

Evaluating the Magnitude of Financial Market Frictions: Evidence from Firm-Level Data

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Abstract

We investigate the extent to which firm-level data are consistent with the microeconomic foundations of the benchmark financial accelerator model of Bernanke, Gertler, and Gilchrist (1999). To that purpose, we construct a new dataset that directly links firm-specific balance sheet variables to credit spreads on publicly-traded debt. The estimated leverage-spread schedule exhibits statistically significant nonlinearities that are consistent with the theoretical predictions of the model. We then use the observed data on financial leverage, spreads, and market-based measures of default risk to solve for key structural parameters of the model. Our results indicate that a substantial degree of financial market frictions is necessary to match the default probabilities implied by the model with market-based measures of default risk. Moreover, we quantify the magnitude of the model-implied external finance premium, show how it is related to various firm characteristics, and examine its behavior during the most recent economic downturn. Finally, we identify several directions in which the basic framework needs to be extended to account for other cyclical and cross-sectional features of the data.

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1 Introduction

Since Fisher's (1993) debt-deflation explanation of the Great Depression, economists have emphasized the role of financial factors in amplifying shocks to the economy. A large literature on the macroeconomic significance of financial market frictions has emerged, focusing both on the closed and on the open economy. The former includes, among others, Bernanke and Gertler (1989), Carlstrom and Fuerst (1997), Kiyotaki and Moore (1997), Bernanke, Gertler, and Gilchrist (1999) (BGG hereafter), and Christiano, Motto, and Rostagno (2002). The latter, following the 1997-98 Asian financial crisis, includes Krugman (1999), Aghion, Bacchetta, and Banerjee (2000), Cespedes, Chang, and Velasco (2000), Caballero and Krishnamurthy (2001), and Gertler, Gilchrist and Natalucci (2003).

In this paper, we investigate the extent to which firm-level data are consistent with the microeconomic foundations of the benchmark BGG financial accelerator model. In particular, we show that the model implies a non-linear relationship between financial leverage and the external finance premium. We then analyze a new dataset that directly links firm-specific balance sheet variables to credit spreads on publicly-traded debt. The estimated leverage-spread schedule exhibits statistically significant non-linearities that are broadly consistent with the theoretical predictions of the model. Furthermore, a substantial degree of financial market friction (in the form of bankruptcy costs) is necessary to match the default probabilities implied by the model with market-based measures of default risk. Finally, we identify several directions in which the basic framework needs to be extended to account for other cyclical and cross-sectional features of the data.

The paper is organized as follows. Section 2 revisits the BGG framework, focusing on the optimal contract. Section 3 describes our new dataset. Section 4 presents our empirical results, describing the estimated relationship between credit spreads and leverage ratios and comparing it with the theoretical predictions of the model. Section 5 makes use of the firm-level data to obtain times series of relevant model-based variables. Here we highlight the importance of the financial frictions and point at some possible extensions of the BGG framework. Section 6 then concludes.

2 Revisiting the BGG (1999) Framework

The main objective of BGG (1999) is to incorporate credit market frictions in a dynamic general equilibrium model with money and sticky prices. Drawing from the literature on asymmetric information and agency costs, the model focuses on the role of these frictions in explaining business cycle fluctuations. According to BGG, their model “exhibits a financial accelerator, in that endogenous developments in credit markets work to amplify and propagate shocks to the macroeconomy.” A key factor in the amplification mechanism is the negative relationship between *external finance premium* (cost of externally-raised funds minus opportunity cost of internal funds) and the *leverage ratio* of borrowers (debt relative to net worth). To the extent that firms have insufficient wealth with which to finance investment projects, this negative relationship arises because lenders must be compensated for the higher agency costs related to the divergence of interests between borrowers and lenders. In equilibrium, higher agency costs imply a larger external finance premium.

With procyclical net worth, reflecting unexpected movements in return to capital and *ex post* real borrowing costs, the external finance premium moves countercyclically. Because of these endogenous fluctuations in net worth, movements in the external finance premium are highly persistent. As a result, fluctuations of macroeconomic variables are magnified and propagated throughout the economy. In the remainder of this section, we analyze the optimization problem of the credit-constrained entrepreneurs in the BGG environment. Our aim is to obtain analytic expressions for the key relationships underlying the financial accelerator mechanism.

2.1 The Optimization Problem

At the end of period t , each individual entrepreneur purchases (homogeneous) capital to be used in production during the following period.¹ The *ex ante* revenue expected from the investment project is given by $R_{t+1}^k Q_t K_{t+1}$, where K_{t+1} is the quantity of capital that the entrepreneur purchases at unit price Q_t (measured relative to the price of the final good), and R_{t+1}^k is the expected gross rate of return. Realized revenue is given by $\omega_{t+1} R_{t+1}^k Q_t K_{t+1}$, where ω_{t+1}

¹ We follow the terminology used in BGG, but for simplicity, we omit the firm-specific superscript j .

is an idiosyncratic productivity shock with mean equal to one and the probability density function $f(\omega)$.

To finance her capital purchases, the entrepreneur uses both internal and external funds. In particular, the borrower has net worth N_t at the end of period t , and therefore borrows the amount B_t to purchase the requisite amount of capital:

$$Q_t K_{t+1} = B_t + N_t.$$

At the contractual gross loan rate R_{t+1}^b , the entrepreneur's profit is given by

$$\omega_{t+1} R_{t+1}^k Q_t K_{t+1} - R_{t+1}^b B_t.$$

The lender has access to funds at the risk-free gross interest rate R_{t+1} . If the lender had complete information about the idiosyncratic shock ω_{t+1} , then arbitrage would ensure that $R_{t+1}^k = R_{t+1}^b = R_{t+1}$; that is, there would be no external finance premium. When the borrower and lender have asymmetric information about the firm's productivity, however, the optimal debt contract recognizes the likelihood and cost of default. In particular, if the realized level of productivity falls below a certain threshold, the entrepreneur will be faced with negative profits and will hence choose to default on the loan.

To find this threshold, note that the entrepreneur's profit can be rewritten as

$(\omega_{t+1} - \bar{\omega}_{t+1}) R_{t+1}^k Q_t K_{t+1}$, where the threshold value $\bar{\omega}_{t+1}$ is given by

$$\bar{\omega}_{t+1} \equiv \frac{\frac{B_t}{N_t} R_{t+1}^b}{\left(1 + \frac{B_t}{N_t}\right) R_{t+1}^k}$$

Thus, the entrepreneur chooses to default on the loan whenever $\omega_{t+1} < \bar{\omega}_{t+1}$, and simply walks away from the project with nothing. Accordingly, the expected return to the entrepreneur is given by $\Psi(\bar{\omega}_{t+1}) R_{t+1}^k Q_t K_{t+1}$, where

$$\Psi(\bar{\omega}) = \int_{\bar{\omega}}^{\infty} (\omega - \bar{\omega}) f(\omega) d\omega.$$

In the case of default, the lender incurs bankruptcy costs that are assumed to be proportional to the realized revenue from the project. In particular, when the borrower defaults on the loan,

the lender receives net revenue $(1 - \mu)\omega_{t+1}R_{t+1}^k Q_t K_{t+1}$, where $0 < \mu < 1$. Thus, the expected return to the lender can be expressed as $\zeta(\bar{\omega}_{t+1})R_{t+1}^k Q_t K_{t+1}$, where

$$\zeta(\bar{\omega}) = \bar{\omega} \int_{\bar{\omega}}^{\infty} f(\omega) d\omega + (1 - \mu) \int_0^{\bar{\omega}} \omega f(\omega) d\omega.$$

Following BGG and assuming log-normality with mean-preserving spread for the distribution of the productivity shock, that is, $\log(\omega) \approx N\left(\frac{-\sigma^2}{2}, \sigma^2\right)$, we obtain

$$\Psi(\bar{\omega}) = 1 - \Phi\left(\frac{\ln \bar{\omega} - 0.5\sigma^2}{\sigma}\right) - \bar{\omega} \left[1 - \Phi\left(\frac{\ln \bar{\omega} + 0.5\sigma^2}{\sigma}\right) \right]$$

and

$$\zeta(\bar{\omega}) = 1 - \Psi(\bar{\omega}) - \mu \Phi\left(\frac{\ln \bar{\omega} - 0.5\sigma^2}{\sigma}\right)$$

where $\Phi(\cdot)$ is the CDF of the standard normal distribution.

The optimal contracting problem can now be written as

$$\max_{B_t, \bar{\omega}_{t+1}} \Psi(\bar{\omega}_{t+1}) R_{t+1}^k Q_t (B_t + N_t) + \lambda \left[\zeta(\bar{\omega}_{t+1}) R_{t+1}^k Q_t (B_t + N_t) - R_{t+1} B_t \right],$$

where the entrepreneur chooses the amount to borrow, B_t , and the productivity cutoff, $\bar{\omega}_{t+1}$, to maximize the expected return, subject to the constraint that the lender earns the risk-free rate R_{t+1} .²

The first-order conditions can be rearranged to obtain the following expressions:³

$$\frac{R_{t+1}^k}{R_{t+1}} = \frac{\Psi'(\bar{\omega}_{t+1})}{\Psi(\bar{\omega}_{t+1}) \zeta'(\bar{\omega}_{t+1}) - \Psi'(\bar{\omega}_{t+1}) \zeta(\bar{\omega}_{t+1})}; \quad (1)$$

$$\frac{B_t}{N_t} = - \frac{\Psi'(\bar{\omega}_{t+1}) \zeta(\bar{\omega}_{t+1})}{\Psi(\bar{\omega}_{t+1}) \zeta'(\bar{\omega}_{t+1})}. \quad (2)$$

Given the expected gross rate of return R_{t+1}^k , and the risk-free rate R_{t+1} , equation (1) implies the optimal productivity cutoff $\bar{\omega}_{t+1}$. Equation (2), in turn, implies the optimal leverage ratio $\frac{B_t}{N_t}$.

