Bonds vs. Equities: Information for Investment*

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Abstract

We provide a simple model of investment by a firm funded with debt and equity and robust empirical evidence to demonstrate that, once we control for the debt overhang problem with credit spreads, *asset* volatility is an unambiguously *positive* signal for investment, while *equity* volatility sends a mixed signal: Elevated volatility raises the option value of equity and increases investment for financially sound firms, but it exacerbates debt overhang and decreases investment for firms close to default. Our study provides a simple unified understanding of the structural and empirical relationships between investment, credit spreads, equity vs. asset volatility, leverage, and Tobin's q.

Keywords: Credit Spreads, Uncertainty, Investment, Equity Volatility, Leverage, Debt Overhang

JEL Classifications: E22, E32, G31

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1 Introduction

Bond- and equity-market measures of risk are commonly used in macroeconomic forecasting, and many economists have argued that uncertainty should adversely affect firm investment.[1,2] This paper presents a simple model and robust empirical evidence to clarify the impact of these risk measures on investment. We argue that prior studies have found that bond-market measures of risk predict economic activity better than equity-market measures because equity volatility is a mixed signal for investment. Because equity volatility is levered asset volatility, it contains information about both the dampening effects of leverage due to debt overhang and the option value of higher volatility for equity holders with limited liability. However, once we control for the debt overhang problem with credit spreads, *asset* volatility captures only equity holders' option value of investment and is an unambiguously *positive* signal for investment.

We construct a parsimonious model of investment and test its predictions empirically. The model features a firm with a given level of asset volatility and capital structure (the level of debt) in place. At date zero, equity holders choose the level of investment. At date one, equity holders observe productivity and output and choose whether or not to default. We depart from Modigliani and Miller's (1958) theorem by assuming that equity holders make investment decisions, and their interests may not be aligned with those of debt holders. As a result, the divergent effects of equity holders' option-like claim and their loss of the marginal returns to investment from debt overhang drive a wedge between debt- and equity-market measures as signals for investment. The first-order conditions for investment and the threshold for pro-

[1]Friedman and Kuttner (1992) show that the spread between commercial paper and Treasury bills forecasts recessions. Gilchrist and Zakrajšek (2012) use firm-level data to construct a credit spread measure with substantial predictive power for aggregate investment, employment, and output. See also the important contributions of Friedman and Kuttner (1998); Stock and Watson (1989); Bernanke (1990); Gertler and Lown (1999); Gilchrist, Yankov, and Zakrajšek (2009); Giesecke, Longstaff, Schaefer, and Strebulaev (2014); Krishnamurthy and Muir (2017).

[2]See the large literature on investment with adjustment costs following Pindyck (1991); Dixit, Dixit, and Pindyck (1994); and more recently Bloom (2009).

ductivity below which equity holders choose to default, along with the given asset volatility and debt level, pin down credit spreads, equity volatility, and Tobin's q.

To isolate the effects of different measures of risk on investment, we perform comparative statics in our model for different empirically relevant variables. That is, rather than simply varying the parameters, we study the effects of varying empirically observable variables, holding other observables constant. We then bring these comparative statics to the data and document empirical support for the structural relationship between credit spreads, asset volatility, leverage, equity volatility, Tobin's q, and investment.

Our first key finding is that, of the risk measures, only credit spreads and asset volatility are clean signals for investment. Credit spreads capture debt overhang, while asset volatility capture option value. As a result, holding asset volatility constant, the elasticity of investment with respect to credit spreads is always negative (due to debt overhang). Conversely, holding credit spreads constant, the elasticity of investment with respect to *asset* volatility is always *positive* (due to option value).[3] While this second result may seem surprising in the context of the large and growing literature on uncertainty and investment, our empirical findings robustly support asset volatility as a measure of the upside-option value of investment for equity holders.

Next, we show that leverage is not a sufficient control for debt overhang when trying to recover the effect of volatility on investment. The reason is that leverage does not effectively capture the firm's distance to default, since the effective distance is a function of *both* leverage *and* asset volatility. Because leverage does not measure both aspects of distance to default, if asset volatility increases while holding leverage constant, there are two effects. First, option value increases—but second, debt overhang also increases as the distance to default shrinks. Distance to default

[3] Our result—that asset volatility has a positive relation to investment—is consistent with the "Oi-Hartman-Abel" effect (Oi, 1961; Hartman, 1972; Abel, 1983), in which firms can expand to take advantage of positive shocks and shrink to avoid negative ones, making them risk-loving. However, our results for the relationship between equity volatility and investment suggest that leverage is at least one key driver of option value.

could shrink faster or more slowly than option value increases, and these two effects compete for the overall effect on investment of a change in volatility. Thus, it is crucial to control for *credit spreads*, not just leverage, to recover the unambiguously positive option value effect of volatility on investment. This is an important lesson for empirical studies of investment that use leverage as a control for the effects of debt on investment.

The comparative statics from our model also demonstrate why, even controlling for credit spreads, equity volatility is an ambiguous signal for investment. This is because equity volatility is a compound signal of the negative effects of leverage and the positive effects of asset volatility. Thus, if equity volatility increases, the change in investment can be positive (if the option value effect dominates) or negative (if the debt overhang effect dominates).

Our model can also speak to the potential for equity holders to engage in risk shifting, as in (Jensen and Meckling, 1976). We provide a condition whereby equity and debt holders' incentives are misaligned, and show that this condition essentially requires the debt overhang problem to dominate the option value. As call-option holders on the firm's assets, equity holders always benefit from an increase in risk, and thus choose riskier investments when available. However, increased volatility may not always adversely affect debt holders, as higher volatility might encourage equity holders to invest more and default less frequently. If, on the other hand, an increase in asset volatility prompts shareholders to reduce investment and default more often, then equity and debt holders have conflicting interests concerning an increase in risk. Thus, our model provides clear intuition for the (perhaps surprising) relationship between debt overhang and risk-shifting incentives. Risk-shifting—due to a misalignment of incentives between debt and equity holders—only occurs when the debt overhang problem dominates equity holders' option value, such that equity holders invest less and default more often.[4]

Our final theoretical result concerns Tobin's q. As in standard neoclassical models

[4]We thank the *Journal of Finance* associate editor for suggesting this analysis.

following Tobin (1969), Tobin's q captures all marginal costs and benefits of investment.[5] As in Philippon (2009), credit spreads represent a bond-market measure of Tobin's q, because credit spreads capture the loss in equity holders' marginal return from investment due to debt overhang.[6] However, we extend the result of Philippon (2009) to show that the bond market's q is incomplete: Credit spreads do not capture the option value of higher asset volatility, while Tobin's q does.

We test the predictions of the model using regressions that closely follow our theoretical comparative statics. We establish three sets of empirical findings. First, we confirm that the sensitivity of investment to *asset* volatility is positive for all firms—once we control for credit spreads. This may seem surprising, given the common intuition from real options (e.g., Pindyck, 1991) and the effects of volatility as a measure of "uncertainty" (e.g., Bloom, 2009). Importantly, the option value of investment for equity holders we focus on is driven by the *level* of asset volatility, as in the models of capital structure and credit risk of Merton (1974) and Leland (1994). By contrast, the literature on uncertainty and investment focuses on the short-run effect of *changes* in volatility on real options to invest, and most of that literature studies equity (not asset) volatility. Thus, our results are not necessarily a challenge to the wait-and-see mechanism of Bloom (2009) or Alfaro, Bloom, and Lin (2018), since changes in volatility can still have a temporary negative effect.

At least two interpretations of the novel empirical result whereby asset volatility is robustly positively related to investment are possible. First, as in our model, asset volatility can boost the option value of equity, alleviate the debt overhang effect, and incentivize equity holders to invest more (a causal channel). Alternatively, the uncertainty from future investment could feed back into the volatility of current asset values (an endogeneity channel). We show, using lags and leads of asset volatility and instrumental variables following the methodology introduced by Alfaro, Bloom,

[5] See also the important contributions connecting q-theory to investment with non-convex costs and uncertainty of Abel, Dixit, Eberly, and Pindyck (1996) and Abel and Eberly (1996, 1994, 1999).

[6] See also Proposition 2 in Philippon (2009), which expresses q as approximately equal to $\frac{\psi}{\delta(1+r)}\frac{1+r_t}{1+y_t}$, where r is the risk-free rate, y is the corporate bond yield, ψ is leverage, and δ is the risk-neutral default rate.

and Lin (2018), that the first explanation is more likely.

Our second key empirical result addresses the horse race between credit spreads and equity volatility as signals for investment, as documented by Gilchrist, Sim, and Zakrajšek (2014).[7] We confirm the main result in that study—that credit spreads are robustly negatively related to investment and drive out equity volatility in predicting investment. However, we show that the reason that equity volatility is driven out by credit spreads is because of robust, systematic heterogeneity in the empirical elasticity of investment to equity volatility in the cross-section of firms. The elasticity of investment to equity volatility is positive for firms far enough away from default and negative otherwise. These systematically different signs in the cross-section wash out in pooled data and confound aggregate inference. We use our model to provide intuition for this finding.

By contrast, the elasticity of investment to credit spreads is always negative. Importantly, we provide empirical evidence against the hypothesis that bond markets predict investment better because they have more smart money. To do this, we repeat the analysis using credit spreads that are constructed using equity market data, leverage ratios, and historical default rates as inputs into a structural model.[8] These fair-value credit spreads are constructed without any bond market data and thus cannot be driven by bond market investors. Empirical results using this equity-market measure of bond spreads are virtually identical to those using bond-market spreads.

In order to provide additional evidence that our findings are explained by the structural relationships in credit risk models, we establish that equity volatility and credit spreads are largely influenced by asset volatility and leverage. Notably, our analysis reveals that the majority of the fluctuations in credit spreads can be attributed to leverage, whereas asset volatility primarily accounts for the variations in

[7] Gilchrist, Sim, and Zakrajšek (2014) emphasize the role of financial frictions in exacerbating the negative effects from uncertainty on investment. See also Christiano, Motto, and Rostagno (2014) and Arellano, Bai, and Kehoe (2019).

[8] See Arora, Bohn, and Zhu (2005) and Nazeran and Dwyer (2015).

equity volatility, especially for firms further from default. This finding provides a rationale for why higher equity volatility positively impacts investment decisions for financially stable firms.[9] For healthy firms, higher equity volatility signals greater option value and better investment opportunities—but for more distressed firms, greater equity volatility exacerbates the debt overhang problem.

In the data, in line with the literature on risk-shifting, we find that the sufficient condition for the presence of risk-shifting incentives derived in our model is satisfied for firms with high credit spreads. Thus, our study provides a theoretical and empirical reconciliation between the debt overhang and risk-shifting effects of leverage on equity holders' incentives.

We control for Tobin's q in our baseline estimations. We also show that, empirically, both credit spreads (Philippon, 2009) and asset volatility contain additional information for investment at firm level. The finding that asset volatility is a robust positive signal for investment is consistent with our model, although in the model q fully captures the information in both credit spreads and volatility. Our empirical findings of additional information from credit and volatility signals are consistent with the large literature following Fazzari, Hubbard, and Petersen (1988), which documents the poor performance of q-theory empirically, as well as the presence of measurement error (e.g., Erickson and Whited, 2012).

In relation to the literature, a key contribution of our study is to clarify the distinction between the information in different measures of firm-level volatility that have been used extensively in the literature on uncertainty and investment following Bloom (2009), and to integrate insights from capital structure and credit risk

[9] Building on the seminal work of Merton (1974) and Leland (1994), Atkeson, Eisfeldt, and Weill (2017) show theoretically that under very minimal assumptions, the inverse of equity volatility is bounded above by distance to insolvency and below by distance to default. Empirically, they document a tight log-linear relationship between the inverse of equity volatility and credit spreads. See also Campbell and Taksler (2003), who show that idiosyncratic equity volatility explains as much of the cross-sectional variation in bond yields as credit spreads do. Our empirical work also addresses the role of the fundamental part of credit spreads in driving our results, as opposed to the non-fundamental part emphasized by Collin-Dufresn, Goldstein, and Martin (2001) and Gilchrist and Zakrajšek (2012).

models. A large existing literature brings the insights of Jensen and Meckling (1976) and Myers (1977) to the data.[10] Most of that literature offers rich dynamic settings and focuses on quantitative effects. For example, Hennessy (2004) shows that debt overhang inhibits investment in long-lived assets and provides a structural estimation based on an augmented q-theory. We advance the intuition from that literature by providing a one-period structural model that is as parsimonious as possible in order to clearly illustrate the most fundamental insights about the economic forces tying investment to volatility and credit risk. Importantly, our simple model is nested in most models of firm investment with outstanding debt that are more complex and offer additional predictions. Still, using this model we are able to generate new insights and clear predictions regarding the relationship between investment, leverage, credit spreads, asset and equity volatility, and Tobin's q. Indeed, our parsimonious approach allows us to clarify several prior results from the empirical literature on risk and investment.

