuers: 1.1% per quarter for repayers versus 0.4% for issuers.\(^3\) Repayers have a strikingly lower investment rate than issuers: 4% versus 8.6%. Leverage for repayers is higher than for issuers (32% versus 26%). On the other hand, the repayers and issuers are of similar size (logarithm of book assets is 4.786 for repayers and 4.795 for issuers).

\subsection{Dispersion in Expected Defaults}

The previous section shows that repayers have significantly higher average default probabilities than issuers as measured by the Merton (1974) EDF. We now examine the time series properties of these EDFs. Panel A of Figure 1 shows the time series of the EDFs for repayers and for issuers. This figure shows that EDF for repayers lies above that for issuers for nearly the entire sample: repayers are closer to default not only on average but in almost every period. The EDFs for repayers are also far more volatile than those for issuers, spiking during recessions. For instance, while the EDF for repayers is below 2% (per quarter) for most of the sample, during the financial crisis, it spikes

\(^3\)EDF in the data 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.
as high as 7%.

Motivated by the findings above, we construct a measure of dispersion in credit quality. We compute the average expected default frequency (EDF) for the firms in the highest quintile (the repayers) and subtract the average expected default frequency for the firms in the lowest quintile (the issuers). Our dispersion measure is thus:

$$\text{Dispersion}_t = \frac{1}{N} \sum_{j \in \text{Repayers}} EDF_{jt} - \frac{1}{N} \sum_{i \in \text{Issuers}} EDF_{it},$$

where $N$ is the number of firms in each quintile. Panel B of Figure 1 shows our measure of dispersion. As discussed above, it is positive for almost the entire sample, because repayers have higher default probabilities than issuers. Following the pattern of repayer EDF, the dispersion in EDFs spikes during recessions.

Our measure recalls the credit quality proxy of Greenwood and Hanson (2013). Greenwood and Hanson also sort firms by debt issuance. They form a measure called Issuer EDF: the EDF of firms issuing debt minus the EDF of firms repaying debt. Besides a trivial difference in the sign of our measure, there is a substantive difference with material implications. Greenwood and Hanson determine the breakpoints for EDFs based on NYSE deciles. They then substitute the EDF value of that firm for their NYSE decile. One can thus interpret their index of credit conditions as the average decile of issuers versus that of the repayers. Their interpretation of variation in the measure focuses on issuers, rather than repayers: times when issuers have relatively high EDFs are times when markets inefficiently oversupply credit. We find that, in addition to being a more natural and transparent construction, a measure based on raw EDF also offers greater predictive power, as shown in the online appendix.

However, the deciles-based measure in Greenwood and Hanson (2013) ob-
scures important features of the data. As we show in Figure 1, the difference between repayer and issuer EDF is almost always positive throughout the sample. Firms that are close to default appear to be the ones repaying debt, as one might expect from a rational model. Moreover, our portfolio EDFs show clearly how the cross-sectional distribution is largely driven by repayers that are close to default. While repayers and issuers EDFs are not dramatically different during booms, their credit worthiness deteriorates dramatically in recessions. It is apparent that it is this sharply countercyclical behavior of repayers default frequencies that drives the variation in EDF spreads over time.

2.3 Predicting Macro Aggregates

Measures of credit market conditions have attracted attention because the are often useful predictors of future business cycle conditions and asset prices (Gilchrist and Zakrajšek, 2012). We now show that this is also the case for our measure of dispersion.

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

$$\bar{y}_{t-t+k} = \beta_0 + \beta_1 Dispersion_t + \epsilon_{t+1},$$

(3)

where $\bar{y}$ denotes the average GDP or investment growth between period $t$ and $t+k$.

Table 3 shows that the spread in EDFs across portfolios is a useful predictor of the key macro-aggregates. Panel A shows that $Dispersion$ predicts 1-quarter ahead GDP growth with a $R^2$ of 8% and a highly statistically significant coefficient. While the $R^2$ decline as the horizon lengthens, the coefficients

$^4$Forecasting $k$ periods ahead growth rates yields similar results.
remain statistically significant at horizons up one year. Panel B shows that Dispersion is an even more powerful predictor of investment growth. The table shows that, 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 1.26 percentage point increase in the future quarterly growth rate in investment and a 0.3 percentage point quarterly increase in GDP. We conclude that the cross sectional dispersion in portfolio EDFs captures important variation in future business cycle fluctuations.

Although we do not report them here for brevity, our online appendix reports a number of additional findings. It includes annual regressions, and tests of the robustness of our measure to the inclusion of other variables that have been commonly recognized in the literature to have a predictive power for macroeconomic activity. We also find that Dispersion has a large positive correlation of 0.69 with the excess bond premium proposed by Gilchrist and Zakrajšek (2012), a benchmark measure of credit conditions, but also one that requires significantly more information to compute.

Section 5 builds on our theoretical insights to develop additional evidence on the importance of these credit measures.

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 continuously-compounded government bond return of comparable maturity. That is, we estimate

\[
\bar{r}_{t \rightarrow t+k} = \beta_0 + \beta_1 \text{Dispersion}_t + \epsilon_{t+1}
\]

(4)
where $r_{x_{t\rightarrow t+k}}$ denotes the continuously compounded excess return measured from period $t$ to $t+k$, and $\bar{r_{x_{t\rightarrow t+k}}}$ is the average, namely this quantity scaled by $k$. As with macro-aggregates, we consider horizons ranging from 1 quarter to 2 years.

We obtain a statistically significant positive slope on Dispersion at all horizons, and for both types of bonds, with the exception of investment-grade bonds at the quarterly horizon. $R^2$ statistics are economically significant, between 13 and 16% for investment-grade corporates at longer horizons, and 18-30% for high-yield corporates at longer horizons. 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. In the Online Appendix, we show that the out-of-sample $R^2$ for the regression of high yield bonds excess returns at the 1 quarter horizon is 13%. The implied annualized Sharpe ratio for an active investor in high yield bonds, using only real-time information, would then be 0.65, significantly higher than the estimated ratio of 0.24 for a buy and hold strategy that mimics the Barclays’ High Yield Index.\(^5\)

Our return predictability measures confirm the empirical findings of Greenwood and Hanson (2013), who show that a measure that is similar in some respects predicts returns. However, we do not interpret these findings as evidence of (time varying) inefficient credit supply. The strong correlation between Dispersion and future changes in business cycle conditions documented above hints at the possibility of a risk based explanation for these facts. Because default probabilities widen dramatically when prospects for future economic activity deteriorate it seems perfectly plausible to instead attribute these movements in expected returns to time variation in the market price of risk. The next section develops a detailed model that formalizes this argument.