² The participation constraint for the entrepreneur must also be satisfied..

Therefore, as in BGG, the optimality conditions generate a nonlinear schedule that relates the leverage ratio, $\frac{B_t}{N_t}$, to the external finance premium, $\frac{R_{t+1}^k}{R_{t+1}}$. BGG, however, focus on the log-linear approximation of this relationship:

$$E_t \left\{ r_{t+1}^k \right\} - r_{t+1} = \eta (b_t - n_t),$$

consequently disregarding the potential role of nonlinearities in transmitting and propagating shocks to the macroeconomy.

The goal of this paper is to investigate the empirical and theoretical implications of potential nonlinearities. We use of the definition of the contractual rate R_{t+1}^b , from the definition of the threshold $\bar{\omega}_{t+1}$, to obtain a relationship that links the *observable* credit spread to the *unobservable* external finance premium:

$$\frac{R_{t+1}^b}{R_{t+1}} = \bar{\omega}_{t+1} \left(1 + \frac{B_t}{N_t} \right) \frac{R_{t+1}^k}{R_{t+1}}. \quad (3)$$

Combining this relationship with equations (1) and (2), we then obtain a nonlinear schedule relating the leverage ratio $\frac{B_t}{N_t}$ to the credit spread $\frac{R_{t+1}^b}{R_{t+1}}$. The leverage-spread schedule slopes

upward, because firms with higher leverage ratios have a higher default probability and, therefore, are charged a higher credit spread to compensate the lender for greater risk.

The leverage-spread schedule in the BGG framework is a function of the standard deviation of the log-normally distributed idiosyncratic productivity shock (σ) and the fraction of realized payoffs lost in bankruptcy (μ). Figure 1A shows the relationship between leverage and the probability of default, leverage and the external finance premium, and leverage and the credit spread for different values of σ (σ equal to 0.125, 0.25, 0.5), with $\mu=0.12$. As σ increases, which means that riskier investment projects are being financed, the default probability increases (for given leverage), as does the external finance premium and the credit spread. In other words, the lender, for given leverage ratio, demands a higher spread in order to be compensated for greater risk.

³ See BGG for the conditions that guarantee an interior solution (i.e., a solution without credit rationing).

Figure 1B shows the same schedules for different values of μ (μ equal to 0, 0.12, 0.24, 0.36), with $\sigma=0.28$. For $\mu=0$ (i.e., the frictionless case), the default probability is high, but because there are no costs associated with bankruptcy, the credit spread is low, and the external finance premium is zero. As μ increases, the lender faces larger costs in the case of bankruptcy. Consequently, the optimal contract between the borrower and the lender stipulates a lower productivity threshold, which, in turn, implies a lower probability of default for a given leverage ratio. To be compensated for the higher bankruptcy costs, the lender charges a higher external finance premium and credit spread. Note that as μ increases, the external finance premium exceeds the credit spread (for given leverage), because the latter, according to equation (3), narrows as it incorporates the lower productivity threshold $\bar{\omega}_{t+1}$.

By considering the log-linear approximation of the leverage-external-finance-premium schedule, BGG pick a specific point along this relationship (the steady state of the model for given parameters) and focus only on the neighborhood around this point. In terms of the green schedule in Figure 1A, which is closest to the calibration used by BGG, this corresponds to the point associated with a leverage ratio of one (log of leverage ratio equal to zero) and an external finance premium of about 200 basis points.⁴ For this calibration and small variations around the steady state, the schedule is approximately linear, and the log-linearization appears to provide an adequate approximation. For firms with higher leverage on this schedule, however, nonlinearities appear to be quite important and could play a significant role in explaining how shocks are transmitted and propagated through the economy.

The extent to which there is a relationship between leverage and credit spreads and the extent to which this relationship exhibits nonlinearities consistent with the BGG framework is an empirical question, which is the subject of the next section.

3 Data

To examine the relationship between leverage and credit spreads, we construct a new data set, in which we explicitly link firm-level balance sheet data with firm-level credit spreads. Our new dataset is an unbalanced panel of quarterly data for 955 publicly-traded Compustat firms in

⁴ To be more precise, we should first map the credit spread into the external finance premium to replicate the steady state in BGG.

the nonfarm, nonfinancial corporate sector from 1997 to 2000 (24 quarters). The distinguishing feature of these firms is that part of their long-term debt is in the form of bonds that are actively traded in the secondary market. For these firms, we have linked their quarterly income and balance sheet variables reported in Compustat with market prices of their outstanding securities obtained from Merrill-Lynch.⁵

Because Merrill-Lynch tracks secondary prices on individual corporate bond issues (with an outstanding maturity of at least one year) and because a firm at any point in time is likely to have a number of different issues outstanding, we must control for their different maturities when calculating an overall firm-specific spread or yield. To do so, we match the daily yield on each individual bond issued by the firm to the estimated Treasury yield of the same maturity. The Treasury yield curve is estimated daily using the techniques proposed by Svensson (1994) on a large sample of off-the-run Treasury coupon securities. To calculate an overall firm-specific spread, we average the resulting spreads on outstanding bonds using the product of market values of bonds and their effective durations as weights.⁶ Hence, our dataset incorporates firm-specific heterogeneity and a market-based proxy of the firm-specific premium on external funds. Table 1 contains key summary statistics of our data.

Table 1:

Variable	Mean	25th Percentile	Median	75th Percentile
Sales ¹	1862.49	207.65	595.60	1749.05
Mkt. Capitalization ¹	9632.04	533.27	1922.81	6721.94
Leverage Ratio ²	2.29	0.21	0.51	1.24
Credit Spread (%)	4.33	1.27	2.30	4.19
Traded Debt Share ³	0.53	0.34	0.52	0.71
Panel Dimensions				
No. of Firms = 955	Min. Tenure = 4	Median Tenure = 13	Max. Tenure = 24	Obs. = 13834

1. Millions of 1996 chain-weighted dollars.

2. The ratio of book-value of total long-term debt to market capitalization.

3. The ratio of book-value of publicly-traded corporate bonds to book-value of total long-term debt.

⁵ The Merrill-Lynch bond price data are available daily starting in 1997. In matching firms from Compustat to Merrill-Lynch data base, we restricted our attention to firms that reported at least 4 consecutive quarters of income and balance sheet data.

Most of the firms in our dataset are quite large. The average firm has more than \$1.8 billion in sales and a market capitalization of almost \$10 billion. The distribution of firm size, however, is highly skewed: The median firm has about \$600 million of sales and a market capitalization of almost \$2 billion. The distribution of leverage ratios—defined as the book-value of long-term debt relative to the market-value of common equity—is also skewed, with the average ratio more than four times the median. A significant fraction of firms in our sample have leverage ratios greater than one. The relatively high leverage in our sample largely reflects the steep fall in equity prices that started in the spring of 2000, which significantly reduced the market capitalization of firms in our sample, thereby driving up their leverage ratios. Firms in our sample have a significant fraction of their long-term debt in the form of bonds that are publicly traded. The median ratio of the par-value of traded bonds outstanding to the book-value of total long-term debt is more than one-half, suggesting that market prices on outstanding bonds likely provide an accurate gauge of the cost of external finance for these firms.

Although our sample includes only 955 nonfarm nonfinancial corporations, it is representative of the sector as a whole. The upper panel of Figure 2 compares the (weighted) median growth rate of real sales for the 955 firms in our dataset with the (weighted) median growth rate of sales for the entire nonfarm nonfinancial sector in Compustat. The two series are highly correlated and exhibit virtually identical business cycle dynamics. The lower panel compares the (weighted) median leverage of firms in our sample with the corresponding statistic for the Compustat's nonfarm nonfinancial sector and an alternative aggregate measure of leverage obtained from the Flow of Funds accounts. The three measures are highly correlated over time. They all exhibit a sharp run-up leading to the 1990-91 recession, followed by a steady decline over most of the past decade. Leverage in the nonfarm nonfinancial corporate sector bottomed out in the late 1990s and then rose sharply following the bursting of the stock market bubble in the spring of 2000.

Credit spreads in our sample are also representative of the spreads in the corporate bond market as a whole, when controlling for the maturity of bonds outstanding and the credit quality of issuers. Figure 3 compares (weighted) average credit spreads for firms in our sample with aggregate credit spread indexes published by Merrill-Lynch for different credit quality firms (the

⁶ The use of the dollar duration of bonds as weights in computing a yield on a portfolio of bonds represents a first-order Taylor series approximation to the portfolio yield (see Choi and Park (2002) for further details).

AA 7-10 years, BBB 7-10 years, and the below-investment grade (high-yield) index). In both the investment-grade and the speculative-grade segments of the market, spreads in our dataset closely match their respective aggregate index.