While the focus of our study is at firm level, our findings suggest fruitful directions for future work on the relation between equity volatility, credit spreads, and aggregate economic activity. In Figure 1, we plot the time series and cross-section of the estimated firm-level elasticities of investment with respect to equity volatility. Firms with lower credit spreads that are further away from default display a positive elasticity of investment, while firms with higher credit spreads display a negative elasticity. Aggregate effects are driven by the movement of the entire cross-section of firms away from and closer to their respective default boundaries. Thus, a positive shock to equity volatility has a more strongly negative impact on investment when the entire cross section of firms is closer to default. In contrast, Figure 2 shows that the elasticity of investment to credit spreads is negative for all firm-quarters. We also confirm that our micro-results aggregate with a recursive vector autoregression (VAR) model of the aggregate time series of investment, asset volatility, and credit

[10] See, among many others, Mello and Parsons (1992); Mauer and Triantis (1994); Leland (1998); Parrino and Weisbach (1999); Morellec (2001); Titman and Tsyplakov (2007); Eisdorfer (2008); Gomes and Schmid (2010); Bhamra, Kuehn, and Strebulaev (2010); Kuehn and Schmid (2014); Gilje (2016); Favara, Morellec, Schroth, and Valta (2017); Geelen, Hajda, and Morellec (2022).

spreads. Those results confirm that the aggregate investment response to a positive shock to asset volatility is positive, while the response to a positive shock to credit spreads is negative. Our study thus contributes to understanding why there appears to be a connection between bond markets and the macroeconomy.[11] We argue that bond markets appear to have a tighter relationship to the macroeconomy, because while credit spreads have an unambiguous (negative) relationship with firm-level investment, equity volatility is a mixed signal of positive option value and negative debt overhang. The evidence we present is less consistent with the idea that bond markets have a tighter link with fundamentals due to a "smarter" investor base.

Finally, our study yields important suggestions for future empirical work. First, researchers should use asset volatility rather than equity volatility to measure the effects of option values and/or "uncertainty."[12] Second, controlling for leverage is not as clean as controlling for credit spreads. Only credit spreads hold distance to default and the effect of financial frictions such as debt overhang constant.

The remainder of the paper is organized as follows. Section 2 presents our model to build economic intuition. Section 3 presents our firm-level empirical results. In Section 4, we show that our results hold at aggregate level, and Section 5 concludes.

2 A Model of Debt Overhang and Option Value

In this section, we develop a simple but general credit risk-model to clarify the structural relationships between investment, leverage, credit spreads, volatility and

[11] Friedman and Kuttner (1992) show that the spread between commercial paper and Treasury bills forecasts recessions. See also the important contributions of Friedman and Kuttner (1998); Stock and Watson (1989); Bernanke (1990); Gertler and Lown (1999); Gilchrist, Yankov, and Zakrajšek (2009); Giesecke, Longstaff, Schaefer, and Strebulaev (2014); and Krishnamurthy and Muir (2017).

[12] Choi and Richardson (2016) and Choi, Richardson, and Whitelaw (2022) also emphasize the difference between equity and asset volatility. Jurado, Ludvigson, and Ng (2015) provide evidence that standard measures of uncertainty based on conditional volatilities are imperfect uncertainty measures.

Tobin's q. We analyze the investment choices of a firm facing productivity risk that has outstanding debt already in place. Two forces drive the investment decision: debt overhang and the option value of equity. The key violation of the Modigliani and Miller (1958) theorem in our model is that the incentives of equity and debtholders are not aligned. Equity holders choose investment and make a trade-off between the option value of investment and the losses from debt overhang. We find that conditional on a firm's credit spread, asset volatility is a clean measure of the positive effect of the option value of investment. Also, conditional on a firm's underlying asset volatility, its credit spread is a clean measure of the negative impact of debt overhang on investment. Thus, credit spread and asset volatility are jointly unambiguous negative and positive signals for investment. By contrast, the signal provided by equity volatility is ambiguous and can change in the cross-section.[13]

Consider a firm in a two-date economy that has funded itself partly with debt; that is, it has leverage in place at date zero. Given this level of debt in place and the underlying distribution of productivity shocks at date one, shareholders choose how much to invest in the firm subject to a convex total cost of investment. At date one, a random productivity shock is realized, and after observing output, shareholders decide whether to default. We make the following assumptions regarding the firm and its investments.

First, the model requires some concavity for an interior optimum. Either a convex investment cost or a concave production function is sufficient. For simplicity, we use a linear productive function and a convex investment cost function.

Assumption 1 (Investments)**.** *The firm has the option to invest in capital that produce output at date one equal to iz, where i is investment and z is a random*

[13]Other frameworks can generate the positive relationship between investment and volatility, such as the "Oi-Hartman-Abel" effect (Oi, 1961; Hartman, 1972; Abel, 1983); investment lags (Bar-Ilan and Strange, 1996; Grigoris and Segal, 2021); or managerial compensation (Glover and Levine, 2015). See, however, Panousi and Papanikolaou (2012) for related evidence that the negative relation between idiosyncratic equity volatility and investment is stronger when managerial ownership is higher. Our contribution is to show that even in the most simple, static Merton (1974) framework with investment, the positive relationship between asset volatility and investment arises naturally.

productivity shock. The strictly convex function $\phi(i)$ captures the total cost of investment, including resource costs and any adjustment costs.

Second, we assume that debt is in place at date zero, that there is a separation between debt and equity holders, and that the value of the firm in default is zero. We provide two key robustness analyses in the Online Appendices. We show that our results are robust to a relaxation of Assumption 2 that features complete or partial recovery of the firms' assets upon bankruptcy in Online Appendix D and that our results hold in a dynamic extension of our model with endogenous capital structure based on DeMarzo and He (2020) in Online Appendix E.[14]

Assumption 2 (Debt and Equity)**.** *The firm is funded by debt and equity with imperfectly aligned interests. The debt claim has a given face value b that is due at date one after output is realized. After output is realized at date one, shareholders decide whether to default. Upon default, the entirety of the firm's value is lost. Furthermore, shareholders cannot liquidate the firm ($i \geq 0$).*

Next, we normalize the interest rate to zero, normalize the mean productivity shock to one, and assume risk-neutral asset pricing in Walrasian markets.

Assumption 3 (Pricing)**.** *All securities are traded in perfect Walrasian markets. We normalize the risk-free interest rate to zero and set the prices of securities equal to their expected payoff with respect to a risk-neutral distribution $F(z;\sigma)$ of the firm's asset productivity z with full support on $[0,\infty)$. We normalize the size of the productivity shock by assuming that $\mathbb{E}[z] = 1$.*

Given our assumptions about payouts and pricing, it follows that the value of equity e and debt d are given by

$$e(b,\sigma) = \max_{i,\underline{z}} \int_{\underline{z}}^{\infty} (iz - b)dF(z;\sigma) - \phi(i) \text{ and} \tag{1}$$

$$d(b,\sigma) = (1 - F(\underline{z}(b,\sigma);\sigma))b, \tag{2}$$

[14]Consistent with Favara, Morellec, Schroth, and Valta (2017), the impact of debt overhang would be alleviated if equity holders could appropriate a fraction of the firm's value in default.

where $\underline{z}$ is the threshold productivity level below which equity holders choose to default. The value of equity is the value of output less the face value of debt for realizations of productivity above the default threshold, less the cost of investment. The value of debt is the face value times the cumulative probability of productivity realizations above the default threshold.

The first-order conditions for investment i and default threshold $\underline{z}$ imply that, at an optimum, i and $\underline{z}$ satisfy

$$\int_{\underline{z}}^{\infty} z dF(z;\sigma) = \phi_i(i), \tag{3}$$

$$i\underline{z} = b. \tag{4}$$

The first equation states that the marginal benefit of investment equals the marginal cost.[15] The second equation equates the output lost at the default threshold and the face value of debt. In other words, the left-hand side $i\underline{z}$ represents the lowest level of production such that the value of equity is not negative after repaying the debt.

The credit spread of the firm is defined as[16]

$$cs(\underline{z},\sigma) \equiv F(\underline{z};\sigma)/(1 - F(\underline{z};\sigma)). \tag{5}$$

We define book leverage as b.[17]

To streamline our analysis, we also make assumptions on the distribution of productivity shocks, $F(z;\sigma)$, which are satisfied by most risk distributions used in financial theory (including the Black–Scholes–Merton model).

Assumption 4 (Vega)**.** *Distribution of the productivity shock $F(z;\sigma)$ is such that*

[15]For ease of notation, we sometimes write $f_x(x) \equiv \frac{\partial f(x)}{\partial x}$ and $x^+ \equiv \max\{0, x\}$.
[16]The credit spread is the difference between the yield of corporate bond y and the risk-free rate. Since the risk-free rate is assumed to be 0 in this simple model and the yield is given by $y = b/d - 1$, we get $cs = F/(1 - F)$.
[17]We already normalized the size of the firm by assuming there is no capital in place in the first time period and that $\mathbb{E}[z] = 1$.

vega is always positive:

$$\nu(\underline{z}, \sigma) = \frac{\partial}{\partial \sigma} \mathbb{E}\left[(z - \underline{z})^{+}\right] > 0 \tag{6}$$

for $\underline{z} > 0$. *Furthermore, the standard deviation* σ *of* z *is a finite moment of the distribution* $F(z;\sigma)$.

Note that this assumption does not preclude the probability that default increases with volatility, which only requires an increase in the mass of productivity realizations below the default threshold.

The model has two free parameters, leverage b and asset volatility σ, and two endogenous decision variables, investment i and the default threshold $\underline{z}$. Without measurement error, in our model, simply observing two non-perfectly correlated functions of the parameters and endogenous variables is sufficient to identify these two parameters. We use this simple model to study the behavior of investment following changes in the key observable variables used in empirical studies of risk and investment: asset volatility σ, leverage b, credit spread cs, equity volatility σ^e, and Tobin's q. Below, we perform comparative statics for the key observable variables holding other key variables constant. In doing so, we provide directly testable predictions for our empirical analysis in Section 3.

In Proposition 1, we state the elasticities of investment, controlling for asset volatility and credit spread.[18] When the credit spread increases, holding asset volatility constant, the debt overhang problem intensifies and equity holders have lower incentives to invest. As asset volatility increases, holding credit spread constant, the option value of equity alleviates the debt overhang problem and induces equity holders to invest more. When there is no debt ($b = 0$) and therefore no credit risk ($\underline{z} = 0$), these partial derivatives are equal to 0 and investment is undistorted.

Proposition 1 (Asset Volatility and Credit Spread)**.** *Holding asset volatility con-*

[18]We relegate all proofs to Online Appendix D.

stant, the partial derivative of investment with respect to credit spread is given by

$$\frac{\partial i}{\partial cs} = -\frac{\underline{z}(1 - F(\underline{z};\sigma))^2}{\phi_{ii}(i)} \leq 0. \tag{7}$$

Holding credit spread constant, the partial derivative of investment with respect to asset volatility is given by

$$\frac{\partial i}{\partial \sigma} = \frac{\nu(\underline{z},\sigma)}{\phi_{ii}(i)} \geq 0. \tag{8}$$

The first part of Proposition 1 shows the negative impact of credit spread on investment. The numerator in Equation (7) $\underline{z} \times (1 - F(\underline{z};\sigma))^2$ represents the marginal product lost in default $\underline{z}$ times a term that arises due to the nonlinearity of the firm's credit spread with respect to the default probability. If the credit spread were instead approximated with F, that term would be equal to 1. The denominator demonstrates the role of the convexity of the adjustment cost function. If the cost of adjusting the stock of capital is more convex in investment, the impact of a higher credit spread is attenuated, since firms do not have to adjust the stock of capital that much to reduce the marginal cost of investment. Our results also hold with linear investment costs but a concave production function. In that case, when the production function is more concave the effect of a higher credit spread is smaller because: this is because equity holders do not have to reduce investment by as much to increase the marginal product of investment.