\(^5\)See Cochrane (1999) for details on this calculation.
3 Model

In this section we show how we can interpret the empirical findings above through the lens of a partial equilibrium model with heterogeneous firms. The model’s structure is purposefully simple to highlight the key mechanisms. It consists of two elementary units: a production sector and a stochastic discount factor that summarizes investors’ attitude towards risk and discounting.

The production sector is made of 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 economic adverse event.

Perhaps the most striking assumption is that we choose to 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 exactly the role of real production and investment decisions in generating the main empirical findings.

3.1 The Stochastic Discount Factor

We assume all financial claims are owned and priced by an infinitely-lived representative household with an Epstein and Zin (1989) utility function. The representative agent’s utility is identified by a time preference rate \( \beta \in (0, 1) \), a relative risk aversion parameter \( \gamma \) and an elasticity of intertemporal substitution \( \psi \). It follows that the stochastic discount factor is given by:

\[
M_{t+1} = \beta^\theta \left( \frac{C_{t+1}}{C_t} \right)^{-\gamma} \left( \frac{S_{t+1} + 1}{S_t} \right)^{-1+\theta}
\]  

(5)
where $S_t$ denotes the wealth-consumption ratio and $\theta = \frac{1-\gamma}{1-\pi}$.

Given this it is straightforward to define the 1-period conditional risk-free rate, $r^f_t = \frac{1}{E_t[M_{t+1}]}$, and the 1-period conditional expected return on the consumption claim $E_t[r^c_{t+1}] = E_t \left[ \frac{C_{t+1}}{C_t} \frac{1+S_{t+1}}{S_t} \right]$.

### 3.2 Consumption and Uncertainty

The stochastic process for aggregate consumption is assumed to be:

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

(6)

where $\epsilon_{c,t+1}$ is a normal i.i.d. shock with mean zero and variance $\sigma^2_c$. Importantly, this process also allows for rare economic disasters (e.g. Rietz (1988), Barro (2006)). We let $x_{t+1}$ be an indicator function that equals 1 if a disaster occurs at $t+1$. The magnitude of the disaster, $\xi_{t+1}$, follows an i.i.d. normal distribution with mean $\mu_\xi$ and variance $\sigma^2_{\xi}$.

As Wachter (2013), the time-$t$ probability that a disaster will occur at time next period, denoted $p_t$, follows a first-order autoregressive process. To keep the probability positive, we model the log of $p_t$:

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

(7)

where $\epsilon_{p,t+1} \sim \mathcal{N}(0, \sigma^2_p)$ is assumed independent of $\xi_{t+1}$.

Given these assumptions, it can be shown that the stochastic discount factor equals:

$$M_{t+1} = \beta^\theta e^{-\gamma(\mu_c + \sigma_c \epsilon_{c,t+1} + \xi_{t+1} x_{t+1})} \left( \frac{S(p_{t+1}) + 1}{S(p_t)} \right)^{-1+\theta}.$$ 

(8)

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6In what follows, we will not impose market clearing; however we will link aggregate consumption to production. It is in this sense that our model is partial equilibrium. 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.

7Computing the wealth-consumption ratio requires solving the fixed point problem im-
3.3 Firms

The production sector of the economy comprises a continuum of potentially heterogeneous firms. Firms seek to maximize the present value of their distributions taking the investors’ stochastic discount factor as given.

3.3.1 Technology

Each firm \( i \) is endowed with the following Cobb-Douglas production function:

\[
Y_{it} = z_{it}^{1-\alpha} K_{it}^\alpha,
\]

where \( K_{it} \) denotes firm \( i \)'s capital level at time \( t \), and \( z_{it} \) is the firm-specific productivity level, which follows the stochastic process:

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

where \( \omega_{i,t+1} \) is an iid \( \sim N(0, \sigma^2) \) that summarizes the impact of the firm-specific TFP shocks, while \( \phi_i \) captures firm \( i \)'s exposure to the realization of the disaster, \( \xi_{t+1} \). The firm-specific drift term, \( \mu_i \), ensures that expected growth rates of productivity and output are identical for all firms \( i \) and also consistent with expected consumption growth.\(^8\) Equation 10 specifies that firms have heterogeneous exposures to disasters. For simplicity, we assume they have homogeneous exposures to the aggregate TFP shock.

\[\text{plied by system of non-linear equations:}\]

\[
E_t \left[ \beta^\theta \left( \frac{C_{t+1}}{C_t} \right)^{1-\gamma} \left( S(p_{t+1}) + 1 \right)^\theta \right] = S(p_t)^\theta.
\]

\(^8\)That is

\[
\mu_i = \mu_c + \log \left( E_t[e^{\phi_i \xi_{t+1} x_{t+1}}] \right) - \log \left( E_t[e^{\phi_i \xi_{t+1} x_{t+1}}] \right).
\]
3.3.2 Investment Opportunities

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

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

(12)

where $\delta$ is depreciation and $I_{it}$ is firm $i$’s investment at time $t$. Equation 12 captures the fact that maintaining the existing capital stock entails paying a depreciation cost. More significantly, it captures the assumption that an economic disaster also leads to a destruction of a firm’s stock of capital in the amount of $e^{\phi \xi_{t+1} x_{t+1}}$. As Gourio (2012) shows, this assumption is necessary for the existence of balanced growth.

We introduce standard adjustment costs Hayashi (1982). We assume that each dollar of added productive capacity requires $1 + \lambda(I_{it}, K_{it})$ dollars of expenditures, where

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

(13)

It follows that a firm’s net cash flows to its investors (payout), denoted $\Pi_{it}$, equals

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

(14)

The term $z_{it} f$ represents a fixed cost of production that firms need to pay to operate in each period.

3.3.3 Firm Value, Optimal Investment and Payout

To solve the firm’s problem, it is helpful to define planned capital stock, $\tilde{K}_{it} = \frac{K_{it}}{e^{\phi \xi_{t+1} x_{t+1}}}$, namely what $K_t$ would be if there were no disaster. Equation 12 implies
that planned capital obeys the law of motion

\[ \tilde{K}_{i,t+1} = (1 - \delta) \tilde{K}_{it} e^{\phi_i x_{it}} + I_{it}. \]  

As we show in Appendix C, firm \( i \)'s value at time \( t \) satisfies the fixed-point problem

\[
V(\tilde{K}_{it}, z_{it}, p_t) = \max_{I_{it}, \tilde{K}_{i,t+1}} \left[ z_{it}^{1-\alpha} \left( \tilde{K}_{it} e^{\phi_i x_{it}} \right)^{\alpha} - I_{it} - \lambda (I_{it}, \tilde{K}_{it} e^{\phi_i x_{it}}) - z_{it} f + \mathbb{E}_t[M_{t+1} V(\tilde{K}_{i,t+1}, z_{i,t+1}, p_{t+1})] \right]
\]

where the expectation term is computed by integrating over aggregate and idiosyncratic shocks, including the disaster events.