4 Empirical Analysis

Given our data, we can directly examine the relationship between leverage and credit spreads and compare it to the one implied by the BGG framework. Figure 4 shows the scatter plot of log-leverage against the credit spread for our sample of 955 firms over the period 1997:Q1 to 2002:Q4. The pattern is suggestive of a nonlinear link between the firms' financial conditions and their credit spreads that is broadly consistent with the theoretical leverage-spread schedules shown in figures 1A and 1B. In particular, the empirical relationship appears to be approximately linear for low-leverage firms but nonlinear, though with a much greater dispersion, for firms with greater financial leverage.

To investigate this link more formally, we estimate a sequence of cross-sectional semi-parametric regressions of the form:

$$s_{it} = \alpha_t + \beta_t z_{it-1} + f_t(z_{it-1}) + \theta_t' x_{it-1} + u_{it},$$

where s_{it} is the average credit spread of firm i in period t , z_{it-1} is the log-leverage of firm i at the end of period $t-1$, and u_{it} is a zero-mean random error term. The time-varying function $f_t(\cdot)$ of firm's i log-leverage ratio allows for the departure from the time-varying linear leverage-spread schedule and can be used to assess the statistical and economic significance of nonlinearities across time.⁷ The vector x_{it-1} contains industry dummies (3-digit NAICS) and dummies for the firm's bond rating at the end of period $t-1$; both of these indicators are included to control for any differences in the conditional mean of the leverage-spread schedule across industries and across firms of different credit quality. In the BGG framework, these differences would arise from the

⁷ We estimate the nonparametric part of the model using cubic spline functions with 4 degrees of freedom. To ensure that our results are not driven by a small number of extreme observations, we trimmed the bottom 2.5th percentile and the top 97.5th percentile of the leverage distribution and the top 97.5th percentile of the credit spread distribution before estimation.

variation in the bankruptcy parameter μ or the variation in the variance of idiosyncratic productivity shock σ across different classes of firms.

The solid line in top panel of Figure 5 shows the sequence of chi-squared test statistics for the test of the null hypothesis that the estimate of f_t is equal to zero, thus implying a linear leverage-spread schedule. A comparison of test statistics with their bootstrapped critical values indicates that the nonparametric component is statistically significant at better than 1-percent level in every period, a result that confirms the impression from Figure 4 of a nonlinear relationship between leverage and credit spreads. As indicated by the bottom two panels, the estimated linear relationship—the intercept term (α_t) and the slope coefficient (β_t)—is upward sloping and exhibits significant variation over the course of the business cycle. Both parameters increased at the time of Russian default in 1998:Q3, suggesting both an upward shift and a steepening in the leverage-spread schedule. The schedule moved higher in the spring of 2000 after the collapse of the stock market, and it rose again in 2002 after further revelations of corporate malfeasance.

Figure 6 shows the sequence of predicted leverage-spread schedules from our regression specification. Although the schedule varies considerably over time, its general nonlinear shape is remarkably constant: The relationship is approximately linear for low leverage firms and steepens significantly as the firm's leverage increases. There appear to be two distinct shifts in the leverage-spread schedule over our sample period. Consistent with Figure 5, the first shift happened during the Russian default and its aftermath, when the entire schedule moved notably higher in essentially a parallel shift. The second shift occurred in early 2000 after major stock indexes began their downward spiral. The latter shift was also accompanied by an increase in the slope of the leverage-spread schedule and by the move of the inflection point—the point at which the slope of the schedule changes—toward lower leverage. Thus, not only does the leverage-spread schedule move upward when economic conditions deteriorate, but it also becomes steeper for a larger proportion of firms. These empirical findings are broadly consistent with the theoretical predictions of the BGG model, which, as shown in Section 2, implies an upward-sloping, nonlinear schedule relating the leverage ratio to the credit spread.

5 Reassessing BGG in Light of the Empirical Evidence

In this section, we make use of the firm-level data on credit spreads and leverage ratios to derive model-based, firm-level standard deviations of the log-normally distributed idiosyncratic productivity shock (σ), external finance premiums $\left(\frac{R^k}{R}\right)$, and probabilities of default.

In particular, using the FOCs from the optimization problem and the credit spread equation in Section 2, we solve the following system of two non-linear equations

$$\left(\frac{B}{N}\right)_{i,t} = -\frac{\Psi'(\bar{\omega}_{i,t+1})\zeta'(\bar{\omega}_{i,t+1})}{\Psi(\bar{\omega}_{i,t+1})\zeta(\bar{\omega}_{i,t+1})}$$

$$\left(\frac{R^b}{R}\right)_{i,t+1} = \bar{\omega}_{i,t+1} \left[1 + \left(\frac{B}{N}\right)_{i,t}\right] \frac{\Psi'(\bar{\omega}_{i,t+1})}{\Psi(\bar{\omega}_{i,t+1})\zeta'(\bar{\omega}_{i,t+1}) - \Psi'(\bar{\omega}_{i,t+1})\zeta(\bar{\omega}_{i,t+1})}$$

in the two variables $\bar{\omega}_{i,t+1}$ and $\sigma_{i,t+1}$ for given bankruptcy cost parameter μ , where $\left(\frac{B}{N}\right)_{i,t}$ and

$\left(\frac{R^b}{R}\right)_{i,t+1}$ are firm i 's observed leverage ratio and credit spread, respectively. For every

firm/quarter observations, we obtain the solution $(\bar{\omega}_{i,t+1}, \sigma_{i,t+1})$ which is, among others, a function of μ .

Figure 7A and 7B show the time-series of the model-implied weighted-average of σ , external finance premium, and probability of default for four different values of the bankruptcy cost parameter μ (i.e., μ equal to 0, 0.12, 0.24, 0.36).⁸ Notice that $\mu=0$ corresponds to the case without credit market frictions. To assess the relevance of financial frictions in explaining the behavior of the economy over the business cycle, we also include the actual default rate on corporate bonds and the expected year-ahead default probability, so that we compare them with the model-implied probability of default.

The standard deviation of the idiosyncratic shock, σ , raises up to the 1998:Q3 Russian default, is basically unchanged through the year 2000 and starts declining at the onset of the

⁸ The model-implied σ is weighted by sales, the external finance premium by market value of debt, and the probability of default by book value of debt.

NBER-declared recession. Moreover, as μ increases, the schedule moves downward, as the lender is inclined to finance less risky projects when bankruptcy costs are higher.

The external finance premium rises during the latest recession, declines at the end of 2001, and jumps again during the corporate governance scandals in 2002. The premium is zero when there are no financial frictions. As μ increases, the schedule moves higher.

The model-implied probability of default increases sharply during the 1998 Russian default and keeps rising through the year 2000. It is constant during the latest recession and increases sharply again in mid-2002. As μ increases, the schedule shifts downward, because the model implies a lower productivity threshold, as discussed in Section 2.

With regard to the role of financial frictions, notice that the model generates an unreasonably high probability of default with $\mu=0$, implying that financial frictions are a necessary ingredient. An interesting question is how large μ must be. We find that a substantial degree of financial market friction (we show the $\mu=0.36$ case here) is necessary to match the model-implied default probability with market-based measures of default risk. It is interesting to note that this value of μ is quite close to some empirical estimates of bankruptcy costs.

The scatter plot in the upper panel of Figure 8 shows the relationship between leverage and the model-implied probability of default for $\mu=0.36$. As expected, higher leverage ratios are associated with higher probability of default. The scatter plot in the lower panel of Figure 8, instead, shows the relationship between leverage and the model-implied standard deviation of the idiosyncratic shock (σ), again for $\mu=0.36$. In this case, the model implies an empirically counterintuitive relationship between σ and leverage, with a lower σ associated with a higher leverage ratio. The explanation for this is that, in the model, as the leverage ratio raises, so does the probability of default (for given σ). This, in turn, implies a large external finance premium, as well as a larger credit spread. As shown in Figure 1A, however, as the leverage increases, the curvature of the external finance premium-leverage schedule is such that the model would generate extremely large premiums, and therefore unrealistic credit spreads. To match observed credit spread, instead of a movement along the schedule for given σ we need a shift of the schedule to the right, i.e., lower values of σ .

We suspect that this shortcoming of the model likely reflects a number of simplifying assumptions, including the Gaussian distribution of idiosyncratic productivity shocks, as well as the absence of time-varying bankruptcy costs and aggregate risk aversion, and the absence of a liquidity premium.

6 Directions for Future Research

In future research, we plan to extend our work in several directions. From the empirical point of view, we plan to investigate the Bernanke and Campbell (1988) so-called “financial fragility” argument. In particular, we are interested in the issue of whether economic shocks have different effects on high-debt and low-debt firms. This relates to the cyclical variations of the spread-leverage schedule that we discussed in the empirical section. Furthermore, we would like to use our firm-level dataset to examine the link between firm-specific credit spreads and investment expenditures.

From the theoretical point of view, it would be interesting to consider the implications of greater heterogeneity across firms, with low-risk firms having a shallow slope of the leverage-spread schedule and high-risk firms having a steeper schedule. We also plan to use perturbation methods to obtain second-order approx. of the model around its steady state, characterize the optimal monetary policy, and compare the welfare performance of alternative simple rules.

Finally, it would also be interesting to extend our empirical analysis to the open economy framework, considering different measures of leverage and spread for emerging markets.