The second part of Proposition 1 shows that investment reacts positively to an increase in volatility because the payout to shareholders is nonlinear with limited downside and unlimited upside. That is, vega $\nu(\underline{z},\sigma)$ is positive. Thus, in this simple model with fairly general and standard assumptions, the signs of the effects of credit spread and asset volatility on investment are unambiguous. Increase in the firm's credit spread cs signals increase in the negative effect of the debt-overhang burden, and increase in asset volatility σ signals increase in the positive effect of the option value of equity.

[Figure 3 here.]

In Figure 3, we illustrate the optimal investment function with a log-normal distribution of risk. The comparative statics in Proposition 1 are clearly illustrated for this standard financial risk distribution.

We now compare the straightforward roles of credit spreads and asset volatility in determining investment with the more intricate relation between *leverage* and asset volatility in investment decisions. This analysis exemplifies why credit spreads and asset volatility are clean empirical measures of the effects of debt overhang and option value on investment decisions. It also shows why controlling for credit spreads is superior to controlling for leverage in empirical studies of investment. Intuitively, leverage only controls for one aspect of a firm's financial soundness. Leverage determines the debt-to-equity ratio, but a firm that faces larger shocks can support less leverage. In other words, leverage alone lacks the information in credit spreads regarding asset volatility, while credit spreads contain information about the effective size of the equity cushion relative to the size of the shocks the firm faces.

Proposition 2 (Asset Volatility and Leverage)**.** *Holding asset volatility constant, the partial derivative of investment with respect to leverage is given by*

$$\frac{\partial i}{\partial b} = -\frac{\underline{z} f(\underline{z};\sigma)}{\varphi(i,\underline{z},\sigma)} \leq 0, \tag{9}$$

where

$$\varphi(i,\underline{z},\sigma) \equiv \phi_{ii}(i)i - \underline{z}^2 f(\underline{z};\sigma) \geq 0. \tag{10}$$

Holding leverage constant, the partial derivative of investment with respect to asset volatility is given by

$$\frac{\partial i}{\partial \sigma} = \frac{i}{\varphi(i,\underline{z},\sigma)} \big(\nu(\underline{z},\sigma) - \underline{z} F_\sigma(\underline{z};\sigma)\big). \tag{11}$$

Proposition 2 shows that if, instead of controlling for the firm's credit spread cs, we control for leverage b, the elasticities of investment become more intricate. In Equation (9), the numerator represents the marginal product lost to default, as in Proposition 1. In the denominator, the term φ captures the feedback loop between investment and default decisions. Following a decrease in investment, shareholders default more often as output and incentives to pay back the debt decrease. That additional force was not present in Proposition 1, since changing credit spread $cs(\underline{z};\sigma)$ controls for default decision $\underline{z}$ directly. Holding leverage constant instead controls for $b = i\underline{z}$ (see the first-order condition for $\underline{z}$ in Equation (4)), which is a function of both i and $\underline{z}$. This term φ is always positive due to the second-order conditions for a maximum, and the sign of the effect of leverage on investment, holding asset volatility constant, is always negative.

However, turning to the effect of asset volatility on investment, holding leverage constant, the sign now becomes ambiguous. Intuitively, there are two effects of increasing asset volatility while holding leverage constant. The first is that the option value of investment increases. The second is that the debt-overhang problem also intensifies. The term $\nu(\underline{z},\sigma) - \underline{z}F_\sigma(\underline{z};\sigma)$ captures this horse race between option value and what is lost in default as asset volatility increases. If the option value effect is strong, this term will be positive. If the increase in asset volatility moves a large probability mass into the default region ($\underline{z}F_\sigma(\underline{z};\sigma) > 0$), this term can be negative. In other words, when the marginal increase in investment returns lost to default $zF_\sigma(\underline{z};\sigma)$ dominates the marginal increase in the option value $\nu(\underline{z},\sigma)$, shareholders reduce investment following an increase in volatility. Holding leverage $b = i\underline{z}$ constant means that investment and the default threshold move in opposite directions but does not assert which effect dominates.

However, turning to the effect of asset volatility on investment, holding leverage constant, the sign now becomes ambiguous. Intuitively, there are two effects of increasing asset volatility while holding leverage constant. The first is that the option value of investment increases. The second is that the debt-overhang problem also intensifies. In order to hold leverage $b = i\underline{z}$ constant as asset volatility increases and changes equity holders' investment decision, the default threshold $\underline{z}$ must change in the opposite direction of investment and the distance to default could shrink faster than the increase in the option value. The term $\nu(\underline{z}, \sigma) - \underline{z} F_\sigma(\underline{z}; \sigma)$ captures this horse race between option value and what is lost in default as asset volatility increases. If the option value effect is strong, this term will be positive. If the increase in asset volatility moves a large probability mass into the default region ($\underline{z} F_\sigma(\underline{z}; \sigma) > 0$), this term can be negative. In other words, when the marginal increase in investment returns lost to default $z F_\sigma(\underline{z}; \sigma)$ dominates the marginal increase in the option value $\nu(\underline{z}, \sigma)$, shareholders reduce investment following an increase in volatility.

[Figure 4 here.]

Which effect dominates is highly dependent on the shape of the distribution $F(z; \sigma)$. In Figure 4, we plot the optimal investment decision as a function of asset volatility σ when holding leverage b constant and assuming a log-normal distribution for z. The monotonic relation between leverage and investment, holding asset volatility constant, is clear. However, the relation between investment and asset volatility, holding leverage constant, is nonmonotonic. In this example with a log-normal distribution, when leverage is high, the option-value effect dominates, while the debt-overhang effect dominates when leverage is low.

Next, we consider changes in investment when controlling for credit spread and equity volatility, which is often the specification chosen in empirical work.[19] First, we define equity volatility as

$$\sigma^e(\underline{z}, \sigma) \equiv \frac{\sigma}{\mathbb{E}\left[(z - \underline{z})^+\right]}. \tag{12}$$

Thus, equity is simply levered asset volatility,[20] where the denominator represents the impact of leverage on equity volatility. If the debt burden from leverage b increases,

[19]Given Proposition 2, controlling for leverage instead of credit spreads would yield the same result: The signs of the elasticities are ambiguous.

[20]Given our model, equity volatility could include the impact of investment and the truncation

then default threshold $\underline{z}$ increases as well and equity's expected payoff per unit of capital $\mathbb{E}\left[(z-\underline{z})^{+}\right]$ decreases. Conversely, if the firm is funded entirely by equity ($b=0$), then $\underline{z}$ is equal to zero—the lower bound of the support. In that case, equity volatility is equal to asset volatility ($\sigma^e(\underline{z},\sigma)=\sigma$), since $\mathbb{E}[z]=1$.

Proposition 3 (Equity Volatility and Credit Spread)**.** *Holding equity volatility constant, the partial derivative of investment with respect to credit spread is given by*

$$\frac{\partial i}{\partial cs} = -\frac{\underline{z}(1-F(\underline{z};\sigma))^2}{\phi_{ii}(i)}\xi_{cs}(\underline{z},\sigma), \tag{13}$$

where

$$\xi_{cs}(\underline{z},\sigma) \equiv \frac{\int_{\underline{z}}^{\infty} z/\underline{z}dF_\sigma(z;\sigma)\sigma^e_{\underline{z}}(\underline{z},\sigma)+f(\underline{z};\sigma)\sigma^e_\sigma(\underline{z},\sigma)}{f(\underline{z};\sigma)\sigma^e_\sigma(\underline{z},\sigma)-F_\sigma(\underline{z};\sigma)\sigma^e_{\underline{z}}(\underline{z},\sigma)}. \tag{14}$$

Holding credit spread constant, the partial derivative of investment with respect to equity volatility is given by

$$\frac{\partial i}{\partial \sigma^e} = \frac{\nu(\underline{z},\sigma)}{\phi_{ii}(i)}\xi_{\sigma^e}(\underline{z},\sigma), \tag{15}$$

where

$$\xi_{\sigma^e}(\underline{z},\sigma) \equiv \frac{f(\underline{z};\sigma)}{f(\underline{z};\sigma)\sigma^e_\sigma(\underline{z},\sigma)-F_\sigma(\underline{z};\sigma)\sigma^e_{\underline{z}}(\underline{z},\sigma)}. \tag{16}$$

We define the wedges ξ_{cs} and ξ_{σ^e} to clarify the distinction between Propositions 1 and 3. It is easiest to start with the relation between investment and equity volatility, holding credit spread constant. To understand the additional complexity that arises

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of equity volatility above the default threshold and be defined as

$$\frac{\sqrt{\mathbb{V}ar\left[i(z-\underline{z})^{+}-\phi(i)\right]}}{\mathbb{E}\left[i(z-\underline{z})^{+}-\phi(i)\right]}.$$

In this case, our key insight—that equity volatility is an ambiguous signal for investment—still holds, but the elasticities become undecipherable.

when equity instead of asset volatility is used as a signal of uncertainty, it is useful to look at the partial derivative of equity volatility with respect to asset volatility σ and default threshold $\underline{z}$:

$$\sigma^e_\sigma(\underline{z},\sigma) = \frac{1}{\mathbb{E}\left[(z-\underline{z})^+\right]} - \frac{\sigma\nu(\underline{z},\sigma)}{\mathbb{E}\left[(z-\underline{z})^+\right]^2} \qquad \text{and} \qquad \sigma^e_{\underline{z}}(\underline{z},\sigma) = \frac{\sigma\left(1-F(\underline{z};\sigma)\right)}{\mathbb{E}\left[(z-\underline{z})^+\right]^2} \geq 0. \tag{17}$$

As shown in these equations, when the option value impact of asset volatility $\nu(\underline{z},\sigma)$ is large, equity volatility decreases following a positive shock to asset volatility. Indeed, the increase in the payoff to equity holders (the denominator of σ^e) gets larger than the relative increase in asset volatility (the numerator of σ^e). Add to that effect that the partial derivative of σ^e with respect to the default threshold is positive and—to keep the credit spread cs constant—default threshold $\underline{z}$ needs to decrease, and it is not surprising that following a positive asset volatility shock, equity volatility might decrease. Corollary 1 makes this argument explicit.

Corollary 1 (Equity Volatility and Asset Volatility)**.** *If the total derivative of the default threshold with respect to asset volatility is such that*

$$\frac{d\underline{z}}{d\sigma} < \frac{\sigma\nu(\underline{z},\sigma) - \mathbb{E}\left[(z-\underline{z})^+\right]}{\sigma(1-F(\underline{z};\sigma))}, \tag{18}$$

then the total derivative of equity volatility with respect to asset volatility is negative:

$$\frac{d\sigma^e(\underline{z},\sigma)}{d\sigma} < 0. \tag{19}$$

These additional forces are captured by the wedges ξ_{cs} and ξ_{σ^e}. The forces that drive these wedges cause the signs of the elasticities of Proposition 3 to be highly dependent on the shape of the risk distribution F and the level of leverage and volatility of the firm, in contrast to the robustly positive signs of the elasticity for asset volatility in Proposition 1.

These nonmonotonicities also complicate the mapping of investment decisions in the (cs, σ^e)-space. Lemma 1 formally states this complexity.

Lemma 1 (Existence of Credit Spread and Equity Volatility Pair)**.** *Given* $(cs, \sigma^e) \in [0,1] \times \mathbb{R}^+$*, there does not always exist a solution* $(\underline{z}, \sigma) \in \mathbb{R}^+ \times \mathbb{R}^+$ *to the following system of two equations:*

$$cs = \frac{F(\underline{z};\sigma)}{1 - F(\underline{z};\sigma)}, \qquad \sigma^e = \frac{\sigma}{\mathbb{E}\left[(z - \underline{z})^+\right]}. \tag{20}$$

Furthermore, the solution might not be unique.