The full model solution is characterized in Appendix C. We show that optimal investment must satisfy the Euler equation

\[
1 = \mathbb{E}_t [M_{t+1} R^I_i],
\]

where the endogenous return to capital accumulation, \( R^I_i \), equals

\[
R^I_i = \frac{e^{\phi_i x_{i,t+1}+1}}{1 + \lambda_f (I_{it}, K_{it})} \left( \alpha \frac{Y_{i,t+1}}{K_{i,t+1}} - \lambda_K (I_{it+1}, K_{i,t+1}) + \frac{1 - \delta}{1 + \lambda_f (I_{i,t+1}, K_{i,t+1})} \right).
\]  

Given this optimal investment choice, net investor payout relative to beginning-of-period asset value is given by:

\[
\frac{\Pi_{it}}{K_{it}} = \left[ \frac{z_{it}}{K_{it}} \right]^{1-\alpha} - \frac{I_{it}}{K_{it}} - \frac{\lambda (I_{it}, K_{it})}{K_{it}} - \frac{z_{it} f}{K_{it}}.
\]  

By abstracting from any capital structure choice, this expression allows us to establish a direct link between investment and payout choices. It follows that net issuers will be firms with relatively high investment, a feature evident
in the summary statistics presented in Table 2.

Although a link between total investor payout and exact debt repayment decisions requires specific assumptions about capital structure, virtually all existing capital structure models deliver a strong positive relation between the two. Abstracting from specific financing frictions driving the choice of leverage and debt repayments allows us to highlight the key role of investment and profitability without any significant loss of generality.

3.3.4 Debt Claims

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 thus assume that each firm is endowed with an exogenous amount of debt, with a face value of $B_{it}$, which is calibrated to match the observed leverage ratios across portfolios. Let $b_{it} = \frac{B_{it}}{z_{it}}$ and $v_{it} = \frac{V_{it}}{z_{it}}$. For each firm, we calibrate an initial condition for $b_{i0} = \kappa_{i0}$. To capture the partial adjustment of leverage to firm value, we set

\[ b_{i,t+1} - b_{i,t} = \kappa_1(v_{it} - v_{i,t-1}). \]  

(18)

Given the face value of debt, it is straightforward to use (1) to construct the model’s implied expected default frequencies as well as the associated spread in $EDF$ between high and low payout firms.

Returns on debt can be computed from the changes in the implied market value of debt, $D_{it}$. This value can be derived by numerically evaluating the implicit options written on firms’ assets and applying put-call parity on the value of firm $i$’s assets:

\[ D_{it} = B_{it} e^{-r_f t} - P(V_{it} - \Pi_{it}, B_{it}, r_f) \]  

(19)
where \( P(\cdot) \) denotes the value of a put option on firm’s assets. With this value at hand we can readily compute firm-specific debt returns.

### 3.3.5 Aggregation and the Cross Section of Firms

After computing the optimal investment decision we can easily construct all other firm level variables. Given an exogenous distribution of firms \( f(\phi_i) \) it is also straightforward to construct any relevant economy wide aggregates. Specifically, aggregate output and investment can be computed as follows:

\[
Y_t = \int Y_t df, \quad I_t = \int I_t df
\]

### 4 Findings

This section describes the quantitative implications of our model and compares them with our earlier empirical results. We start with a description of our choices for the key parameter values. We solve the model using a standard numerical methods and simulate the resulting artificial economy to investigate its properties. Our quantitative results are based on averaging 200 independent samples with 50 years (200 quarters) of firm-level data. Each sample path contains 5000 firms. Additional computational details are provided in the appendix.

#### 4.1 Parameter Choices

To match the sampling frequency used in our empirical analysis, our model is also calibrated at quarterly frequency. Whenever possible, we choose parameter values that are commonly used in the literature. Notably, the preference parameters, \( \beta \) and \( \gamma \) are chosen to produce plausible values for the real risk free rate and the average premium on a consumption claim in our economy. We
set the elasticity of intertemporal substitution, $\psi$, equal to a standard value of 2 (e.g. Gourio (2012)).

The parameters that pin down the distribution of disasters are also calibrated to match the evidence in prior studies (e.g. Barro (2006) and Backus, Chernov, and Martin (2011)). The annualized average probability of disaster is set to about 2%. The quarterly process for the log of the disaster probability is highly persistent with an autoregression coefficient of about 0.9 and has an unconditional standard deviation around 1.15. We assume the average consumption lost in a disaster state is 30% with a volatility of 15%. Finally, the average trend and volatility of aggregate consumption growth outside of disaster states, $\mu_c$ and $\sigma_c$ respectively, are chosen to be consistent with post war US macroeconomic data. This implicitly assumes no disaster realizations during this period.

Regarding the parameters characterizing firm level technology, we follow Cooper and Ejarque (2003) and set the degree of returns to scale, $\alpha$, equal to 0.7. The fixed cost parameter, $f$ is set so that we match the observed profitability ratio in the data.

As usual, the maintenance cost of capital $\delta$ is set to 4.25% per quarter, and ensures that we match the average level of investment to capital ratios in our data. Similarly, the adjustment cost parameter, $\eta$, is chosen so that we can replicate the volatility of investment in our data.

The process for firm-specific productivity (10) combines a normal component with differential sensitivities, $\phi_i$ to disaster realizations. As a result firm level investment and issuance decisions will 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 equally distributed at intervals of 0.5 between 1 and 3.9. As discussed earlier, the firm

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9Because our results are based on the highest and lowest quintiles, they are relatively insensitive to the form of this distribution
specific drift ensures that all productivity growth is expected to be the same for all firms. Finally, the parameters characterizing the exogenous process for debt, $\kappa^0_i$ and $\kappa^1_i$, are set to match the average portfolio leverage ratios (35%). Given this and the different shock sensitivities above, the volatility of the idiosyncratic shocks is set to match portfolio expected default frequencies.