References

- Aghion, P., P. Bacchetta, and A. Banerjee (2000):** “A Simple Model of Monetary Policy and Currency Crises,” *European Economic Review*, 44, 728-738.
- Bernanke, B. S. and J.Y. Campbell (1988):** “Is There a Corporate Debt Crisis?,” *Brookings Papers on Economic Activity*, Vol. No. 1, 83-139.
- Bernanke, B. S. and M. Gertler (1989):** “Agency Costs, Net Worth, and Business Fluctuations,” *American Economic Review*, 79, 14-31.
- Bernanke, B. S., M. Gertler, and S. Gilchrist (1999):** “The Financial Accelerator in a Quantitative Business Cycle Framework,” in *Handbook of Macroeconomics*, Volume I, ed. by J. B. Taylor and M. Woodford.
- Caballero, R. J. and A. Krishnamurthy (2000):** “Emerging Market Crises: an Asset Prices Perspective” mimeo.
- Carlstrom, C., and T. Fuerst (1997):** “Agency Costs, Net Worth, and Business Fluctuations: a Computable General Equilibrium Analysis,” *American Economic Review*, 87, 893-910.
- Céspedes, L. P., R. Chang, and A. Velasco (2000):** “Balance Sheets and Exchange Rate Policy,” NBER Working Paper No. 7840.
- Choi, Y. and J. Park (2002):** “An Improved Approach to Calculate the Yield and Duration of a Bond Portfolio,” *Journal of Applied Finance*, Fall/Winter, 55-60.
- Christiano, L., R. Motto, and M. Rostagno (2004):** “The Great Depression and the Friedman-Schwartz Hypothesis,” mimeo.
- Fisher, I. (1933):** “The Debt-Deflation Theory of Great Depressions,” *Econometrica*, 1, 337-357.
- Garbade, K.D. (1996):** *Fixed Income Analytics*. The MIT Press, Cambridge, MA.
- Gertler, M., R.G. Hubbard, and A. Kashyap (1991):** “Interest Rate Spreads, Credit Constraints, and Investment Fluctuations: An Empirical Investigation,” in *Financial Markets and Financial Crises*, ed. by R.G. Hubbard. University of Chicago Press for NBER, Chicago.
- Gertler, M., S. Gilchrist, and F.M. Natalucci (2003):** “External Constraints on Monetary Policy and the Financial Accelerator,” NBER Working Paper No. 10128.
- Kiyotaki, N. and J. Moore (1997):** “Credit Cycles,” *Journal of Political Economy*, 105, 211-248.

Krugman, P. (1999): “Analytical Afterthoughts on the Asian Crisis,” mimeo.

Schaller, H., and S. Ng (1996): “The Risky Spread, Investment, and Monetary Policy Transmission: Evidence on the Role of Asymmetric Information,” *Review of Economics and Statistics*, 78, 375-383.

Svensson, L. E. O. (1994): “Estimating and Interpreting Forward Interest Rates: Sweden 1992-1994,” CEPR Discussion Paper No. 1051.

Figure 1A: Implications of Idiosyncratic Risk
(annual rates in percent)

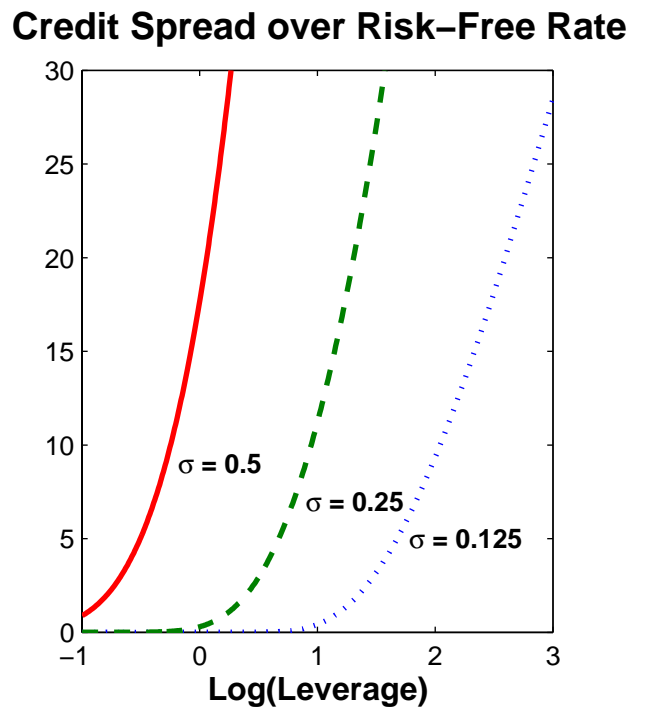
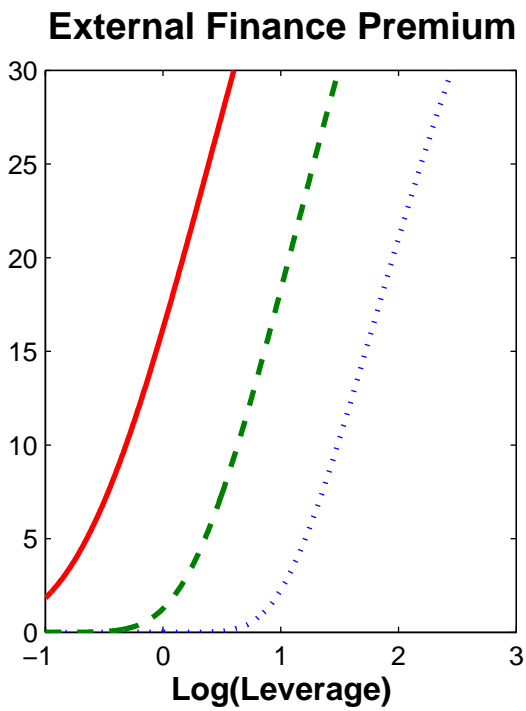
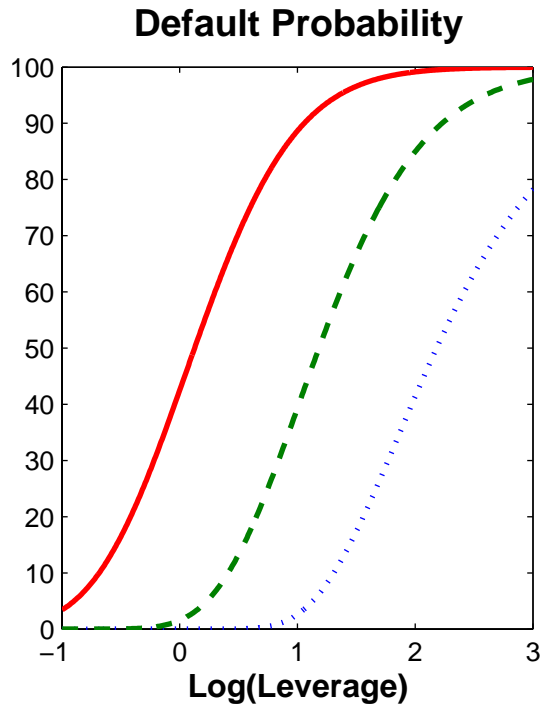
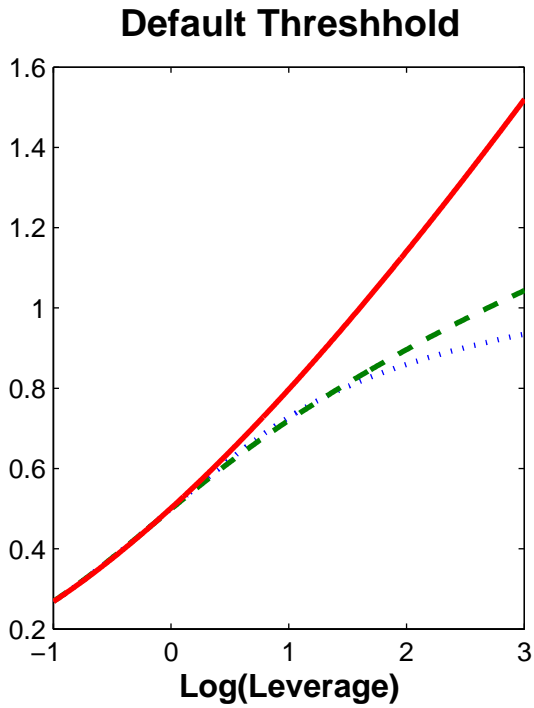


Figure 1B: Implications of Monitoring Costs
(annual rates in percent)