Given the result in Lemma 1, to illustrate the results for equity volatility—instead of directly plotting investment as a function of cs and σ^e—we show the sign of the wedges in the (cs, σ)-space for two distributions: a log-normal distribution and a log-normal mixture distribution. Figure 5 presents the results. In the case of the log-normal distribution, the wedges are (i) both positive (white area), which implies that the signs of the elasticities are identical to those in Proposition 1; (ii) both negative (light gray area), which implies that the signs of the elasticities are opposite to those in Proposition 1; or (iii) the wedge for credit spread is negative and the wedge for equity volatility is positive (dark gray area).

[Figure 5 here.]

The mixture distribution is a mixture of two log-normal distributions (see Figure 5's caption for details) and is therefore bimodal. This risk distribution could correspond to a technology in which the productivity shock is drawn from either a bad (low mean) or a good (high mean) distribution. In this case, an increase in uncertainty could have a large effect on the option value without substantially impacting default risk—the dark gray area, in which the elasticities of investment with respect to credit spread and equity volatility are both negative. This example illustrates how our empirical result, whereby the elasticity of investment with respect to equity volatility is positive for low credit spread levels but negative for high levels of credit spread, can arise,[21] while the elasticity with respect to credit spread is negative. The numerical example also highlights the fact that predictions regarding cross-sectional differences in the sign of the elasticity of investment with respect to equity volatility (and also cross-sectional differences in the *magnitude* of the elasticity of investment with respect to *asset* volatility) are highly dependent on the specific functional form of the risk distribution $F(z;\sigma)$.

Our model can also speak to whether credit spreads can effectively summarize the information in Tobin's q (see Philippon, 2009). In our model, as in most standard models, q fully summarizes the marginal benefit of investment. While credit spreads can effectively capture the disincentive to invest when some output is lost below the default threshold, it does not capture the information on asset volatility that summaries the option value for equity holders of capturing payoffs above the default threshold.

We illustrate our simple model's prediction for the relationship between Tobin's q and investment. As in Philippon (2009), we define Tobin's q by the market value of the firm scaled by its end-of-period assets:

$$q = \int_{\underline{z}}^{\infty} z dF(z;\sigma) = \phi_i(i). \tag{21}$$

As is the case in most models of investment, Tobin's q equals the marginal cost of investment, $\phi_i(i)$, as implied by the first-order condition for investment in Equation (3). Thus, observing q directly pins down investment level i, and credit spread and asset volatility have no additional predictive information for investment.[22] Of

[21] Fixing asset volatility at 0.3, the elasticity of investment with respect to equity volatility is positive for low credit spread levels ($cs \leq 0.15$) and negative for high levels of credit spread ($0.30 \leq cs \leq 0.8$) in the example in Figure 5.

[22] This result also holds if debt holders can recover a fraction α of the firm's capital after default. Indeed, in that case Tobin's q becomes

$$q = \int_{\underline{z}}^{\infty} z dF(z;\sigma) + \alpha \int_{0}^{\underline{z}} z dF(z;\sigma) = (1-\alpha)\phi_i(i) + \alpha, \tag{22}$$

since $\int_0^{\infty} z dF(z;\sigma) = 1$.

course, in the presence of measurement error, other signals for investment incentives not perfectly correlated with q can have additional predictive content, as in our empirical analysis.

We next explain why credit spreads are incomplete signals for q. The difference arises because although credit spreads can capture debt overhang, they don't capture option value. To see this, suppose F is a normal distribution. In this case we have

$$q = (1 - F(\underline{z};\sigma)) + \sigma^2 f(\underline{z};\sigma). \tag{23}$$

The first term in Equation (23) captures the fact that returns to investment are lost below the default threshold. This can be captured by the credit spread as $cs = F/(1 - F)$. However, the second term depends on asset volatility and this option-value effect is not captured by the credit spread.

Finally, we provide a refinement to the intuition for risk-shifting from the extensive literature on asset substitution (Jensen and Meckling, 1976). Specifically, we provide a condition for equity and debtholders' incentives to be misaligned, and show that this condition essentially requires that the debt overhang problem dominates the option value. In our basic model, shareholders would always augment the risk of their investment project if presented with an opportunity to do so, since vega is positive. That is, $\frac{\partial e(b,\sigma)}{\partial \sigma} > 0$. However, increased volatility may not always adversely affect debt holders. Thus, incentives for equity holders to take on "excessive" risk, or to engage in risk-shifting, are not always present, even given a separation between debt and equity holders. As shown in Proposition 2, higher volatility might encourage equity holders to invest more and default less frequently for a given debt level b, therefore benefits bond holders.

Corollary 2 (Risk-shifting)**.** *If*

$$\frac{\partial i}{\partial \sigma} = \frac{i}{\varphi(i,\underline{z},\sigma)}\big(\nu(\underline{z},\sigma) - \underline{z}F_\sigma(\underline{z};\sigma)\big) < 0, \tag{24}$$

then

$$\frac{\partial d(b,\sigma)}{\partial \sigma} < 0 \quad \textit{and} \quad \frac{\partial^2 e(b,\sigma)}{\partial \sigma \partial b} > 0. \tag{25}$$

Corollary 2 provides a sufficient condition under which equity and debt holders have conflicting interests with respect to an increase in risk. This occurs when the debt-overhang problem dominates the option value, which causes shareholders to reduce their investments in response to an increase in volatility and default more often, which harms bond holders (see Equation (24)). In line with the literature on risk-shifting, we also find that, if that condition is satisfied, the incentive for shareholders to engage in more risky projects increases with leverage (see Equation (25)). The necessary condition in Equation (24) provides a way to empirically test for the presence of risk-shifting incentives, which we confirm for firms with high credit spreads. However, it is important to note that higher leverage does not necessarily imply greater incentives for equity holders to risk shift. If the option-value effect of higher volatility dominates, then the greater risk is actually beneficial for both debt and equity holders, since equity holders default less often.

3 Empirical Results: Firm Level

This section presents empirical tests of the model's predictions. Our quarterly dataset, which describes firms' credit spreads, asset and equity volatilities, and investment rates (as well as controls), covers the period from 1984 to 2018. We use S&P's Compustat quarterly database for firm-level accounting variables. Investment rate is defined as capital expenditures in quarter t scaled by net property, plant, and equipment in quarter $t-1$.[23] We compute our benchmark measure of equity volatility

[23] We construct an alternative measure of investment rate, defined as capital expenditures plus R&D and 30% of SG&A, divided by the lagged sum of net PP&E and intangible capital. The intangible capital series is downloaded from the online database made available by Eisfeldt, Kim, and Papanikolaou (forthcoming), and the method for constructing the intangible capital series can be found in Eisfeldt and Papanikolaou (2013). See also Peters and Taylor (2017). We show in Online

with daily returns from the Center for Research in Security Prices (CRSP) database. Robustness checks include using idiosyncratic equity volatility and implied equity volatility. We construct our baseline measure of asset volatility by first delevering equity returns and then computing the standard deviation of these delevered returns. Robustness checks include using idiosyncratic asset volatility, implied asset volatility, asset volatility derived from Merton's model, and residual asset volatility using the residual of a panel regression of equity volatility on leverage. Credit spreads are collected from the Lehman/Warga (1984-2005) and ICE databases (1997-2018) and equity implied volatilities from OptionMetrics. Appendix Section A details sample construction and precise definitions for each variable we study. Our main sample contains 1,407 unique firms and 48,672 firm-quarter observations. Table I presents notation, short variable descriptions, sample coverage, and summary statistics.

[Table I here.]

To establish our facts, we use a set of firm-level panel regressions of investment rates on lagged measures of volatility and credit spreads:

$$\log[I/K]_{i,t} = \beta_1 \log X^{\sigma}_{i,t-1} + \beta_2 \log X^{cs}_{i,t-1} + \boldsymbol{\gamma}\mathbf{X}_{i,t-1} + \eta_i + \lambda_t + \epsilon_{i,t}, \tag{26}$$

where $\log[I/K]_{i,t}$ is the log of the investment rate of firm i in quarter t; $X^{\sigma}_{i,t-1}$ denotes measures of volatility (such as asset volatility $\sigma_{i,t-1}$ or equity volatility $\sigma^{e}_{i,t-1}$); and $X^{cs}_{i,t-1}$ denotes measures of credit risk (such as credit spreads $cs_{i,t}$, fair value spreads $\hat{cs}_{i,t-1}$, or market leverage $[MA/ME]_{i,t-1}$), all lagged by 1 quarter. We control for firm and time fixed effects (η_i and λ_t). Our control variables $\mathbf{X}_{i,t-1}$ include the lag of firm i's return on equity, log tangibility, log sale ratio, log income ratio, and log Tobin's q.

Appendix Tables OA II and OA III that our main empirical results are robust to this alternative measure of the investment rate.

3.1 Asset Volatility and Credit Spread

[Table II here.]

According to our model, the correct specification to capture the impact of debt overhang and volatility on investment is to use both credit spread and asset volatility as control variables. Table II presents the estimation results of Equation (26) using asset volatility and credit spread. As predicted, asset volatility (credit spread) has a robustly positive (negative) relationship with investment in the full sample. Columns 4-6 show that this positive relationship between asset volatility and investment holds for firms with all levels of credit spreads, a result which stands in contrast to the relationship between investment and equity volatility shown below.

[Table III here.]

In our model, equity holders make investment decisions as a function of debt overhang and the distribution of future productivity realizations. Implied volatility may capture forward-looking risk better than our baseline measure using realized volatility. Table III shows that the results using implied asset volatility are economically stronger than those using realized asset volatility.[24] This result lends support to the idea that it is the expectation of future asset volatility, not past realizations, that drives changes in investment.[25] Our results are also robust to several other measures of asset volatility.[26] These robustness checks help to alleviate concerns regarding the measurement of asset volatility.[27]

[24]We show in Online Appendix Table OA IV that the coefficient on asset volatility is half the size and less statistically significant using realized asset volatility for the same (smaller) sample of firm-year observations for which implied volatility is available.

[25]Lettau and Ludvigson (2002) emphasize the importance of information on future investment returns contained in asset prices.

[26]We present results using idiosyncratic asset volatility, asset volatility derived from Merton's model, and the residual of equity volatility regressed on firm leverage in Online Appendix Tables OA V, OA VI, and OA VII, respectively.

[27]Gomes and Schmid (2010) and Geske, Subrahmanyam, and Zhou (2016) develop frameworks in which asset volatility is not fully captured by volatility derived from Merton's model.

We hypothesize that the positive correlation between investment and asset volatility is most likely driven by one of two mechanisms. Either (i) an increase in business risk renders the value of assets in place more volatile and incentivizes firms to invest more, or (ii) due to higher investments, the value of the firm's assets becomes more uncertain. We argue that the former is the more likely explanation for our results.

[Table IV here.]

The first evidence in support of the direction of causality running from volatility to investment, rather than the reverse, can be found in Table IV. Drawing inspiration from Duffee (1995),[28] we test whether investment is highly correlated with past and/or future asset volatility. If asset volatility increases due to uncertainty that stems from higher investment rates, we would anticipate an increase in asset volatility during the investment period. However, if, as we contend, higher asset volatility enhances the option value of investment, we would expect a stronger association between investment and lags of asset volatility at the time of the investment decision.[29] The coefficients on lagged asset volatility presented in Table IV are not only statistically significant but also economically more substantial than those on leads of asset volatility.

Next, following the instrumental variables strategy of Alfaro, Bloom, and Lin (2018), we address endogeneity in estimating the impact of asset volatility on investment by instrumenting for firm-level volatility with industry-level exposure to volatility shocks. First, we estimate sensitivities to energy, currencies, Treasuries, and policy at industry level as the factor loadings of a regression of a firm's daily delevered stock return on the price growth of energy and 7 currencies, return on Treasury bonds, and changes in daily policy uncertainty from Baker, Bloom, and Davis (2016). Then, we multiply the absolute value of the industry time-varying

[28]Duffee (1995) tests the validity of the financial leverage effect by testing whether equity returns are correlated with current and/or future equity volatility. Here, we test the validity of the investment option value of asset volatility by testing whether investment rates are correlated with past and/or future asset volatility.

[29]See Online Appendix Table OA VIII for leads and lags of implied asset volatility.

sensitivities by the implied *asset* volatilities of the ten factors, which provides 10 instruments for lagged asset volatility. We refer the reader to Appendix A and Alfaro, Bloom, and Lin (2018) for further details on construction of the instrumental variables. Two key differences between our study and theirs is that we focus on levels of volatility instead of shocks to volatility, and on asset volatility instead of equity volatility. While Alfaro, Bloom, and Lin (2018) provide an analysis using shocks to asset volatility constructed by delevering instrumented equity volatility in the appendix to their paper, we directly instrument for the level of asset volatility.