Table 5 summarizes all of our choices regarding parameter values. Table 6 reports the unconditional moments of aggregate asset prices. As we can see, the model is able to generate reasonable values for these prices. The firm-level characteristics for the two extreme portfolios are presented in table 8. Consistent with the data we find that repayers have lower investment rates and higher leverage than issuers. They also have a higher EDF when compared to issuers.

4.2 Quantitative Results

To understand the joint dynamics of macro aggregates and risk premia in our model it is useful to look at a series of impulse responses to the underlying shocks. We then build on this intuition to show how our model with no financial shocks replicates the joint dynamic behavior of aggregate macro quantities and bond returns and, in particular, the key predictability findings.

4.2.1 Firm Behavior

Figure 2 illustrates the response to a sudden increase in the probability of disaster for an individual firm.\textsuperscript{10} As we can see, investment immediately declines and only slowly returns to its (de-trended) level.\textsuperscript{11} Since the level of capital is predetermined and productivity itself is not affected by this shock,

\textsuperscript{10}We use the firm with $\phi = 1$ as an illustration. However, the qualitative results discussed in this section hold regardless of $\phi$.

\textsuperscript{11}The speed of this adjustment is naturally determined by the magnitude of the adjustment costs parameter, $\eta$. 
firm level output responds only with a lag. Eventually however lower levels of investment reduce the stock of capital and with it firm production.

Two of our modeling choices contribute to these results and are worth describing in more detail. First, we abstracted from labor demand. If the firm could adjust the labor employed, shocks to the probability of disaster would lead to immediate changes in output. Second, it is important that a disaster realization leads to capital destruction. If the next period level of capital was not directly reduced by a disaster realization, an increase in the probability of a disaster would lead to an investment boom as capital would be more valuable to smooth consumption.

The right panel shows the response of firm value and EDF. Unsurprisingly, the market value of the firm declines following the rise in disaster probability. Although the exact magnitudes depend on our calibration, the behavior of firm value is extremely robust and will mimic that of investment provided a minimal version of Q theory holds in the model.

The behavior of EDF essentially depends on the response of leverage. Our assumptions regarding the behavior of the face value of debt, $B_{it}$, imply that the leverage increases mechanically in the first period, as the firm value decreases. This in turn produces a corresponding increase in EDF. Although EDF levels remain elevated, the initial effect vanishes over time as the debt levels begins to fall and leverage readjusts. Thus, our model predicts that firm-level EDF will generally rise during those recessions when output is below trend and output growth is negative.

Again, although our assumptions about leverage impact the numerical findings, the qualitative results would remain unchanged even under more complex models of the firm’s capital structure. This is because the basic finding that EDFs are countercyclical is extremely robust and can only be generated in a setting where the value of debt outstanding reacts more slowly than that of equity to economic shocks. Considering different models of capital structure
then would only serve to obscure the model’s main mechanism.

4.2.2 Cross Section and Macroeconomic Aggregates

We now build on the firm-level results to discuss the impact of an increase in the probability of disaster on aggregate output, and investment, which, unsurprisingly, mirror the ones for an individual firm described above.

Figure 3 documents this as well as the response of Dispersion. In our model, this is driven by firm’s differential exposures to aggregate risk, or “asset betas”. Those with large sensitivities are more adversely impacted by this shock and tend to cut their investment spending by more. This in turn leads to lower issuance activity and/or higher payouts to investors.

As a result, the portfolio of repaying firms then will exhibit the largest fluctuations in measured EDF, leading to a wider dispersion in spreads. Hence, just like in the data, dispersion in perceived credit quality is time varying and largely driven by movements in expected default frequencies of repaying firms. Importantly, a widening dispersion is also naturally associated with deteriorating economic conditions.

4.2.3 Predictability

The previous intuition about the workings of the core model can now be used to help us interpret the empirical findings about the predictability of macro aggregates and financial prices. Our main results are in Tables 9 and 10.

Table 9 shows that our model replicates the finding that an increase in Dispersion predicts a sizable decline in aggregate output and investment growth. As we have shown above, in our model, increases in Dispersion are generally associated with high values of the disaster probability. In these states, firms endogenously invest less and this leads to lower output. The table also shows that the overall predictability in GDP growth is similar to that in the data
and roughly constant in the forecast horizon in the model. The estimated coefficients in the model exhibit the same decreasing pattern as in the data. Predictability of investment growth at short horizons is stronger than for GDP in both model and data, and it too declines quickly.

Table 10 investigates the model’s implications for the predictability of bond returns. To construct theoretical counterparts to the investment-grade and high-yield portfolios we sort firms in the model, in every period, according to their estimated EDF, a measure of their credit quality. We then label the firms in the lowest quintile of this EDF distribution as “Investment Grade”. Similarly, those in the highest quintile firms are classified as “High Yield”. We then construct two indices of bond returns by aggregating the individual firm bond returns using the each firm’s debt value as a portfolio weight.

With these measures at hand it is straightforward to construct theoretical counterparts to the earlier empirical regressions. Table 10 shows how the model generates a fair amount of bond returns predictability for both high and low credit quality firms. Moreover, returns on high-yield debt are easier to forecast than those on investment-grade bonds, both in the model and in the data. What drives these results? An increase in Dispersion signals an increase in the risk of economic disaster, because repayers are more sensitive to this risk than issuers. Firms are subject to a greater degree of systematic default risk when the probability of disaster is higher. Thus investors require greater risk premia to hold these bonds, and their returns are predictably high. This is especially the case for high-yield firms, which are the more sensitive to economic news, in this case shocks in the disaster probability.

Interestingly, 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 non-linear. This can explain the observation of Greenwood and
Hanson (2013) that fitted returns are sometimes negative, without assuming investors are irrational.

5 Additional Results

Our model purposefully does not draw a distinction between debt repayments and total repayments to all investors. This begs the question whether the empirical findings for debt repayments are themselves unique.

Accordingly, we now re-examine our earlier results from this standpoint. Thus, rather than grouping firms based on their debt issuance activity, we sort on total security issuance or, equivalently total asset growth, defined as the change in book value of assets divided by assets in the previous period. The literature often interprets asset growth as a proxy for firm investment. The economic mechanism of Section 3 suggests that sorts based on asset growth should identify risky firms just as well as sorts based on debt repayment.