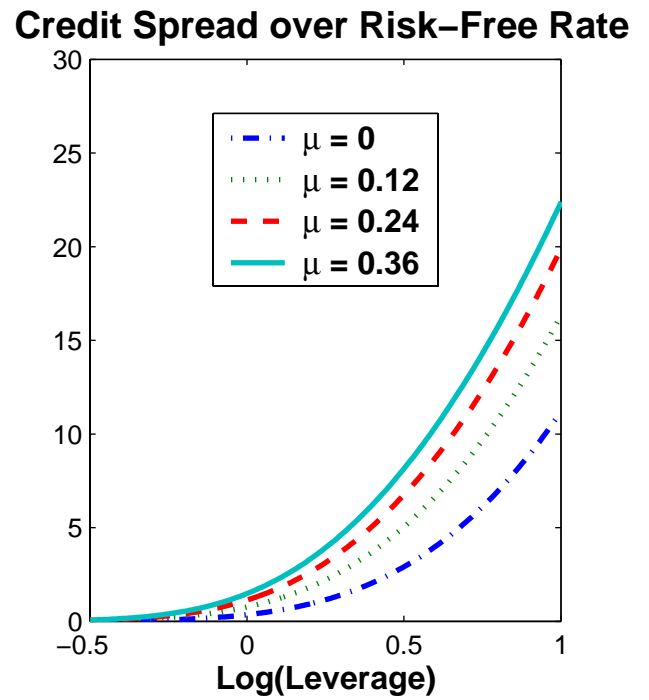
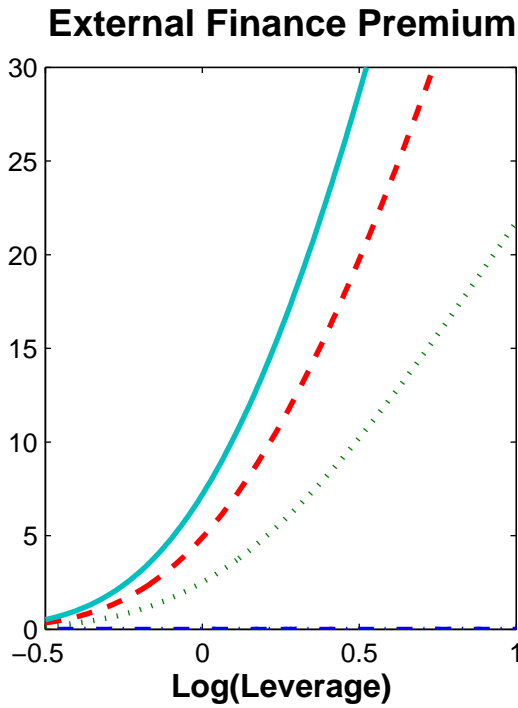
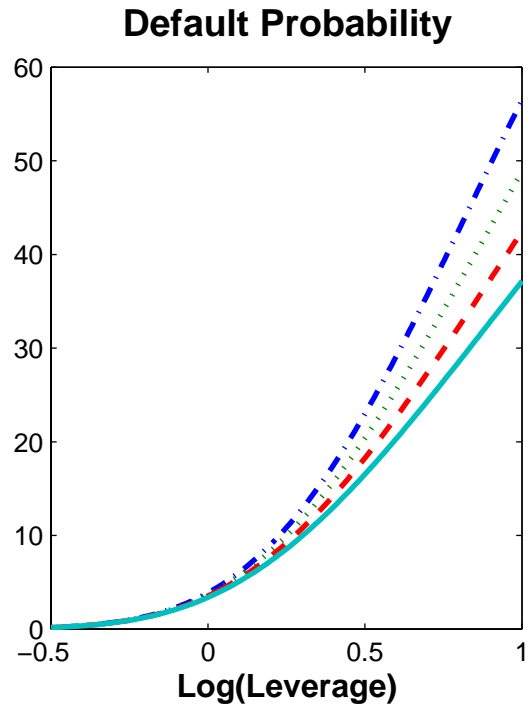
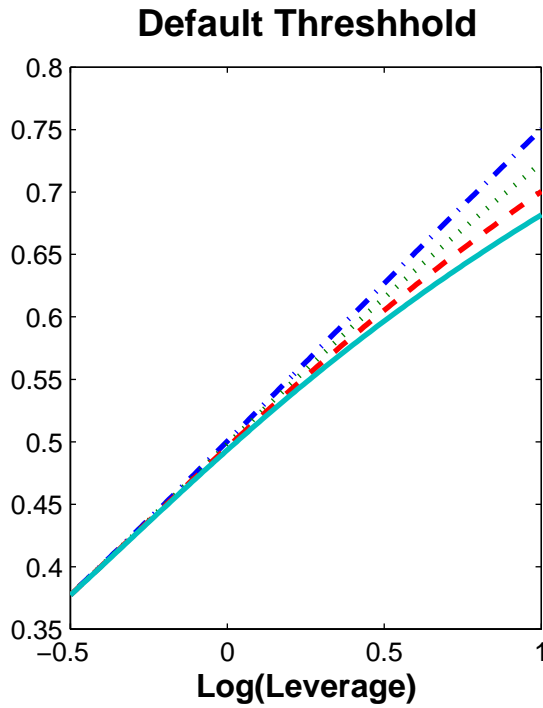
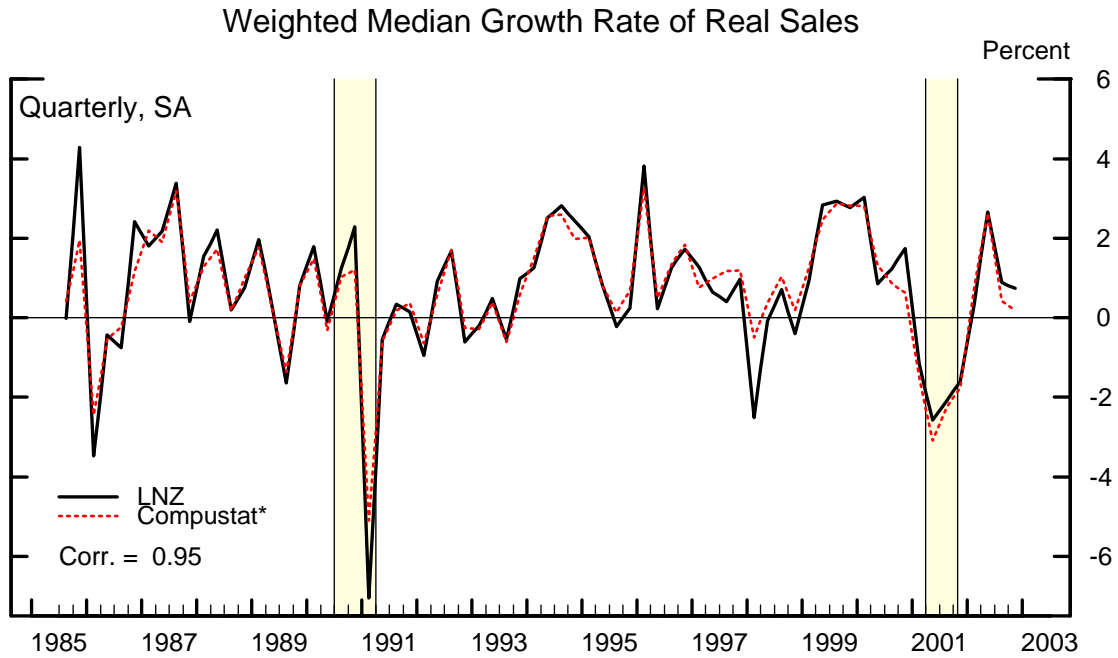
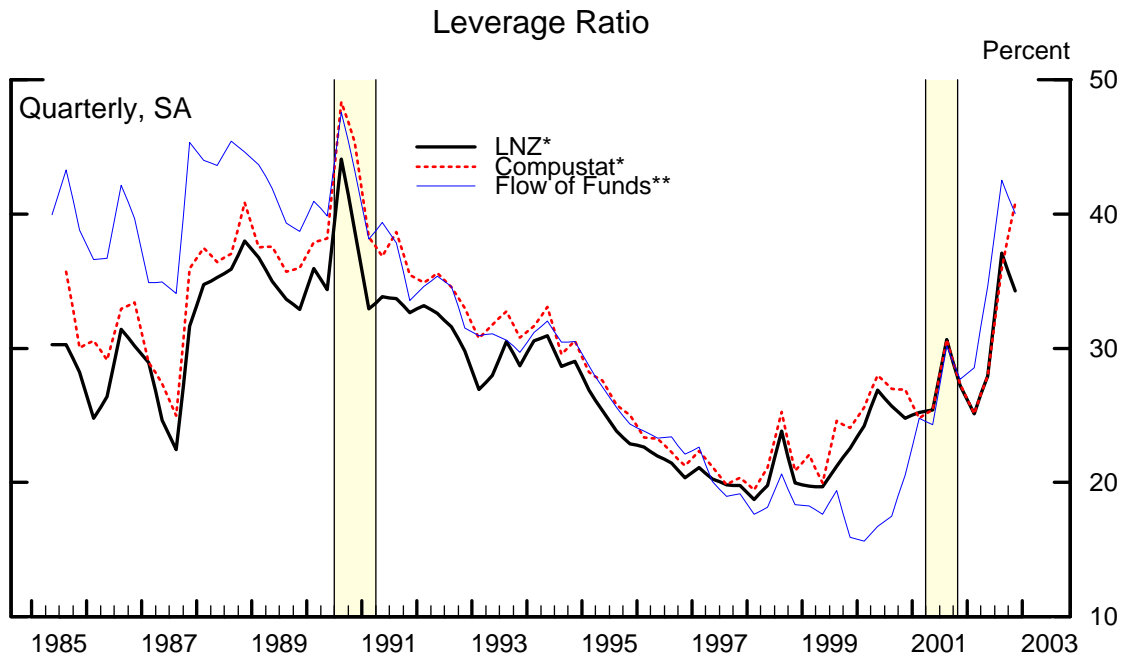


Figure 2



* All nonfarm nonfinancial corporations.



* Median book-value of long-term debt relative to market-value of equity, weighted by firm sales.