[Table V here.]

In Table V, we show that our main results hold in the instrumental variable regression: Asset volatility has a positive impact on investment.[30] For comparison, we also report our results for the negative impact of equity volatility on investment.

The fact that asset volatility is robustly positively related to investment may seem surprising, given the emphasis on a negative relationship between uncertainty and investment in the literature.[31] Our results are not necessarily inconsistent with that literature; the underlying theory and timing in those models differ from ours. We emphasize the misalignment of debt and equity holders' returns to investment and the fact that the level of equity volatility reflects both debt overhang and investment option value. Our key intuition comes from the classic structural models of credit risk and capital structure of Merton (1974) and Leland (1994). The uncertainty literature emphasizes the "wait-and-see" effect of an increase in volatility and focuses on the relationship between investment and *changes* in volatility. In wait-and-see models of investment with fixed adjustment costs, firms reduce investment in the short run when they expect volatility to increase.[32] Even in those models, however, investment

[30] Note that the low Kleibergen-Paap F-statistic indicates that the excluded instruments are correlated with the endogenous regressors, but only weakly.

[31] See Bloom (2009) and the large subsequent literature.

[32] We present the empirical relationship between investment and changes in asset volatility in Online Appendix Table OA IX. The coefficient on the change is negative and the coefficient on the level is positive when both the levels of and changes in the asset volatility are included in the regression.

increases in the long run once higher volatility is realized and firms are pushed outside their inaction regions more often. In this sense, once there is a separation between debt and equity holders, there is a natural tension between "wait-and-see" real option effects—as in the classic models of Pindyck (1991) and Dixit, Dixit, and Pindyck (1994)—and considering equity holders as being long a call option on the firm who benefit from higher volatility, as in Merton (1974).

We also differ from prior studies by studying the impact of *firm-level* uncertainty, instead of focusing on the impact of aggregate and political uncertainty on investment decisions.[33] Furthermore, as predicted by our model, we demonstrate below that using *equity* volatility instead of asset volatility as a proxy for firm-level uncertainty can lead to misleading results.[34]

3.2 Equity Volatility and Credit Spreads

Table VI presents the estimation results of Equation (26) using equity volatility and credit spreads. Columns 1 and 2 show that the individual relationships between investment rates and both equity volatility and credit spreads are negative. Column 3 shows that when credit spreads and equity volatility are included together, the magnitude of the coefficient on equity volatility is cut by about one-third while the coefficient on credit spreads is essentially unchanged. This is the central result in Gilchrist, Sim, and Zakrajšek (2014).

[Table VI here.]

As predicted by our model, we find that the sign of the relationship between equity volatility and investment is not robust and changes sign in the cross-section of firms. Firms far from their default boundary display a positive elasticity of investment to

[33]See Bloom (2009); Baker, Bloom, and Davis (2016); Gulen and Ion (2016); Caldara and Iacoviello (2022).

[34]See Leahy and Whited (1996); Bulan (2005); Baum, Caglayan, and Talavera (2008); Eisdorfer (2008); Alfaro, Bloom, and Lin (2018); Berger, Dew-Becker, and Giglio (2020).

equity volatility, whereas this elasticity is negative for less financially sound firms. The changing sign washes out the effect of equity volatility in pooled data, and confounds aggregate inference.

To see this, consider Columns 4-6 of Table VI, in which we sort firms into terciles based on their credit spreads each quarter.[35] The coefficient on equity volatility is positive for firms with low credit spreads but negative for firms with medium credit spreads and even more negative for firms with high credit spreads. Columns 7 and 8 show that, in controlling for the negative effect on investment rates from the interaction between credit spreads and equity volatility, the effect of equity volatility is positive.[36]

One common explanation for why credit spreads tend to have a more robust relationship with firm-level investment relies on segmented markets. Perhaps there is smarter (and more institutional) money in bond markets, or maybe equity markets are more prone to bubbles and mispricing. Like Philippon (2009), our results suggest that the reason is likely fundamental: Bonds capture downside risk better while equity values include growth options. To show this, we repeat the analysis in Table VI but replace credit spreads with fair value spreads. We construct fair value spreads based on Moody's Annalytics' method described by Nazeran and Dwyer (2015). Moody's Analytics constructs a mapping between firms' distance to default based on equity market data, leverage, and expected default frequencies (Moody's EDF). Fair value spreads are then computed using cumulative expected default frequencies, constant losses given default, the market equity Sharpe ratio, and the correlation between asset returns and market equity returns.

[Table VII here.]

The results are presented in Table VII and are qualitatively identical to Table VI.

[35]This method of splitting uses quarter-specific cutoffs. Using fixed cutoffs to sort all firm-quarter observations leads to similar results.

[36]We present results using idiosyncratic equity volatility and implied equity volatility in Online Appendix Tables OA X and OA XI, respectively.

The coefficient on equity volatility goes from significantly positive to significantly negative as firms' credit spreads increase, while the coefficient on the fair value spread remains significantly negative across terciles of fair value spreads.[37] Since fair value spreads are constructed using only equity market information, the results in Table VII cannot be driven by an informational advantage in the bond market.

[Table VIII here.]

Although the results in Table VII are not driven by bond market information, it is still possible that the residuals of credit spreads, after controlling for fundamentals, have bond-market-specific information that drives out equity volatility. Table VIII demonstrates that this is not the case. The table confirms that it is the information in fair value spreads, and not the residual of credit spreads regressed on fair value spreads, that drives out the information in equity volatility in explaining investment. Columns 1 and 2 show that fair value spreads explain more of the variation in firm-level investment rates than the residuals of credit spreads after controlling for fair value spreads, and the coefficient on fair value spreads is economically and statistically more significant. Comparing Columns 4 and 5 shows that the residual bond market information after controlling for fair value spreads and equity volatility (leaving only bond-market-specific information) does not drive out equity volatility, since the coefficient on equity volatility in Column 5 is nearly the same as in Column 3 in both magnitude and significance. Table VII also shows that there is additional information on investment in the residual bond spreads. Interestingly, this information appears to be orthogonal to the information from equity markets, so at least part of the information for investment from bond markets is captured in equity market data.

Our fair value spread residuals are closely related to the excess bond premia of Gilchrist and Zakrajšek (2012). In Online Appendix Section B, we replicate our main results regarding equity and asset volatility while controlling for fundamental and

[37] Online Appendix Table OA XII presents these results using implied equity volatility.

"excess" bond spreads constructed using the methodology of Gilchrist and Zakrajšek (2012) and reach similar conclusions.[38]

We note that we cannot rule out that an additional reason that bond markets are a preferred source for forecasting information is that there is, for example, noise in equity markets due to irrational exuberance.[39] However, our results show that one reason that bond markets forecast investment more systematically than equity markets is fundamental. The elasticity of firms' investment to equity volatility has a different sign for financially sound and unsound firms while the structural element of credit spreads has an unambiguously negative relationship with investment.

3.3 Drivers of Equity Volatility and Credit Spreads

Structural models of credit risk show that both equity volatility and credit spreads are functions of leverage and asset volatility. However, when examining firms with different levels of financial soundness, there is no change in the relationship between credit spreads and investment. We argue that the change of sign in the relation between equity volatility and investment occurs because whereas equity volatility mainly captures the upside-option value of investment, it also measures the downside pressure from leverage and debt overhang when a firm is nearing default. In contrast, credit spreads mainly capture the debt overhang effects on investment from leverage. To support this explanation, we demonstrate below that variation in equity volatility is mainly driven by variation in asset volatility (for both levels and changes), while variation in credit spreads is mainly driven by variation in leverage (for both levels and changes).

For this exercise, we consider the loadings of credit spreads and equity volatility

[38] The results for equity and asset volatility are presented in Table OB I and Table OB II, respectively.

[39] We do present a robustness analysis using option implied equity volatility from option markets with potentially more sophisticated traders (see Table OA XI in the Online Appendix).

on asset volatility and leverage as estimated by the following equation:

$$\log y_{i,t} = \beta_1 \log \mathring{\sigma}_{i,t} + \beta_2 \log[MA/ME]_{i,t} + \eta_i + \lambda_t + \epsilon_{i,t},$$

where $y_{i,t}$ is either equity volatility ($\sigma^e_{i,t}$) or credit spreads ($cs_{i,t}$), and $[MA/ME]_{i,t}$ is firm-level leverage. We estimate the equation in both levels and first differences. For asset volatility, we use asset volatility derived from Merton's model $\mathring{\sigma}_{i,t}$ for this exercise—instead of delevered equity volatility—so that the empirical decomposition in levels is not mechanical.

[Table IX here.]

Table IX summarizes the results.[40] Panel A reports coefficients for the loadings of the levels of equity volatility and credit spreads on the levels of asset volatility and leverage. Coefficients for equity volatility on asset volatility are about double those on leverage. The bottom panel of Table IX reports the partial R^2 and shows that asset volatility explains 54% of the variation in equity volatility after controlling for time and firm fixed effects, while leverage explains 10%. By contrast, the loadings for credit spreads on leverage are more than three times as large as the loadings on asset volatility. Asset volatility explains little to none of the variation in credit spreads after controlling for firm and time fixed effects, while leverage explains about 21%. The results in Panel B for the loadings of changes in equity volatility and credit spreads on changes in leverage and asset volatility display patterns similar to the level results in terms of magnitudes and significance. The bottom panel shows that changes in asset volatility explain a substantial amount of variation in changes in equity volatility, controlling for firm and time fixed effects (71%). For credit spreads, changes in leverage explain more variation than changes in asset volatility, but the magnitudes are small.[41]

[40] To address endogeneity concerns, in Online Appendix Table OA XIII we use industry-level regressors—constructed as the average of all firms in the same industry, excluding the firm itself—instead of using the firm's asset volatility and leverage directly. This exercise shows similar patterns, whereby equity volatility loads more on asset volatility and credit spreads load more on leverage.

[41] See Collin-Dufresn, Goldstein, and Martin (2001) for a related result. See Campbell and

The results in Table IX show why an increase in equity volatility could either signal an increase in asset volatility (positive for investment) or leverage (negative for investment). Although credit spreads are also a combination of asset volatility and leverage, the loading of credit spreads on asset volatility is not large enough to ever drive a positive relation between credit spreads and investment.

[Table X and Table XI here.]

In Table VI we emphasized the change in sign in the elasticity of investment with respect to equity volatility for firms with high and low credit spreads. In Table X we provide evidence consistent with the idea that this may be because equity volatility is driven more by asset volatility for firms with low credit spreads and more by leverage for firms with high credit spreads. We report loadings on and partial R^2 for equity volatility on asset volatility and leverage by credit spread tercile. The loadings on asset volatility are monotonically decreasing in credit spreads while the loadings on leverage stay roughly constant. The partial R^2 of leverage to explain the level of equity volatility is about 0% for low-credit-spread firms and grows to 15% for high-credit-spread firms. Table XI presents analogous results for credit spreads. Asset volatility is never a key driver of credit spreads, while the loadings of credit spreads on leverage are larger for firms with the highest credit spreads.

3.4 Asset Volatility and Leverage

[Table XII here.]

Given the decomposition of equity volatility as levered asset volatility, a natural question is whether controlling for leverage is sufficient—or better than—controlling for credit spreads. The answer is no. Table XII shows that, using leverage instead of

Taksler (2003), Du, Elkamhi, and Ericsson (2019), and Atkeson, Eisfeldt, and Weill (2017) for studies emphasizing the empirical relationship between equity volatility and credit spreads.

credit spreads to control for firms' financial soundness, the coefficient that describes the relationship between asset volatility and investment, while always positive, is not significant for medium- and high-credit-spread firms. We have shown in our model that it is not enough to hold leverage constant to isolate the option value effect of asset volatility. This is because even with constant leverage, distance to default can still vary. Only credit spreads hold distance to default (and thus the driving force of debt overhang) constant.[42]

[Table XIII here.]

We can also use our empirical setting to compute the sufficient condition for risk-shifting by equity holders from Corollary 2. This condition provides a way of understanding which firms experience conflicting interests between equity and debt holders concerning the desired level of risk. Our estimates in Table XIII using implied asset volatility indicate that when credit spreads are above 200 basis points, equity holders have incentives to increase the level of risk beyond the level desired by bond holders.[43]

3.5 Tobin's q

[Table XIV here.]