Figure 4 shows the analogue of our dispersion measure, except computed from the EDFs of the bottom asset growth quintile minus the EDFs of the top asset growth quintile. The time series is very close to the time series of our repayment-based dispersion measure. Moreover, the predictability properties for returns and for economic growth are also close; for this reason we do not report them. Thus there is not anything special about debt repayment: a similar result holds for asset growth as our model would predict.\footnote{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.}
6 Conclusions

This paper makes three contributions. First, we show that firms who are on average repayers of securities have an Expected Default Frequency that is both higher and more sensitive to cyclical fluctuations than those who are issuers of securities. Moreover, we observe that repayers exhibit lower and less volatile 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 financial prices. 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.

We build a partial equilibrium framework, with heterogeneous firms making optimal investment decision and facing differential exposures towards a rare but extreme 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.
References


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 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’s debt computed as short-term debt (dlcq) plus half of long-term debt (dlttq), $\mu V_i$ is the firm’s asset drift and $\sigma V_i$ the asset volatility. Finally, $\mu V_i$ is estimated by using the firm’s cumulative stock return over the prior 12 months and asset volatility equals $\sigma V_i = \frac{E_{it}}{E_{it} + B_{it}} \sigma E_i + \frac{B_{it}}{E_{it} + B_{it}} (0.05 + 0.25 \sigma E_i)$ where $E_{it}$ refers to the market capitalization of firm $i$ at time $t$ and $\sigma E_i$ is also estimated using the last 12 months.
Appendix B  Model Solution

We use numerical dynamic programming to obtain approximations of the Value function $V(\cdot)$ and Investment policy function $K(\cdot)$ 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 $j$:

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

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

$$y_{jt} = k_{jt}^{\alpha} \quad \text{(B.1)}$$

$$k_{j,t+1} = \frac{(1 - \delta)k_{jt} + i_{jt}}{e^{\mu + \sigma_\epsilon \epsilon_{c,t+1} + \sigma_\omega \omega_{j,t+1}}} \quad \text{(B.2)}$$

The stationary value function solves:

$$v_{jt}(k_{jt}, p_t) = \max_{i_{jt}, k_{j,t+1}} \left[ k_{jt}^{\alpha} - i_{jt} - \lambda(i_{jt}, k_{jt}) - f - \mathbb{E}_t \left[ M_{t+1} e^{\mu + \sigma_\epsilon \epsilon_{c,t+1} + \sigma_\omega \omega_{j,t+1} + \phi_{j,t+1} \xi_{t+1} x_{t+1}} v(k_{j,t+1}, p_{t+1}) \right] \right] \quad \text{(B.3)}$$

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

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
$k \in [\bar{k}, \tilde{k}]$ and disaster probability $p$. We start each firm $j$ with an initial guess for the value function $v^0(k_{j,0}, p_0)$ and iterate over the Bellman equation recursively so that after $l$ iterations, firm $j$ solves:

$$v^{l+1}(k_{jt}, p_t) = k_{jt}^\alpha - i_{jt}(k_{jt}, p_t) - \lambda (i_{jt}(k_{jt}, p_t), k_{jt}) - f + E_t \left[ M_{t+1} e^{\mu + \sigma \phi \epsilon_{t+1} + \sigma \omega j_{t+1} + \phi_j \xi_{t+1} \gamma_{t+1} v^l(k_{jt+1}, p_{t+1}) \right]$$

$$s.t. \quad k_{j,t+1} = \frac{(1 - \delta)k_{jt} + i_{jt}(k_{jt}, p_t)}{e^{\mu + \sigma \phi \epsilon_{t+1} + \sigma \omega j_{t+1}} \tilde{k}_{t+1}}$$

The problem is complicated by the fact that the agent does not choose $k_{t+1}$, because this object is stochastic and affected by capital destruction if a disaster realizes. Instead, the firm chooses the value of capital next period corrected by the possible disaster realization $\tilde{k}_{t+1} = \frac{k_{t+1}}{e^{\sigma \phi \epsilon_{t+1} + \sigma \omega j_{t+1}}}$ (please see Appendix C for a more complete discussion).

Despite the large dimensionality of the state space, the model can be solved quickly since, for any given $p_t$, $\tilde{k}_{t+1}$ is monotonic non-decreasing in $k$.

After solving the problem of each individual firm $j$ we obtain model-implied moments by taking the averages across 200 simulated economies of 38 years each. Each economy consists of 5000 companies equally distributed across 5 equidistant values of the disaster sensitivity $\phi_j \in [1, 3]$. The burn-out sample for each simulation consists of the first 1000 periods.

### Appendix C  Firm’s Problem

This appendix further characterizes the problem of the firm.

As discussed above the main issue for this control problem is that the state variable $k_{t+1}$ is stochastic and is subject to a capital destruction shock which occurs only at the beginning of period $t + 1$. As a result the firm will instead choose investment, $i_t$, and planned capital for next period, $\tilde{k}_{t+1} = \frac{k_{t+1}}{e^{\sigma \phi \epsilon_{t+1} + \sigma \omega j_{t+1}}}$.
As a result, the problem of each individual firm can be written as:

\[
v(\tilde{k}_{it}, p_t) = \max_{i_t, \tilde{k}_{i,t+1}} \left[ z_{it}^{1-\alpha} \left( \tilde{k}_{it} e^{\phi_i \xi_{it}} \right)^\alpha - i_{it} - \lambda \left( I_{it}, \tilde{k}_{it} e^{\phi_i \xi_{it}} \right) - z_{it} f + \right.
+ \mathbb{E}_t \left[ M_{t+1} v(\tilde{k}_{i,t+1}, p_{t+1}) \right]
\]

s.t. \( \tilde{k}_{i,t+1} = (1 - \delta) \tilde{k}_{it} e^{\phi_i \xi_{it}} + i_{it} \) \hfill (C.1)

The F.O.C. with respect to the level of investment and next period capital are

\[
\begin{align*}
[i_{it}] & \quad q_{it} = 1 + \lambda_i \left( i_{it}, \tilde{k}_{it} e^{\phi_i \xi_{it}} \right) \quad \hfill (C.3) \\
[k_{i,t+1}] & \quad q_{it} = \mathbb{E}_t \left[ M_{t+1} \frac{\partial v_{i,t+1}}{\partial k_{i,t+1}} \right] \quad \hfill (C.4)
\end{align*}
\]

while the envelope condition prescribes:

\[
\frac{\partial v_{it}}{\partial k_{it}} = \alpha z_{it}^{1-\alpha} \tilde{k}_{it}^{\alpha-1} e^{\phi_i \xi_{it}} - \lambda_k \left( i_{it}, \tilde{k}_{it} e^{\phi_i \xi_{it}} \right) + q_{it}(1 - \delta) e^{\phi_i \xi_{it}} \hfill (C.5)
\]