** Book-value of bonds and mortgages relative to market-value of equity for nonfarm nonfinancial corporate businesses.

Figure 3

Corporate Bond Credit Spreads

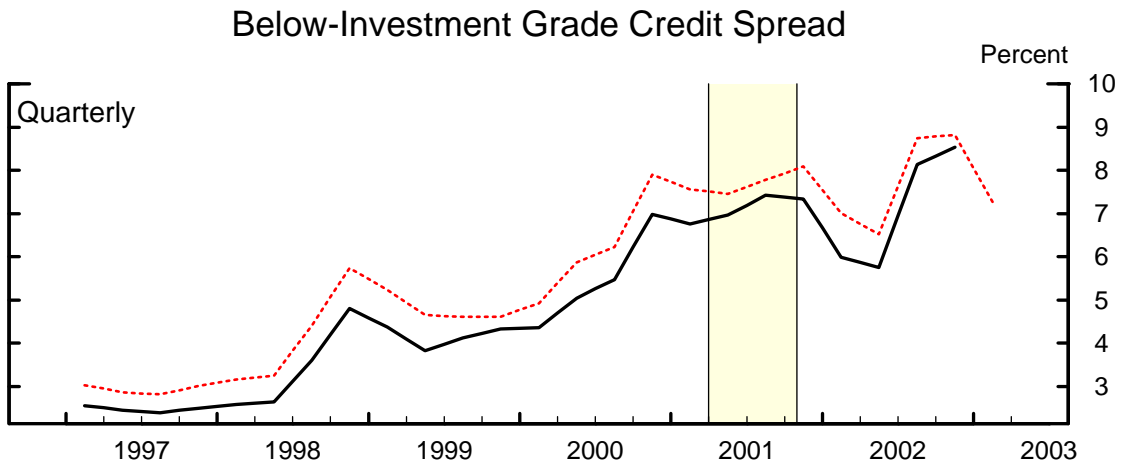
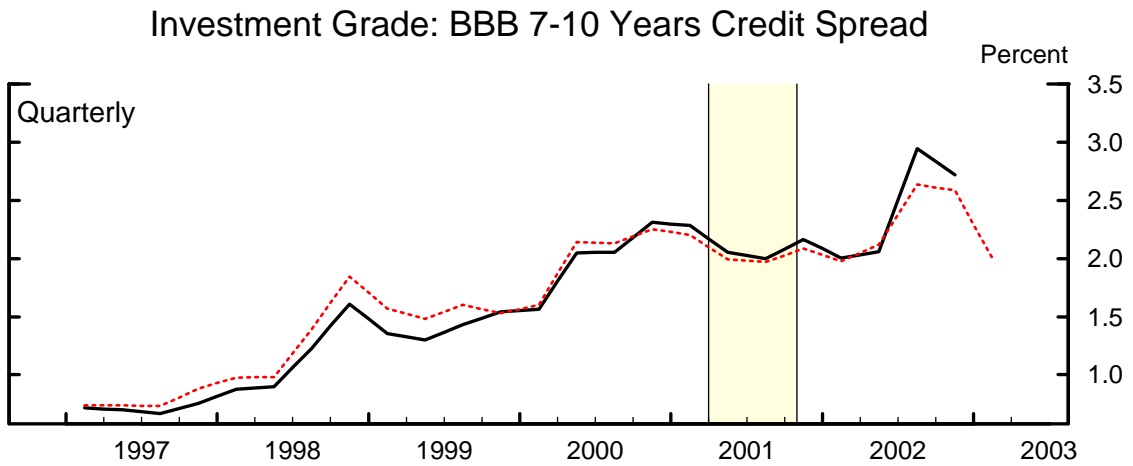
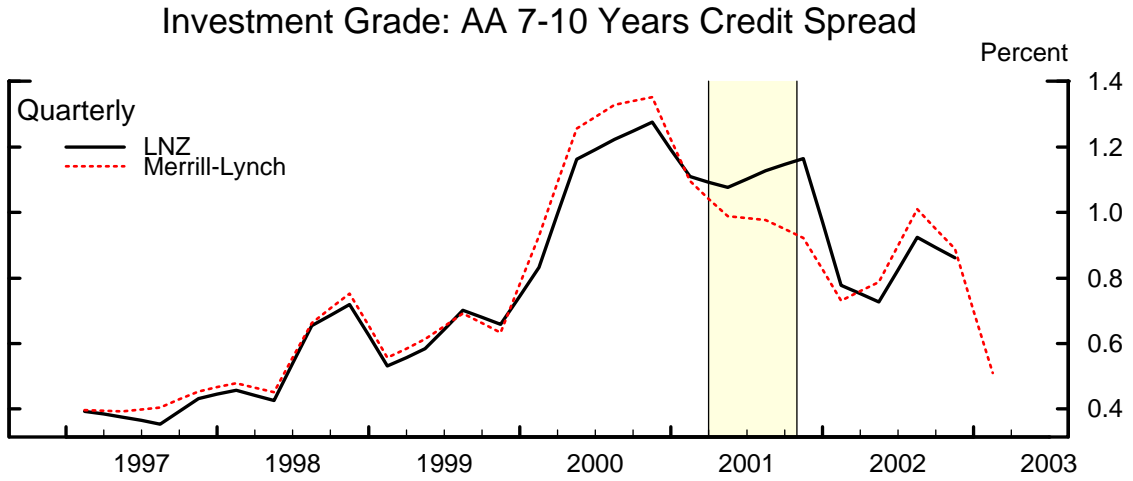


Figure 4

Firm-Level Credit Spreads and Leverage
Sample Period: 1997:Q1 - 2002:Q4

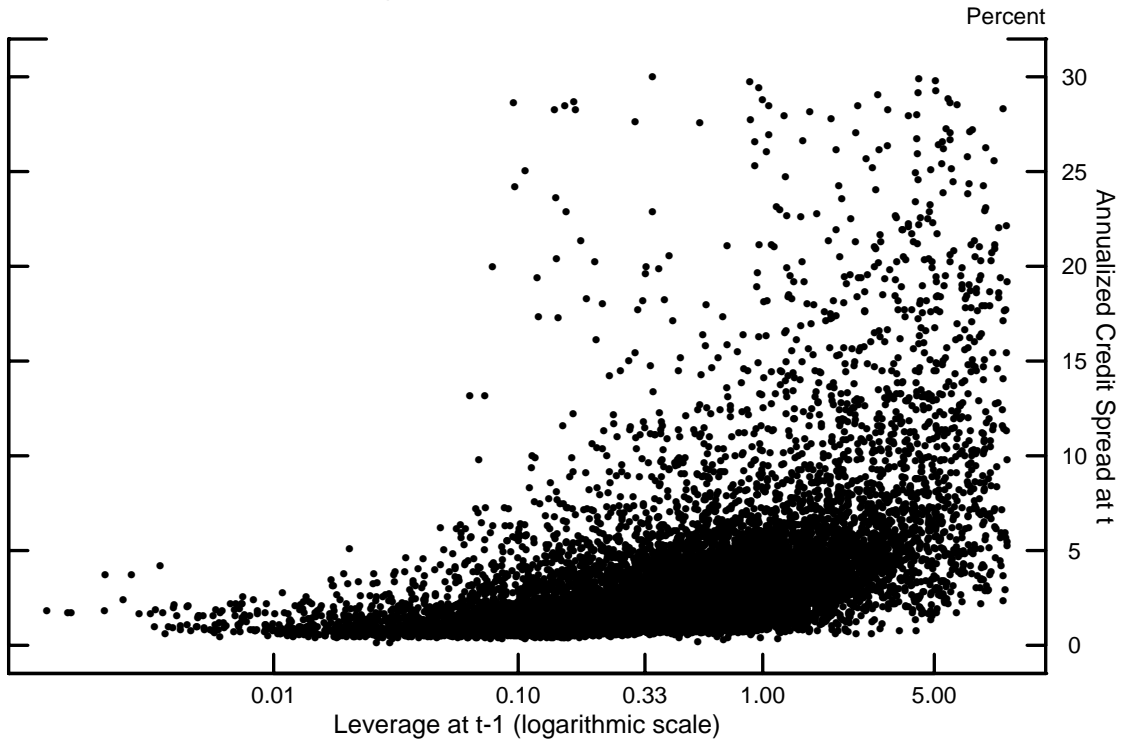
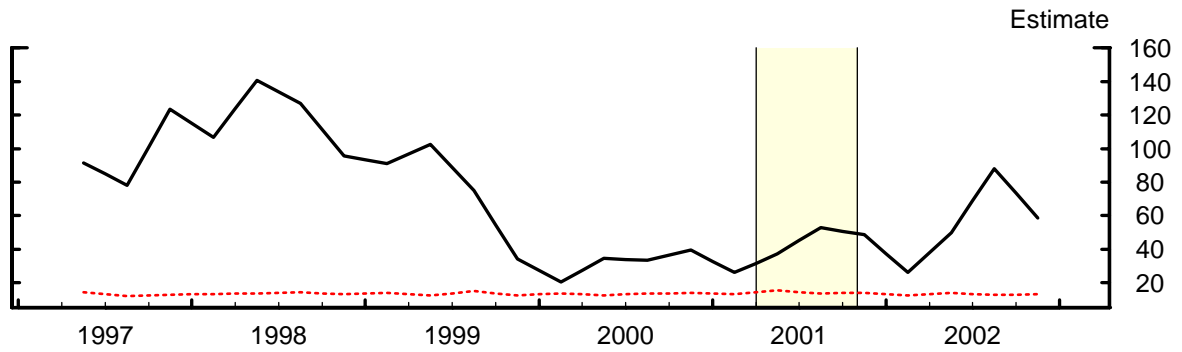