Philippon (2009) shows that an *aggregate* measure of credit spreads empirically outperforms an aggregate equity-market-based measure of Tobin's q in data from 1953 to 2007. We show that this is not the case in *firm-level* data from 1984 to 2018. Table XIV presents the results of comparing the ability of Tobin's q to predict

[42] Table OA XIV in the Online Appendix replicates the result in Table XII using implied volatility.

[43] When using realized asset volatility instead of implied asset volatility, the elasticity of investment to asset volatility is negative but not statistically significant when credit spreads are above 500 basis points. See Online Appendix Table OA XV. We also replicate the risk-shifting analysis of Eisdorfer (2008) in the Online Appendix C.

firm-level investment rates with the ability of credit spreads and asset volatility. At firm level, Tobin's q is a strong predictor of investment rates and is not subsumed by credit spreads. Columns 1 to 3 of Table XIV review the relationship between investment rates, asset volatility, and credit spreads from Table II for comparison. Panel A presents results without additional firm-level controls and Panel B includes these controls. Column 4 shows that the coefficient on Tobin's q is positive and highly significant, and the R^2 of that univariate regression with time and firm fixed effects is higher than for either credit spreads or asset volatility. Column 5 shows that including credit spreads does not drive out Tobin's q. Comparing Columns 2, 4, and 5 of Panel A shows that without additional controls, the economic significance of credit spreads declines more than that of q when both are used together to explain investment rates. However, the decline in economic significance is similar in both variables when additional firm-level controls are included in Panel B. Finally, Column 6 shows that when all three key variables for investment—Tobin's q, asset volatility, and credit spreads—are included, each remains strongly significant. Thus, our study is consistent with the large literature that documents that Tobin's q works better in theory than empirically, since Tobin's q does not drive out credit spreads or asset volatility, as it theoretically should in our model. This result is also consistent with the presence of large measurement error.[44]

Finally, the baseline model in Philippon (2009) cannot be used to understand our findings that the sensitivity of investment to equity volatility changes sign in the cross-section because in that model leverage does not affect firm value or investment—i.e., Modigliani and Miller's (1958) theorem holds.[45] We argue that, to understand the role of risk measures from bond and equity markets on firm-level investment, the key violation of Modigliani and Miller's (1958) assumptions to consider is that equity holders have interests that are misaligned with those of bond holders and that

[44]Examples of earlier work that shows that a simple regression of investment on Tobin's q performs quite poorly include Fazzari, Hubbard, and Petersen (1988); Kaplan and Zingales (1997); Gilchrist and Himmelberg (1995); Erickson and Whited (2000); Gomes (2001); Cooper and Ejarque (2003); Moyen (2004); Hennessy (2004); and Abel and Eberly (2011), among others.

[45]The appendix of that paper relaxes the assumption of no bankruptcy costs, but does not allow for incentive misalignment between debt and equity holders.

leverage generates debt overhang.

3.6 Firms without Observable Credit Spreads

[Table XV here.]

Our analysis so far has focused on the subset of firms with observable credit spreads. Firms that have publicly traded bonds are a subset of firms with publicly traded equity and data in Compustat. In Table XV we demonstrate that our main results are preserved for firms with financial leverage, but without observable bond spreads. Columns 1 and 2 (without additional firm-level controls) and Columns 3 and 4 (adding controls) use distance to default to proxy for firms' financial soundness for firms that have financial leverage but not observable bond spreads. Columns 1 and 3 show that the relationship between equity volatility and investment changes sign in the cross-section of firms, as measured by their distance to default. Distance to default is larger for more financially sound firms, so the positive interaction term between distance to default and equity volatility indicates that the relationship between equity volatility and investment is positive for more financially sound firms and negative for firms closer to their default boundary. The coefficient on distance to default is positive, consistent with more financially sound firms having higher investment rates. The coefficient on equity volatility is negative. This coefficient corresponds to the relationship between investment and equity volatility when distance to default is zero. The sign is consistent with the result in Table VI in which the positive coefficient on equity volatility in Columns 7 and 8 corresponds to the relationship between investment and equity volatility when log credit spreads are equal to zero. Finally, Columns 2 and 4 show that when controlling for distance to default, the relationship between *asset* volatility and investment is positive—as in Table II and as predicted by our model, in which higher volatility indicates a greater option value of investment.

4 Empirical Results: Aggregate Level

Although our main focus is at firm level, we provide evidence indicating that our results may be extended to aggregate effects; we leave a full aggregate study for future work.[46]

Time Series To understand the implications of our findings for the aggregate time series, we first review the plots of the elasticity of investment rates with respect to equity volatility and credit spreads across time and across firms. In Figure 1, we compute the overall coefficient on equity volatility at each credit spread level using estimates on equity volatility ($\log \sigma^e_{i,t}$) and the interaction term ($\log \sigma^e_{i,t} \times \log cs_{i,t}$) reported in Column 7 of Table VI. Each line represents the elasticity of investment to equity volatility for a particular percentile of the credit spread distribution. More financially sound firms, with lower credit spreads, are represented by the top blue line, while less sound firms, with higher credit spreads, are represented by the bottom red line. As can be seen in the figure, the entire distribution of these elasticities shifts over time together with the distribution of credit spreads. In particular, the coefficient is negative for the whole cross-section of firms during the Great Recession, while it is mainly positive in the late 1980s. The other important takeaway from this figure is that the change in sign of the elasticity of investment with respect to credit spreads is made evident by the fact that lower-percentile lines tend to lie above the zero line, while higher credit spread percentiles lie below it.

Figure 2 plots the elasticity of investment with respect to credit spreads in the cross-section of firms with higher and lower equity volatilities. Firms with lower equity volatility have less negative elasticities of investment with respect to credit spreads, as implied by the negative coefficient on the interaction term in Column 7 of Table VI. However, the entire distribution of these elasticities is always negative.

[46]See Lee (2016) for a macroeconomic model that emphasizes the positive role of volatility for aggregate outcomes.

VAR Analysis We use VAR analysis to show that our key micro-level result, whereby the level of asset volatility has a positive impact on investment, holds at macro level. We aggregate the variables in our sample and estimate a simple VAR consisting of the three endogenous variables: the log of total asset volatility ($\log \sigma_t$), the log of credit spread ($\log cs_t$), and the log of investment rate ($\log[I/K]_t$).[47] We employ a standard recursive ordering technique and consider two identification schemes, one in which credit spreads have an immediate impact on asset volatility and one in which asset volatility has an immediate impact on credit spreads.

[Figure 6 here.]

Figure 6 reports the impulse responses of investment rates to credit spreads and asset volatility using the two specifications. As can be clearly seen in the figure by comparing the left and right panels, credit spreads have a negative impact on investment while asset volatility has a positive impact. Comparing panels (a) and (c) of Figure 6, the positive impact of asset volatility on investment is somewhat economically and statistically larger in the first specification, though both are strongly and significantly positive. The slightly stronger result in panel (a) highlights the importance of controlling for credit spreads in order to uncover the option value effect of asset volatility as a strong positive signal for investment in the aggregate.

5 Conclusion

We provide evidence and a simple model to support the idea that although credit spreads are a clean signal of the negative effect of debt overhang on investment—and

[47] We use the value-weighted average of asset volatility $\sigma_{i,t}$, credit spread $cs_{i,t}$, and investment rate $[I/K]_{i,t}$ to generate the corresponding aggregate time series for asset volatility, credit spreads, and investment rate, respectively. We seasonally adjust the investment time series by subtracting a seasonal average computed over the previous 5 years. All variables are detrended using the HP filter with weight $1,600$.

asset volatility is a clean signal of the positive effect of option value on investment—the information in equity volatility and leverage is mixed and ambiguous. Our results suggest that researchers in both corporate finance and macroeconomics should consider the structural relationships between commonly used measures of risk and leverage. In particular, leverage alone does not control for firms' financial soundness because the effectiveness of a firm's equity cushion depends on the size of the shocks the firm faces.

Our theoretical and empirical explanation for these facts build on one violation of Modigliani and Miller (1958): namely, a separation of debt and equity holders and a resulting misalignment of investment incentives. Overall, our study sheds light on the strong theoretical and empirical structural relationships between credit spreads, asset volatility, equity volatility, and Tobin's q. While credit spreads can capture the dampening impact of debt overhang on investment, Tobin's q also contains information about the upside-option value of investment of levered equity holders' claim.

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Figures and Tables

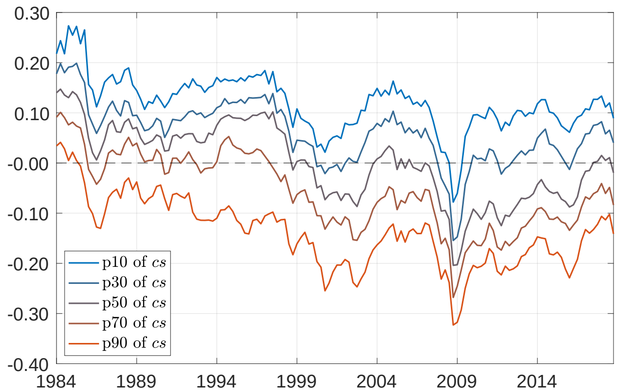

Figure 1: Elasticity of investment with respect to equity volatility. This figure presents the elasticity of investment with respect to equity volatility across time and across firms using estimates from the regressions with interaction terms. In each quarter, we generate five cutoffs in the cross-section of log credit spread: $\{p_{10}, p_{30}, p_{50}, p_{70}, p_{90}\}$. Using the estimates in Column 7 of Table VI on $\log[I/K]_{i,t} = \beta_1 \log \sigma^e_{i,t} + \beta_2 \log cs_{i,t} + \gamma \log \sigma^e_{i,t} \times \log cs_{i,t} + \eta_i + \lambda_t + \epsilon_{i,t}$, the elasticity at each cutoff point is computed as $\beta_1 + \gamma p_n$, $n = 10, 30, 50, 70, 90$.

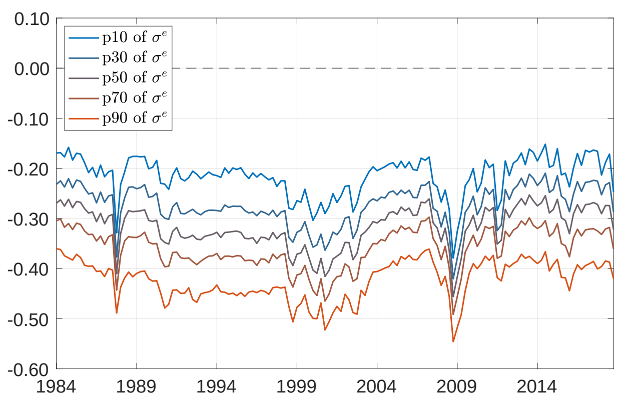

Figure 2: Elasticity of investment with respect to credit spread. This figure presents the elasticity of investment with respect to credit spread across time and across firms using estimates from the regressions with interaction terms. In each quarter, we generate five cutoffs in the cross-section of log equity volatility: $\{p_{10}, p_{30}, p_{50}, p_{70}, p_{90}\}$. Using the estimates in Column 7 of Table VI on $\log[I/K]_{i,t} = \beta_1 \log \sigma^e_{i,t} + \beta_2 \log cs_{i,t} + \gamma \log \sigma^e_{i,t} \times \log cs_{i,t} + \eta_i + \lambda_t + \epsilon_{i,t}$, the elasticity at each cutoff point is computed as $\beta_2 + \gamma p_n$, $n = 10, 30, 50, 70, 90$.

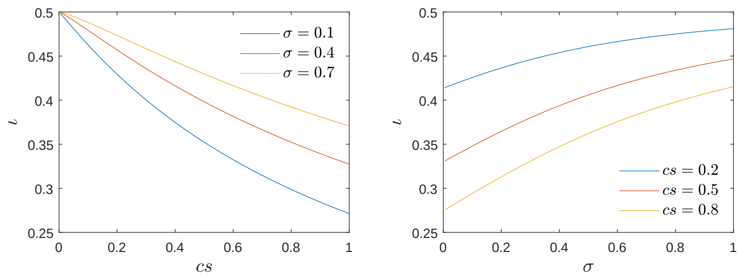

Figure 3: Optimal investment with log-normal distribution. The left figure shows the level of investment i as a function of credit spreads cs for different levels of asset volatility σ, while the right figure shows the level of investment i as a function of asset volatility σ for different levels of credit spreads cs. The adjustment cost function is given by $\phi(i) = i^{\gamma}$ with $\gamma = 2$.