The first-order derivative of the adjustment cost function with respect to investment and capital are:

\[
\begin{align*}
\lambda_i \left( i_{it}, \tilde{k}_{it} e^{\phi_i \xi_{it}} \right) &= 2\eta \left( \frac{i_{it}}{k_{it} e^{\phi_i \xi_{it}}} \right) \hfill (C.6) \\
\lambda_k \left( i_{it}, \tilde{k}_{it} e^{\phi_i \xi_{it}} \right) &= \eta \left( \frac{i_{it}}{k_{it}} \right)^2 e^{-\phi_i \xi_{it}} \hfill (C.7)
\end{align*}
\]
Using this in equation (C.4) yields:

\[
q_{it} = E_t \left[ M_{t+1} \left( \alpha z_{i,t+1}^{1-\alpha} \bar{K}_{i,t+1}^{\alpha-1} e^{\alpha \phi_t \xi_{t+1} x_{t+1}} + \eta \left( \frac{i_{i,t+1}}{k_{i,t+1}} \right)^2 e^{-\phi_t \xi_{t+1} x_{t+1}} \\
+ q_{i,t+1}(1 - \delta) e^{\phi_t \xi_{t+1} x_{t+1}} \right) \right] \tag{C.8}
\]

This can then be solved using standard iterating techniques.

Alternatively, we can rewrite our problem, in terms of the original variable \( k_{it} \), as follows:

\[
q_{it} = E_t \left[ M_{t+1} e^{\phi_t \xi_{t+1} x_{t+1}} \left( \alpha z_{i,t+1}^{1-\alpha} \bar{K}_{i,t+1}^{\alpha-1} e^{(\alpha-1) \phi_t \xi_{t+1} x_{t+1}} + \eta \left( \frac{i_{i,t+1}}{k_{i,t+1}} e^{\phi_t \xi_{t+1} x_{t+1}} \right)^2 \\
+ q_{i,t+1}(1 - \delta) \right) \right] = E_t \left[ M_{t+1} e^{\phi_t \xi_{t+1} x_{t+1}} \left( \alpha \frac{y_{i,t+1}}{k_{i,t+1}} + \eta \left( \frac{i_{i,t+1}}{k_{i,t+1}} \right)^2 + q_{i,t+1}(1 - \delta) \right) \right] \tag{C.9}
\]

Substituting both \( q_{it} \) and \( q_{i,t+1} \) from equation (C.3) we get an expression for the required return on capital, \( R_I^i \):

\[
1 = E_t \left[ M_{t+1} e^{\phi_t \xi_{t+1} x_{t+1}} \left( \alpha \frac{y_{i,t+1}}{k_{i,t+1}} + \eta \left( \frac{i_{i,t+1}}{k_{i,t+1}} \right)^2 + \frac{1 - \delta}{1 + 2\eta \frac{i_{i,t+1}}{k_{i,t+1}}} \right) \right] \tag{C.10}
\]

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

\[
1 = E_t \left[ M_{t+1} e^{\phi_t \xi_{t+1} x_{t+1}} \left( \alpha \frac{y_{i,t+1}}{k_{i,t+1}} + 1 - \delta \right) \right] \tag{C.11}
\]
Table 1. Debt Repayment by Portfolios

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>10%</th>
<th>50%</th>
<th>90%</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (Issuers)</td>
<td>-0.313</td>
<td>-0.091</td>
<td>-0.047</td>
<td>-0.177</td>
</tr>
<tr>
<td>2</td>
<td>-0.043</td>
<td>-0.026</td>
<td>-0.015</td>
<td>-0.028</td>
</tr>
<tr>
<td>3</td>
<td>-0.015</td>
<td>-0.006</td>
<td>0.001</td>
<td>-0.007</td>
</tr>
<tr>
<td>4</td>
<td>0.002</td>
<td>0.010</td>
<td>0.021</td>
<td>0.011</td>
</tr>
<tr>
<td>5 (Repayers)</td>
<td>0.023</td>
<td>0.050</td>
<td>0.162</td>
<td>0.081</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Variable</th>
<th>10%</th>
<th>Median</th>
<th>90%</th>
<th>Average</th>
<th>Standard Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>EDF - Repayers&lt;sub&gt;t&lt;/sub&gt;</td>
<td>0.000</td>
<td>0.000</td>
<td>6.19e⁻⁰⁶</td>
<td>0.011</td>
<td>0.080</td>
</tr>
<tr>
<td>EDF - Issuers&lt;sub&gt;t&lt;/sub&gt;</td>
<td>0.000</td>
<td>0.000</td>
<td>6.45e⁻⁰⁸</td>
<td>0.004</td>
<td>0.046</td>
</tr>
<tr>
<td>Investment - Repayers&lt;sub&gt;t&lt;/sub&gt;</td>
<td>0.000</td>
<td>0.024</td>
<td>0.100</td>
<td>0.040</td>
<td>0.077</td>
</tr>
<tr>
<td>Investment - Issuers&lt;sub&gt;t&lt;/sub&gt;</td>
<td>0.005</td>
<td>0.043</td>
<td>0.194</td>
<td>0.086</td>
<td>0.169</td>
</tr>
<tr>
<td>Leverage - Repayers&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>0.030</td>
<td>0.275</td>
<td>0.702</td>
<td>0.323</td>
<td>0.250</td>
</tr>
<tr>
<td>Leverage - Issuers&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>0.018</td>
<td>0.210</td>
<td>0.604</td>
<td>0.264</td>
<td>0.224</td>
</tr>
<tr>
<td>Size - Repayers&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>2.196</td>
<td>4.616</td>
<td>7.608</td>
<td>4.786</td>
<td>2.076</td>
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<tr>
<td>Size - Issuers&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>2.152</td>
<td>4.633</td>
<td>7.655</td>
<td>4.795</td>
<td>2.104</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Horizon $k$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: GDP</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td>$-0.29^{***}$</td>
<td>$-0.21^{***}$</td>
<td>$-0.16^{***}$</td>
<td>$-0.12^{**}$</td>
<td>$-0.04$</td>
</tr>
<tr>
<td></td>
<td>$[-4.30]$</td>
<td>$[-3.54]$</td>
<td>$[-2.92]$</td>
<td>$[-2.29]$</td>
<td>$[-0.68]$</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.0758</td>
<td>0.0582</td>
<td>0.0435</td>
<td>0.0278</td>
<td>0.0038</td>
</tr>
<tr>
<td><strong>Panel B: Investment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td>$-1.26^{***}$</td>
<td>$-0.88^{***}$</td>
<td>$-0.55^{**}$</td>
<td>$-0.31$</td>
<td>$0.04$</td>
</tr>
<tr>
<td></td>
<td>$[-4.62]$</td>
<td>$[-3.06]$</td>
<td>$[-2.34]$</td>
<td>$[-1.62]$</td>
<td>$[0.24]$</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.1133</td>
<td>0.0752</td>
<td>0.0370</td>
<td>0.0141</td>
<td>0.0004</td>
</tr>
</tbody>
</table>