Figure 5

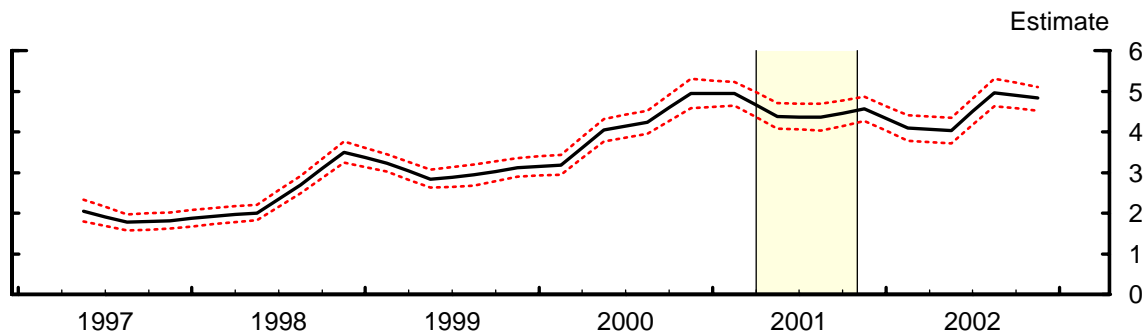
Estimated Time-Varying Parameters of the Leverage-Spread Schedule Semiparametric Specification

Linearity Test Statistic



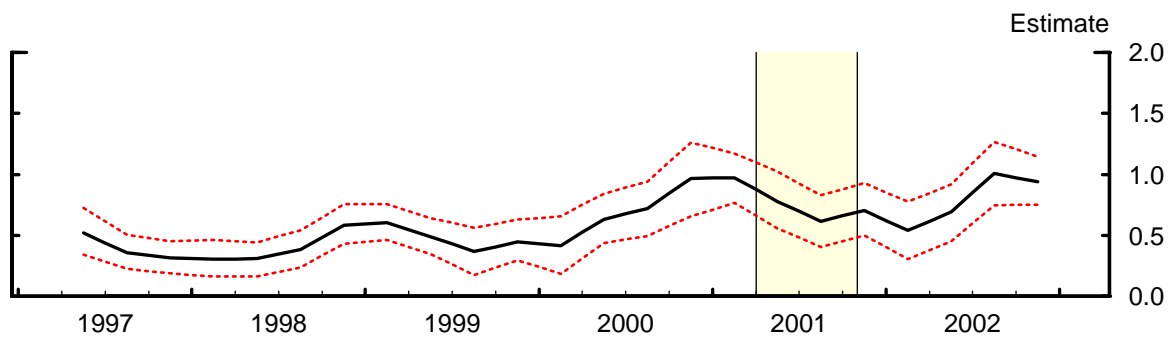
Note: The thin dotted line represents the 1-percent critical value for the test statistic of the null hypothesis that the leverage-spread schedule is linear. The critical value is based on a nonparametric bootstrap with 1000 replications.

Intercept Term



Note: The thin dotted lines represent the 95-percent confidence interval obtained from a nonparametric bootstrap with 1000 replications.

Linear Term



Note: The thin dotted lines represent the 95-percent confidence interval obtained from a nonparametric bootstrap with 1000 replications.

Figure 6

Predicted Time-Varying Leverage-Spread Schedule

Semiparametric Specification

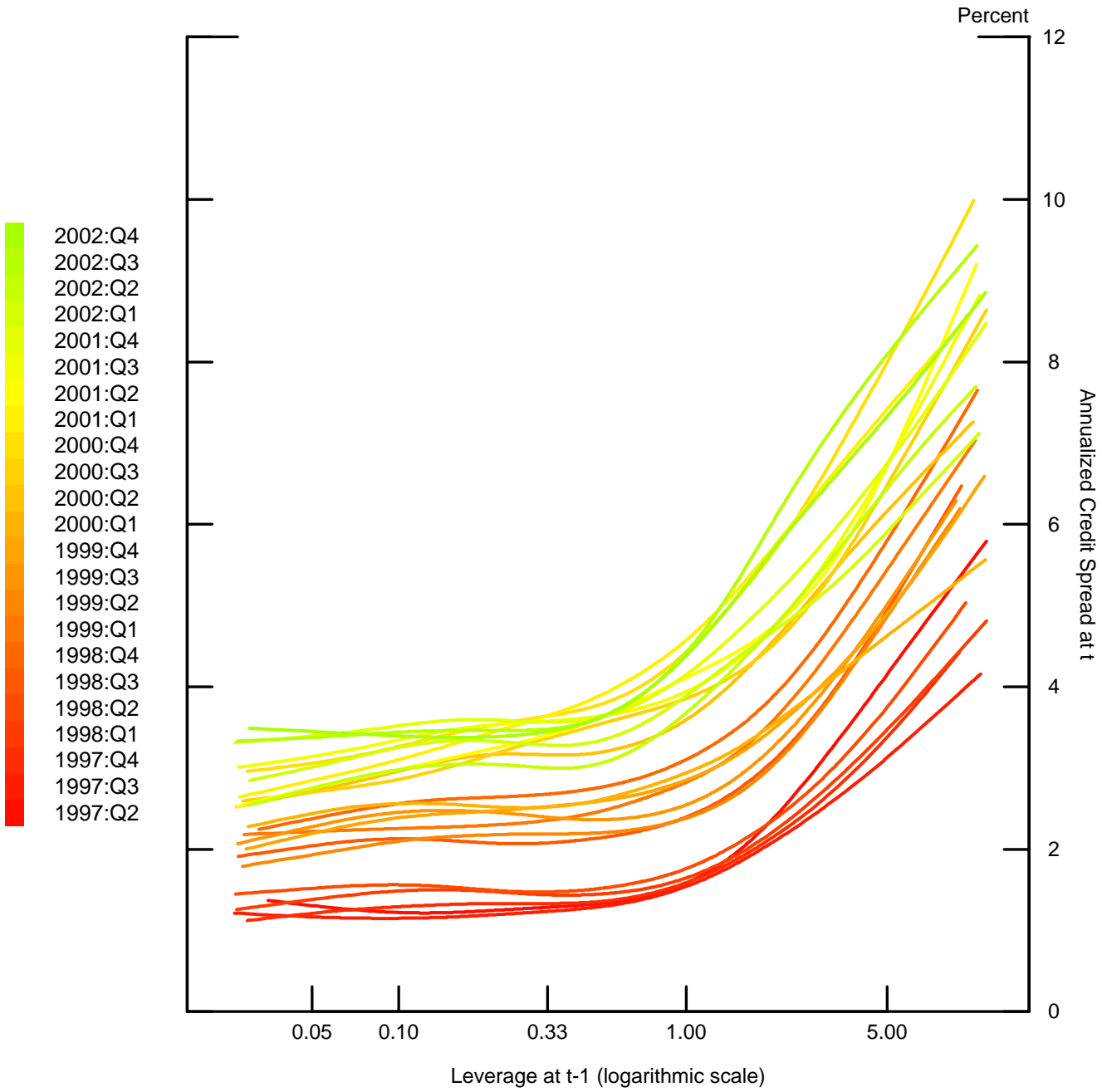
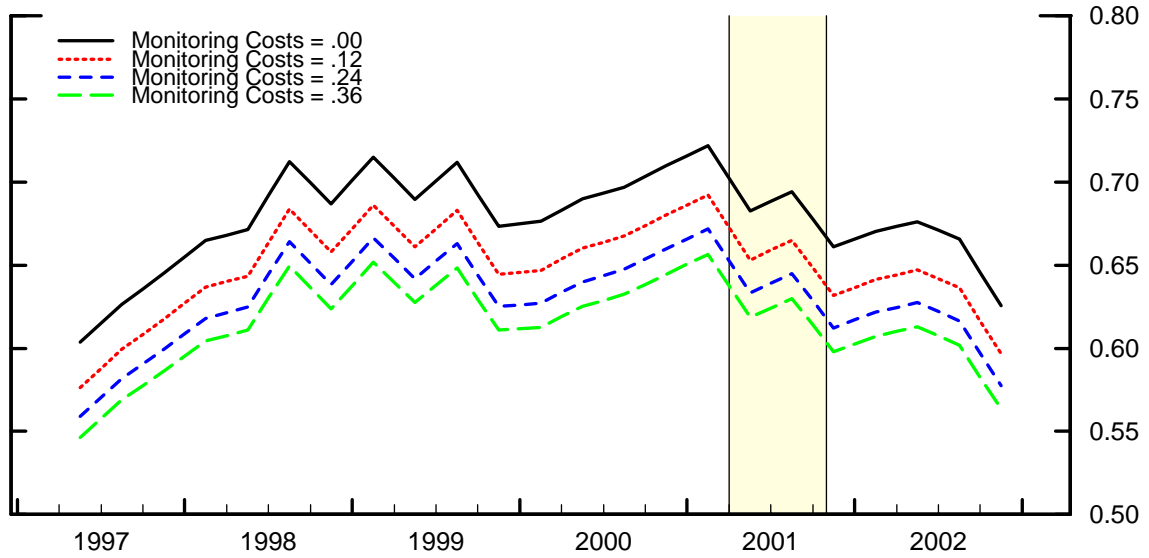