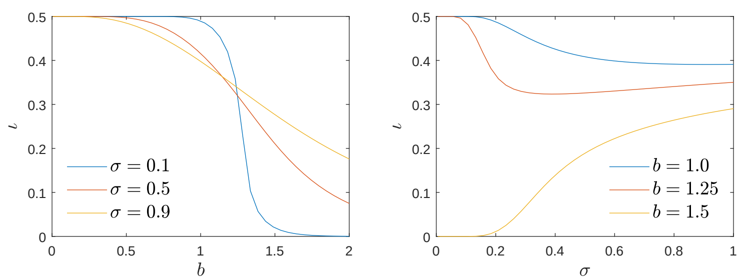

Figure 4: Optimal investment with log-normal distribution. The left figure shows the level of investment i as a function of leverage b for different levels of asset volatility σ, while the right figure shows the level of investment i as a function of asset volatility σ for different levels of leverage b. The adjustment cost function is given by $\phi(i) = i^{\gamma}$ with $\gamma = 2$.

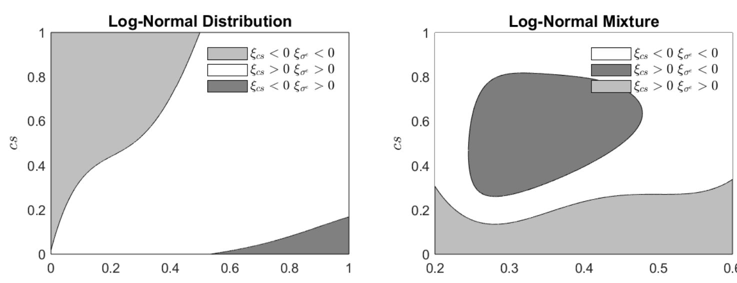

Figure 5: Sign of wedges for log-normal and log-normal mixture. These figures show the sign of the wedges of Proposition 3 in the (cs,σ)-space for the log-normal distribution (left) and a log-normal mixture distribution (right). The mixture distribution is a mixture of two log-normal distributions drawn with 50% probability with parameters $(\mu_1, \hat{\sigma})$ and $(\mu_2, \hat{\sigma})$ such that the unconditional mean of z is 1 and the standard deviation of z is σ. We set $\hat{\sigma} = 0.2$ in this example.

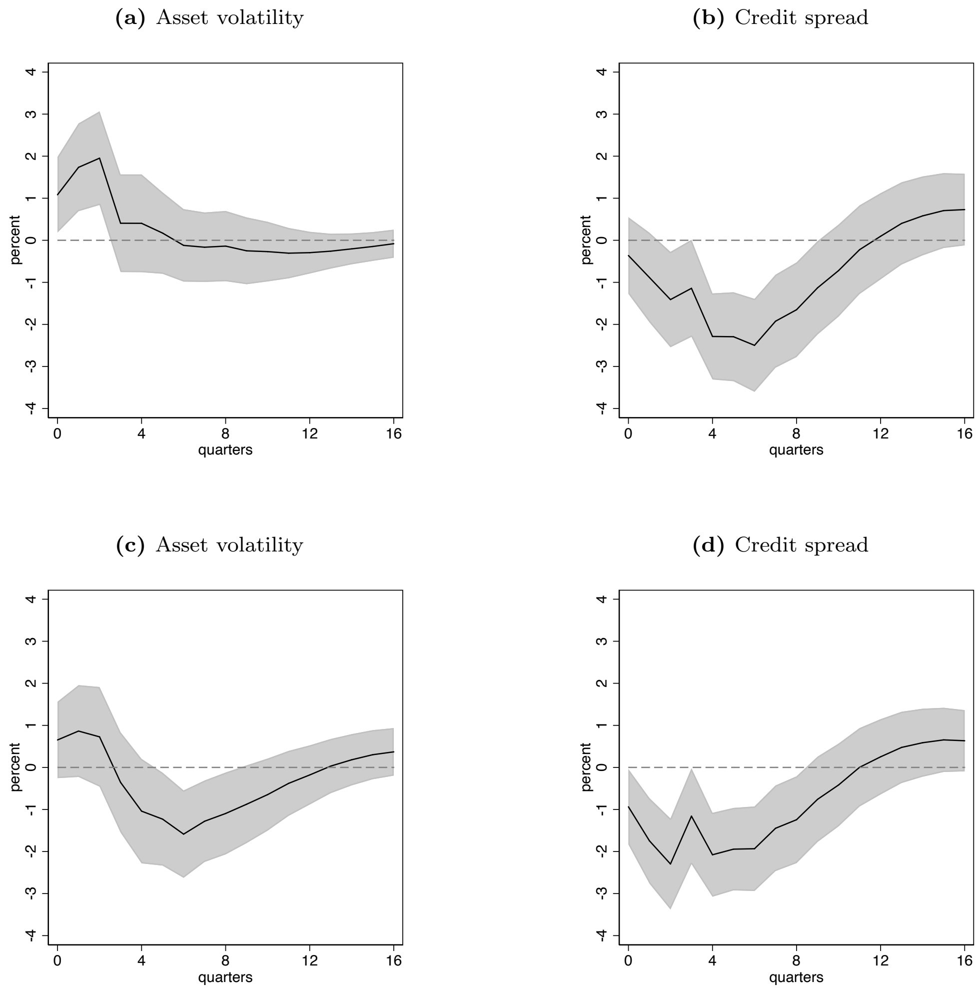

Figure 6: Impulse responses of investment to shocks to asset volatility and credit spreads. This figure plots the impulse responses of investment to an orthogonalized 1 standard deviation shock to asset volatility and credit spread. We use the value-weighted average of asset volatility $\sigma_{i,t}$, credit spread $cs_{i,t}$, and investment rate $[I/K]_{i,t}$ to generate the corresponding aggregate time series for asset volatility (σ), credit spreads (cs), and investment rate (I/K), respectively. The VAR is estimated using four lags of each endogenous variable. Subfigures (a) and (b) correspond to the recursive ordering (cs, σ, I/K). Subfigures (c) and (d) correspond to the recursive ordering (σ, cs, I/K). The shaded bands represent the 95% confidence interval.

Table I

Summary Statistics of Firm-quarter Variables

This table documents the summary statistics of our firm-quarter variables. See Appendix A for detailed variable descriptions.

	Method	Coverage	N	Mean	SD	Min	Max
Credit spreads cs	GZ spread as in Gilchrist and Zakrajšek (2012)	1984-2018	48685	295.89	239.82	8.73	1912.25
Fair value spreads $\widehat{cs}$	Computed using Moody's EDF measure	1984-2018	39219	160.18	252.36	9.15	1821.42
Equity volatility σ^e	Computed using realized equity returns	1984-2018	48685	0.35	0.19	0.07	2.26
Implied equity volatility $\widehat{\sigma}^e$	Implied by at-the-money 30-day forward put options	1996-2018	21304	0.34	0.15	0.12	1.58
Asset volatility σ	Deleveraged by firm-level leverage	1984-2018	48053	0.18	0.09	0.02	1.06
Implied asset volatility $\widehat{\sigma}$	Deleveraged by firm-level leverage	1996-2018	21187	0.19	0.08	0.03	0.78
Merton's asset volatility $\mathring{\sigma}$	Deleveraged using a Merton approach	1984-2018	45923	0.23	0.12	0.04	1.67
Distance-to-default DD	Merton DD as in Bharath and Shumway (2008)	1984-2018	46400	5.86	3.25	-1.90	24.51
Market leverage $[MA/ME]$	Market value of assets divided by market value of equity	1984-2018	48091	2.23	1.72	1.04	50.47
Investment ratio $[I/K]$	Capital expenditures divided by net PP&E	1984-2018	48685	0.05	0.03	-0.07	0.49
Return on equity	Cumulative return realized over the quarter	1984-2018	47932	0.15	0.50	-0.97	16.73
Tangibility ratio	Capital stock divided by total assets	1984-2018	38451	0.69	0.40	0.02	3.98
Sales ratio	Sales divided by capital	1984-2018	47960	1.52	2.81	0.03	49.88
Income ratio	Operating income divided by capital	1984-2018	45323	0.20	0.32	-3.33	6.34
Tobin's q	Market value divided by replacement value of capital stock	1984-2018	36461	2.49	3.79	-1.37	63.86

Table II
Investment, Asset Volatility, and Credit Spreads

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on asset volatility ($\log \sigma_{i,t-1}$) and credit spreads ($\log cs_{i,t-1}$) at firm-quarter level from 1984 to 2018. Columns 4-6 use subsamples sorted by terciles every quarter on credit spreads. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$						
	(1) all	(2) all	(3) all	(4) low cs	(5) mid cs	(6) high cs	(7) all
$\log \sigma_{i,t-1}$	0.266***		0.233***	0.234***	0.190***	0.208***	0.191***
	(16.16)		(14.04)	(10.79)	(7.97)	(7.50)	(10.53)
$\log cs_{i,t-1}$		-0.269***	-0.243***	-0.116***	-0.280***	-0.390***	-0.152***
		(-13.27)	(-12.24)	(-3.17)	(-6.24)	(-9.53)	(-7.53)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓
Controls							✓
Observations	48080	48080	48080	15508	15343	14416	31447
R-squared	0.125	0.131	0.150	0.164	0.148	0.130	0.221

Table III
Investment, Implied Asset Volatility, and Credit Spreads

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on implied asset volatility ($\log\widehat{\sigma}_{i,t-1}$) and credit spreads ($\log cs_{i,t-1}$) at firm-quarter level from 1984 to 2018. Implied asset volatility is deleveraged equity volatility implied from options. Columns 4-6 use subsamples sorted by terciles every quarter on credit spreads. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$						
	(1) all	(2) all	(3) all	(4) low cs	(5) mid cs	(6) high cs	(7) all
$\log\widehat{\sigma}_{i,t-1}$	0.304***		0.288***	0.288***	0.278***	0.187***	0.223***
	(9.55)		(9.20)	(6.00)	(5.17)	(3.36)	(6.05)
$\log cs_{i,t-1}$		-0.329***	-0.320***	-0.177***	-0.357***	-0.594***	-0.177***
		(-10.65)	(-10.44)	(-3.76)	(-5.39)	(-6.97)	(-5.86)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓
Controls							✓
Observations	21475	21475	21475	8621	7126	4766	14779
R-squared	0.122	0.142	0.159	0.160	0.147	0.157	0.238

Table IV
Investment, Credit Spreads, and Leads and Lags of Asset Volatility

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on credit spreads ($\log cs_{i,t-1}$) and different lags and leads of asset volatility ($\log \sigma_{i,t+\tau}, \tau = -4, ..., 4$) at firm-quarter level from 1984 to 2018. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$	
	(1)	(2)
$\log cs_{i,t-1}$	-0.237***	-0.158***
	(-11.44)	(-7.87)
$\log \sigma_{i,t-4}$	0.080***	0.076***
	(6.28)	(5.57)
$\log \sigma_{i,t-3}$	0.046***	0.037***
	(4.38)	(3.07)
$\log \sigma_{i,t-2}$	0.053***	0.038***
	(5.15)	(3.07)
$\log \sigma_{i,t-1}$	0.107***	0.105***
	(10.79)	(8.69)
$\log \sigma_{i,t}$	0.033***	0.011
	(3.25)	(0.88)
$\log \sigma_{i,t+1}$	0.017*	-0.003
	(1.68)	(-0.30)
$\log \sigma_{i,t+2}$	0.009	-0.000
	(1.01)	(-0.01)
$\log \sigma_{i,t+3}$	0.013	0.013
	(1.31)	(1.17)
$\log \sigma_{i,t+4}$	-0.006	-0.008
	(-0.54)	(-0.69)
Firm FE	✓	✓
Time FE	✓	✓
Controls		✓
Observations	41236	27758
R-squared	0.162	0.230

Table V
Equity and Asset Volatility Instrumental Variables

This table presents instrumental variable results of panel regressions of the investment rate ($\log[I/K]_{i,t}$) on asset volatility ($\log \sigma_{i,t-1}$) or equity volatility ($\log \sigma^e_{i,t-1}$) and credit spreads ($\log cs_{i,t-1}$) at firm-year level from 1990 to 2018. The IV approach follows that of Alfaro, Bloom, and Lin (2018). Realized annual volatility measures are instrumented with industry-level (3SIC) non-directional exposure to 10 aggregate sources of uncertainty shocks: the lagged exposure to annual changes in expected volatility of energy, currencies, and 10-year treasuries (as proxied by at-the-money forward-looking implied volatilities of oil, 7 widely traded currencies, and TYVIX) and economic policy uncertainty from Baker, Bloom, and Davis (2016). Annual realized equity volatility σ^e is the 12-month standard deviation of daily stock returns from CRSP. Annual realized asset volatility σ is the 12-month standard deviation of daily stock returns from CRSP unlevered using the daily market-to-book ratio of equity. Control variables include yearly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 year). Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at the 3-digit SIC industry.