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

*Notes:* Estimation of

$$\Delta y_{t\rightarrow t+k} = \alpha + \beta Dispersion_t + \epsilon_{t+k}.$$  

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 report 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

<table>
<thead>
<tr>
<th>Horizon $k$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>8</th>
</tr>
</thead>
</table>

### Panel A: Investment Grade Bonds

<table>
<thead>
<tr>
<th>$\beta$</th>
<th>0.81</th>
<th>0.95***</th>
<th>0.84***</th>
<th>0.71***</th>
<th>0.45***</th>
</tr>
</thead>
<tbody>
<tr>
<td>[1.61]</td>
<td>[3.13]</td>
<td>[3.22]</td>
<td>[3.28]</td>
<td>[3.24]</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$R^2$</th>
<th>0.0555</th>
<th>0.1437</th>
<th>0.1565</th>
<th>0.1474</th>
<th>0.1277</th>
</tr>
</thead>
</table>

### Panel B: High Yield Bonds

<table>
<thead>
<tr>
<th>$\beta$</th>
<th>2.30**</th>
<th>2.23***</th>
<th>1.95***</th>
<th>1.69***</th>
<th>1.24***</th>
</tr>
</thead>
<tbody>
<tr>
<td>[2.54]</td>
<td>[2.90]</td>
<td>[2.84]</td>
<td>[2.90]</td>
<td>[4.61]</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$R^2$</th>
<th>0.1172</th>
<th>0.1793</th>
<th>0.2226</th>
<th>0.2347</th>
<th>0.2996</th>
</tr>
</thead>
</table>

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

**Notes**: Estimation of

$$\bar{r}_{t \rightarrow t+k} = \alpha + \beta\text{Dispersion}_t + \epsilon_{t+k}.$$ 

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 ($\text{Dispersion}$). 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 report 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

<table>
<thead>
<tr>
<th>Description</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative risk aversion</td>
<td>$\gamma$</td>
<td>4.40</td>
</tr>
<tr>
<td>Rate of time preference</td>
<td>$\beta$</td>
<td>0.990</td>
</tr>
<tr>
<td>Elasticity of intertemporal substitution</td>
<td>$\psi$</td>
<td>2</td>
</tr>
<tr>
<td>Average probability of disaster</td>
<td>$\bar{p}$</td>
<td>0.0052</td>
</tr>
<tr>
<td>Persistence of log probability of disaster</td>
<td>$\rho_p$</td>
<td>0.91</td>
</tr>
<tr>
<td>Volatility of log probability of disaster</td>
<td>$\sigma_p$</td>
<td>0.502</td>
</tr>
<tr>
<td>Average size of disaster</td>
<td>$\mu_\xi$</td>
<td>-0.30</td>
</tr>
<tr>
<td>Volatility of disaster size</td>
<td>$\sigma_\xi$</td>
<td>0.15</td>
</tr>
<tr>
<td>Average consumption growth (normal times)</td>
<td>$\mu_c$</td>
<td>0.0028</td>
</tr>
<tr>
<td>Volatility of consumption growth (normal times)</td>
<td>$\sigma_c$</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Notes: The table shows parameter values that are relevant to compute the stochastic discount factor in the economy. We assume the representative agent has Epstein and Zin (1989) utility with risk aversion $\gamma$, elasticity of intertemporal substitution $\psi$, and time discount factor $\beta$. The consumption process 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 $\xi_{t+1}$ is normally distributed with mean $\mu_\xi$ and standard deviation $\sigma_\xi$. We assume that the logarithm of $p_t$ follows a Markov process with persistence $\rho_p$ and volatility $\sigma_p$. We calibrate the model at a quarterly frequency.
Table 6. Aggregate Moments

<table>
<thead>
<tr>
<th>Moment</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average government bond yield</td>
<td>0.0101</td>
<td>0.0107</td>
</tr>
<tr>
<td>Government bond yield volatility</td>
<td>0.0222</td>
<td>0.0218</td>
</tr>
<tr>
<td>Average premium on the consumption claim</td>
<td>0.0532</td>
<td>0.0365</td>
</tr>
<tr>
<td>Volatility of the consumption claim return</td>
<td>0.1226</td>
<td>0.0833</td>
</tr>
</tbody>
</table>

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, multiplied by 0.72 to adjust for leverage. Data are from 1951-2013. In the model, we assume the government bill experiences a loss, conditional on a disaster, with probability 10%; in this case the percentage loss is equal to the percent decline in consumption. Model moments are from a quarterly simulation of length 250,000 years.
### Table 7. Parameter Values for Individual Firms

<table>
<thead>
<tr>
<th>Description</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Returns to scale</td>
<td>$\alpha$</td>
<td>0.70</td>
</tr>
<tr>
<td>Depreciation rate</td>
<td>$\delta$</td>
<td>0.0425</td>
</tr>
<tr>
<td>Adjustment cost on capital</td>
<td>$\eta$</td>
<td>4</td>
</tr>
<tr>
<td>Volatility of idiosyncratic TFP shock (normal times)</td>
<td>$\sigma_\omega$</td>
<td>0.10</td>
</tr>
<tr>
<td>Minimum sensitivity to disasters</td>
<td>min$_i(\phi_i)$</td>
<td>1</td>
</tr>
<tr>
<td>Maximum sensitivity to disasters</td>
<td>max$_i(\phi_i)$</td>
<td>3</td>
</tr>
<tr>
<td>Fixed cost</td>
<td>$f$</td>
<td>2</td>
</tr>
</tbody>
</table>

**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

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

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

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

We calibrate the model at a quarterly frequency. Values for the sensitivity of disaster are in increments of 0.5 starting from the minimum and going to the maximum.
Table 8. Characteristics of Net Repayers and Issuers