Figure 7

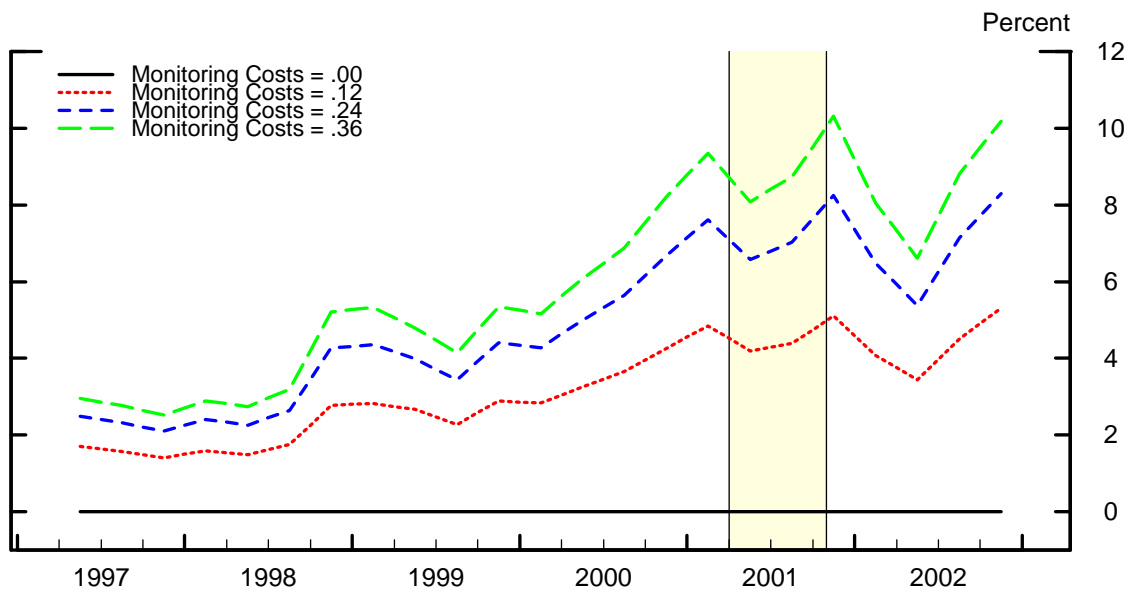
Implications of Monitoring Costs

Model-Implied Standard Deviation of Idiosyncratic Risk



Note. The standard deviation of idiosyncratic risk in a given quarter is the cross-sectional weighted average of firm-specific standard deviations in that quarter, with weights equal to current sales.

Model-Implied External Finance Premium

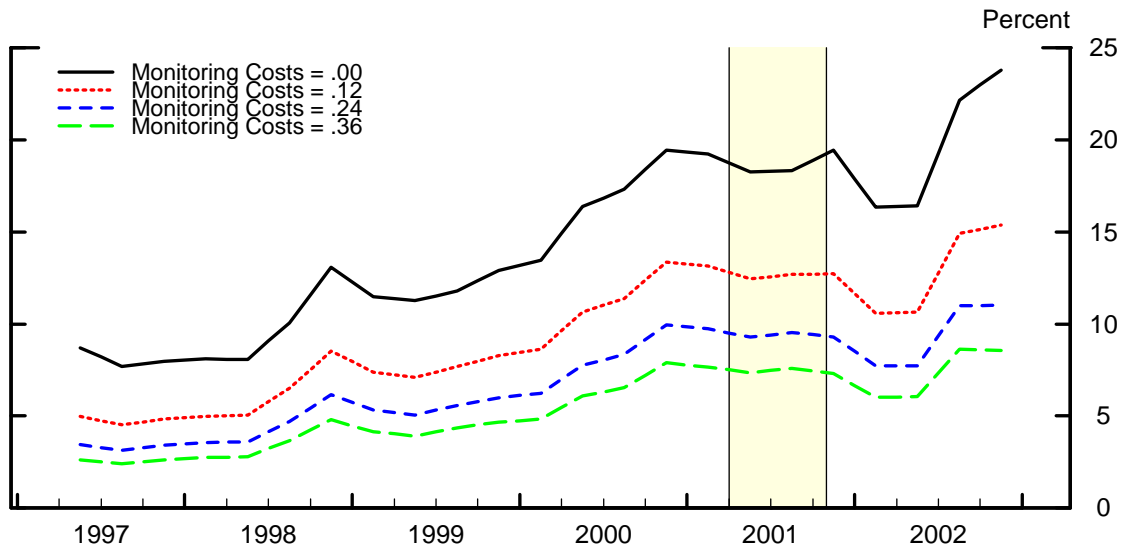


Note. The external finance premium in a given quarter is the cross-sectional weighted average of firm-specific external finance premiums in that quarter, with weights equal to the market-value of bonds outstanding.

Figure 7

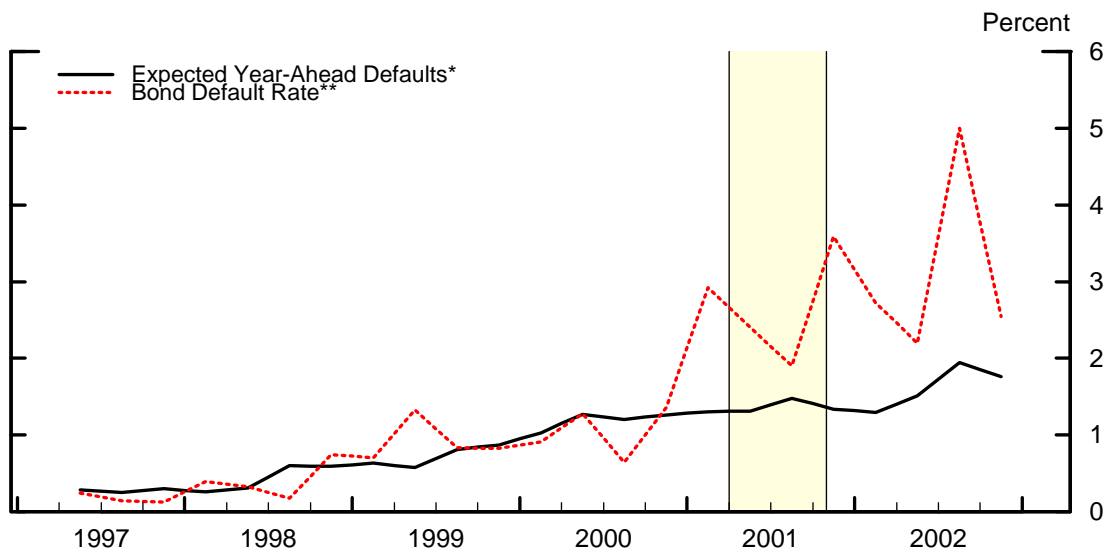
Implications of Monitoring Costs (contd.)

Model-Implied Annualized Probability of Default



Note. The probability of default in a given quarter is the cross-sectional weighted average of firm-specific probabilities of default in that quarter, with weights equal to the face-value of bonds outstanding.

Corporate Credit Quality



* Firm-level estimates of default weighted by firm liabilities as a percent of total liabilities.

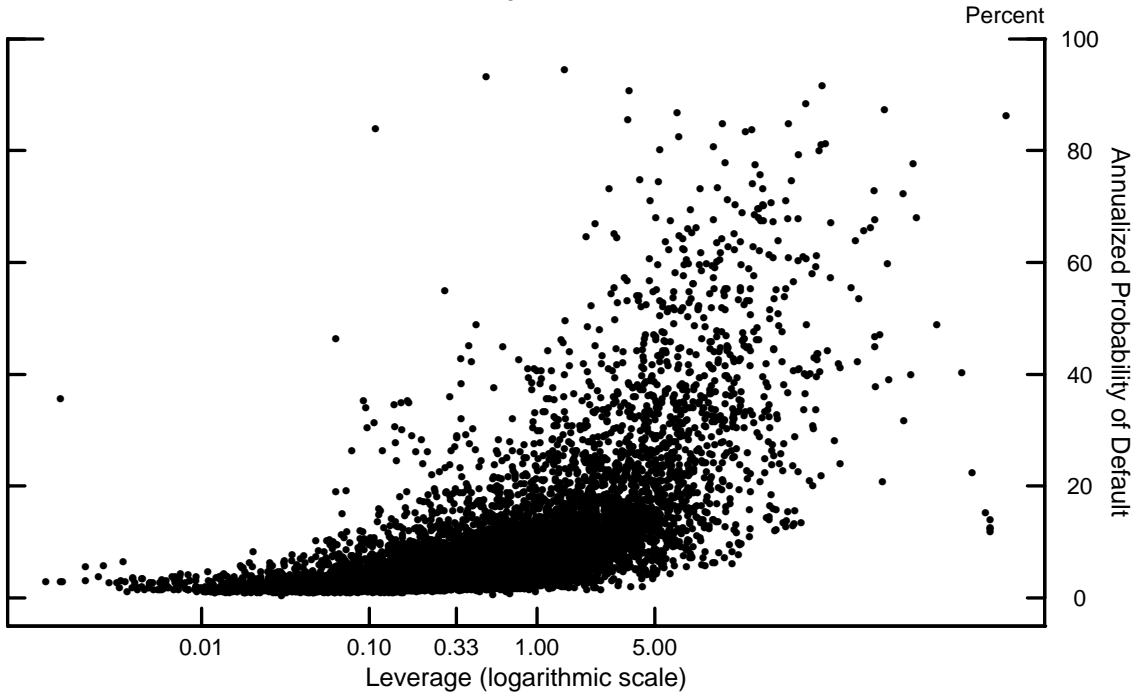
** The default rate is the face-value of bonds that defaulted in a quarter divided by the face-value of all bonds outstanding at the end of the previous quarter.

Source. KMV Corporation and Moody's Investors Service.

Figure 8

Implications of Monitoring Costs

Model-Implied Probability of Default and Leverage
Monitoring Costs = .36



Model-Implied Standard Deviation of Idiosyncratic Risk and Leverage
Monitoring Costs = .36