<table>
<thead>
<tr>
<th>Variable</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>EDF - Repayers$_t$</td>
<td>0.011</td>
<td>0.017</td>
</tr>
<tr>
<td>EDF - Issuers$_t$</td>
<td>0.004</td>
<td>0.006</td>
</tr>
<tr>
<td>Investment - Repayers$_t$</td>
<td>0.040</td>
<td>0.026</td>
</tr>
<tr>
<td>Investment - Issuers$_t$</td>
<td>0.086</td>
<td>0.079</td>
</tr>
<tr>
<td>Leverage - Repayers$_{t-1}$</td>
<td>0.323</td>
<td>0.346</td>
</tr>
<tr>
<td>Leverage - Issuers$_{t-1}$</td>
<td>0.264</td>
<td>0.331</td>
</tr>
</tbody>
</table>

Notes: We simulate 200 paths at a quarterly frequency of length equal to the 1976–2013 sample. Each sample path contains 5000 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 $I_t$ in the model divided by capital $K_t$. Leverage is defined using the book value $B_t$ of debt divided by the market value of assets $V_t$. 
Table 9. Forecasting Macroeconomic Quantities

<table>
<thead>
<tr>
<th>Horizon $k$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>8</th>
</tr>
</thead>
</table>

**Panel A: $\Delta GDP_{t \rightarrow t+k}$**

<table>
<thead>
<tr>
<th>$\beta$</th>
<th>Data</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$-0.29^{***}$</td>
<td>$-0.21^{***}$</td>
<td>$-0.16^{***}$</td>
<td>$-0.12^{**}$</td>
<td>$-0.04$</td>
</tr>
<tr>
<td>Model</td>
<td>$-0.67$</td>
<td>$-0.41$</td>
<td>$-0.33$</td>
<td>$-0.30$</td>
<td>$-0.27$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$R^2$</th>
<th>Data</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$0.0758$</td>
<td>$0.0582$</td>
<td>$0.0435$</td>
<td>$0.0278$</td>
<td>$0.0038$</td>
</tr>
<tr>
<td>Model</td>
<td>$0.0288$</td>
<td>$0.0300$</td>
<td>$0.0349$</td>
<td>$0.0338$</td>
<td>$0.0279$</td>
</tr>
</tbody>
</table>

**Panel B: $\Delta$ Investment $t \rightarrow t+k$**

<table>
<thead>
<tr>
<th>$\beta$</th>
<th>Data</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$-1.26^{***}$</td>
<td>$-0.88^{***}$</td>
<td>$-0.55^{**}$</td>
<td>$-0.31$</td>
<td>$0.04$</td>
</tr>
<tr>
<td>Model</td>
<td>$-4.69$</td>
<td>$-3.46$</td>
<td>$-2.34$</td>
<td>$-1.02$</td>
<td>$3.00$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$R^2$</th>
<th>Data</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$0.1133$</td>
<td>$0.0752$</td>
<td>$0.0370$</td>
<td>$0.0141$</td>
<td>$0.0004$</td>
</tr>
<tr>
<td>Model</td>
<td>$0.2216$</td>
<td>$0.0461$</td>
<td>$0.0183$</td>
<td>$0.0145$</td>
<td>$0.0325$</td>
</tr>
</tbody>
</table>

**Notes:** Estimation of

$$\overline{\Delta y_{t \rightarrow t+k}} = \alpha + \beta Dispersion_t + \epsilon_{t+k}$$

The table reports the OLS coefficients and $R^2$ from the predictive regressions of macroeconomic aggregates onto $Dispersion$ both in the data and (the average 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 $N = 1000$ time-series paths of the same length as the empirical sample.
### Table 10.
Forecasting Excess Returns on Bonds

<table>
<thead>
<tr>
<th>Horizon $k$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Investment Grade</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data</td>
<td>0.81</td>
<td>0.95***</td>
<td>0.84***</td>
<td>0.71***</td>
<td>0.45***</td>
</tr>
<tr>
<td>Model</td>
<td>0.53</td>
<td>0.09</td>
<td>0.08</td>
<td>0.06</td>
<td>0.05</td>
</tr>
<tr>
<td>$R^2$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data</td>
<td>0.0555</td>
<td>0.1437</td>
<td>0.1565</td>
<td>0.1474</td>
<td>0.1277</td>
</tr>
<tr>
<td>Model</td>
<td>0.0765</td>
<td>0.0463</td>
<td>0.0557</td>
<td>0.0639</td>
<td>0.0749</td>
</tr>
<tr>
<td><strong>Panel B: High Yields</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data</td>
<td>2.30**</td>
<td>2.23***</td>
<td>1.95***</td>
<td>1.69***</td>
<td>1.24***</td>
</tr>
<tr>
<td>Model</td>
<td>0.58</td>
<td>1.11</td>
<td>0.94</td>
<td>0.62</td>
<td>0.48</td>
</tr>
<tr>
<td>$R^2$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data</td>
<td>0.1172</td>
<td>0.1793</td>
<td>0.2226</td>
<td>0.2347</td>
<td>0.2996</td>
</tr>
<tr>
<td>Model</td>
<td>0.1529</td>
<td>0.0563</td>
<td>0.0674</td>
<td>0.0766</td>
<td>0.0756</td>
</tr>
</tbody>
</table>

*Notes: Estimation of* \[ r_{t-t+k} = \alpha + \beta Dispersion_t + \epsilon_{t+k} \]*

The table reports the OLS coefficients and $R^2$ from predictive regressions for the average excess returns on investment grade and high yield bonds both in the data and (the average 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 $N = 200$ time-series paths of the same length as the sample for January 1976 to September 2013 at the quarterly frequency.
Panel A: Expected default frequency (EDF) of repayers and issuers

Panel B: Dispersion in credit quality

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 and output (middle) and firm value and EDF (right) to a decrease in disaster probability (left). The figure shows the response to a temporary increase in the quarterly disaster probability from 0.52% to 1.85%. We simulate a series for $p_t$ and compute the solution assuming no TFP shocks. We then perturb the model assuming a change in the probability of disaster to a new value $p_{1t}$. Conditional on $p_{1t}$, we simulate a new sequence $\{p\}_T$ according to the transition probabilities. We repeat the procedure 20,000 times and calculate the average across simulations. The initial capital value for the firm is chosen to be its ergodic mean of capital. Investment, output, value, and EDF are for a firm with $\phi = 1$. 
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 1.85%. We consider two firms with $\phi = 1.5$. 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 then the difference between repayer and issuer EDF (dispersion).
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 top asset growth quintile minus the average EDF of the bottom asset growth quintile. The shaded areas correspond to NBER recessions.