	Dependent Variable: $\log[I/K]_{i,t}$			
	(1)	(2)	(3)	(4)
$\log \sigma^e_{i,t-1}$	-0.649		-0.770*	
	(-1.27)		(-1.89)	
$\log \sigma_{i,t-1}$		0.598***		0.816***
		(3.15)		(3.05)
$\log cs_{i,t-1}$	-0.101	-0.335***	0.082	-0.237***
	(-0.55)	(-8.15)	(0.67)	(-4.97)
First Moments	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Controls			✓	✓
Observations	4543	4649	3865	3993
Kleibergen-Paap F	2.864	6.289	2.190	4.343
Sargan-Hansen p-val	0.243	0.150	0.454	0.145

Table VI
Investment, Equity Volatility, and Credit Spreads

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on equity volatility ($\log \sigma^e_{i,t-1}$) and credit spreads ($\log cs_{i,t-1}$) at firm-quarter level from 1984 to 2018. Columns 4-6 use subsamples sorted by terciles every quarter on credit spreads. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$							
	(1) all	(2) all	(3) all	(4) low cs	(5) mid cs	(6) high cs	(7) all	(8) all
$\log \sigma^e_{i,t-1}$	-0.148***		-0.040**	0.108***	-0.030	-0.121***	0.841***	0.658***
	(-7.71)		(-2.40)	(5.31)	(-1.15)	(-4.31)	(10.57)	(8.16)
$\log cs_{i,t-1}$		-0.271***	-0.260***	-0.138***	-0.286***	-0.405***	-0.435***	-0.332***
		(-13.32)	(-13.09)	(-3.81)	(-6.33)	(-9.55)	(-17.83)	(-13.07)
$\log \sigma^e_{i,t-1} \times \log cs_{i,t-1}$							-0.158***	-0.119***
							(-11.01)	(-8.17)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls								✓
Observations	48655	48655	48655	15579	15501	14737	48655	33993
R-squared	0.106	0.132	0.132	0.147	0.136	0.120	0.140	0.202

Table VII
Investment, Equity Volatility, and Fair Value Spreads

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on equity volatility ($\log \sigma^e_{i,t-1}$) and fair value spreads ($\log \widehat{cs}_{i,t-1}$) at firm-quarter level from 1984 to 2018. Columns 4-6 use subsamples sorted by terciles every quarter on credit spreads. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$							
	(1) all	(2) all	(3) all	(4) low $\widehat{cs}$	(5) mid $\widehat{cs}$	(6) high $\widehat{cs}$	(7) all	(8) all
$\log \sigma^e_{i,t-1}$	-0.138***		0.044**	0.125***	0.067**	-0.038	0.400***	0.326***
	(-6.47)		(2.47)	(5.63)	(2.46)	(-1.37)	(9.11)	(7.12)
$\log \widehat{cs}_{i,t-1}$		-0.170***	-0.177***	-0.116***	-0.114***	-0.236***	-0.258***	-0.158***
		(-16.56)	(-17.45)	(-4.47)	(-4.90)	(-12.87)	(-18.68)	(-10.17)
$\log \sigma^e_{i,t-1} \times \log \widehat{cs}_{i,t-1}$							-0.080***	-0.062***
							(-8.51)	(-6.24)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls								✓
Observations	39213	39213	39213	12514	12476	12100	39213	25531
R-squared	0.105	0.152	0.152	0.148	0.133	0.149	0.159	0.218

Table VIII
Investment, Equity Volatility, and Credit Spread Residuals

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on equity volatility ($\log \sigma^e_{i,t-1}$), fair value spreads ($\log \widehat{cs}_{i,t-1}$), and the residuals in credit spreads after removing fair value spreads ($e_{i,t-1}$) at firm-quarter level from 1984 to 2018. The residual $e_{i,t}$ in column (2) is obtained from the regression $\log cs_{i,t} = \beta \log \widehat{cs}_{i,t} + \eta_i + \lambda_t + \epsilon_{i,t}$, with R^2 of 58% (the R^2 is 50% without any fixed effects) and the residual $e_{i,t}$ in column (5) is obtained from the regression $\log cs_{i,t} = \beta_1 \log \widehat{cs}_{i,t} + \beta_2 \log \sigma^e_{i,t} + \eta_i + \lambda_t \epsilon_{i,t}$, with R^2 of 60% (the R^2 is 52% without any fixed effects). Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
$\log \sigma^e_{i,t-1}$			-0.138***	0.044**	-0.137***
			(-6.47)	(2.47)	(-6.53)
$\log \widehat{cs}_{i,t-1}$	-0.170***			-0.177***	
	(-16.56)			(-17.45)	
$e_{i,t-1}$		-0.146***			-0.157***
		(-6.22)			(-6.67)
Firm FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
Observations	39213	39213	39213	39213	39213
R-squared	0.152	0.107	0.105	0.152	0.113

Table IX
Loadings of Equity Volatility and Credit Spreads

This table presents the loadings of equity volatility and credit spreads on asset volatility (derived from Merton's model) and leverage at firm-quarter level from 1984 to 2018. The regression specification is $\log y_{i,t} = \beta_1 \log \mathring{\sigma}_{i,t} + \beta_2 \log[MA/ME]_{i,t} + \eta_i + \lambda_t + \epsilon_{i,t}$. We report results for estimations in levels in Panel A and results for estimations in first differences in Panel B. All variables are standardized to have mean zero and unit variance. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level. The panels below present the partial R^2 given time and firm fixed effects—that is, the percentage reduction in the residual sum of squares (RSS) by adding each variable in addition to time and firm fixed effects.

Panel A: Levels			Panel B: Changes		
Dependent Variable	$\log \sigma^e_{i,t}$	$\log cs_{i,t}$	Dependent Variable	$\Delta \log \sigma^e_{i,t}$	$\Delta \log cs_{i,t}$
$\log \mathring{\sigma}_{i,t}$	0.858***	0.145***	$\Delta \log \mathring{\sigma}_{i,t}$	0.795***	0.022***
	(74.50)	(14.00)		(73.38)	(3.39)
$\log[MA/ME]_{i,t}$	0.457***	0.449***	$\Delta \log[MA/ME]_{i,t}$	0.099***	0.180***
	(45.71)	(29.86)		(19.71)	(23.88)
Firm FE	✓	✓	Firm FE	✓	✓
Time FE	✓	✓	Time FE	✓	✓
Observations	45438	45438	Observations	44545	44545
R-squared	0.891	0.576	R-squared	0.832	0.311

Partial R^2

Panel C: Levels			Panel D: Changes		
Dependent Variable	$\log \sigma^e_{i,t}$	$\log cs_{i,t}$	Dependent Variable	$\Delta \log \sigma^e_{i,t}$	$\Delta \log cs_{i,t}$
$\log \mathring{\sigma}_{i,t}$	0.541	0.001	$\Delta \log \mathring{\sigma}_{i,t}$	0.709	0.000
$\log[MA/ME]_{i,t}$	0.096	0.209	$\Delta \log[MA/ME]_{i,t}$	0.009	0.022

Table X
Loadings of Equity Volatility in the Cross-Section

This table presents the loadings of equity volatility on asset volatility (derived from Merton's model) and leverage at firm-quarter level from 1984 to 2018 across subsamples sorted by terciles every quarter on credit spreads. The regression specification is $\log y_{i,t} = \beta_1 \log \mathring{\sigma}_{i,t} + \beta_2 \log[MA/ME]_{i,t} + \eta_i + \lambda_t + \epsilon_{i,t}$. We report results for estimations in levels in Panel A and results for estimations in first differences in Panel B. All variables are standardized to have mean zero and unit variance. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level. The panels below present the partial R^2 given time and firm fixed effects—that is, the percentage reduction in the residual sum of squares (RSS) by adding each variable in addition to time and firm fixed effects.

Panel A: Levels				Panel B: Changes			
	Dependent Variable: $\log \sigma^e_{i,t}$				Dependent Variable: $\Delta \log \sigma^e_{i,t}$		
	low *cs*	mid *cs*	high *cs*		low *cs*	mid *cs*	high *cs*
$\log \mathring{\sigma}_{i,t}$	0.928***	0.892***	0.746***	$\Delta \log \mathring{\sigma}_{i,t}$	0.841***	0.789***	0.763***
	(58.24)	(61.76)	(39.64)		(42.32)	(44.10)	(51.33)
$\log[MA/ME]_{i,t}$	0.427***	0.437***	0.431***	$\Delta \log[MA/ME]_{i,t}$	0.105***	0.102***	0.098***
	(20.93)	(23.63)	(38.79)		(7.46)	(11.90)	(15.87)
Firm FE	✓	✓	✓	Firm FE	✓	✓	✓
Time FE	✓	✓	✓	Time FE	✓	✓	✓
Observations	15407	15223	14808	Observations	15203	14962	14380
R-squared	0.935	0.905	0.845	R-squared	0.880	0.831	0.794

Partial R^2							
Panel C: Levels				Panel D: Changes			
	Dependent Variable: $\log \sigma^e_{i,t}$				Dependent Variable: $\Delta \log \sigma^e_{i,t}$		
	low *cs*	mid *cs*	high *cs*		low *cs*	mid *cs*	high *cs*
$\log \mathring{\sigma}_{i,t}$	0.749	0.659	0.415	$\Delta \log \mathring{\sigma}_{i,t}$	0.769	0.709	0.666
$\log[MA/ME]_{i,t}$	0.000	0.012	0.149	$\Delta \log[MA/ME]_{i,t}$	0.006	0.006	0.017

Table XI
Loadings of Credit Spreads in the Cross-Section

This table presents the loadings of credit spreads on asset volatility (derived from Merton's model) and leverage at firm-quarter level from 1984 to 2018 across subsamples sorted by terciles every quarter on credit spreads. The regression specification is $\log y_{i,t} = \beta_1 \log \mathring{\sigma}_{i,t} + \beta_2 \log[MA/ME]_{i,t} + \eta_i + \lambda_t + \epsilon_{i,t}$. We report results for estimations in levels in Panel A and results for estimations in first differences in Panel B. All variables are standardized to have mean zero and unit variance. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level. The panels below present the partial R^2 given time and firm fixed effects—that is, the percentage reduction in the residual sum of squares (RSS) by adding each variable in addition to time and firm fixed effects.

Panel A: Levels				Panel B: Changes			
	Dependent Variable: $\log cs_{i,t}$				Dependent Variable: $\Delta \log cs_{i,t}$		
	low cs	mid cs	high cs		low cs	mid cs	high cs
$\log \mathring{\sigma}_{i,t}$	0.051***	0.047***	0.074***	$\Delta \log \mathring{\sigma}_{i,t}$	0.022*	0.015	0.035***
	(5.01)	(6.14)	(7.82)		(1.78)	(1.58)	(3.77)
$\log[MA/ME]_{i,t}$	0.210***	0.153***	0.271***	$\Delta \log[MA/ME]_{i,t}$	0.080***	0.131***	0.195***
	(10.19)	(11.69)	(26.90)		(3.39)	(8.75)	(22.13)
Firm FE	✓	✓	✓	Firm FE	✓	✓	✓
Time FE	✓	✓	✓	Time FE	✓	✓	✓
Observations	15407	15223	14808	Observations	15203	14962	14380
R-squared	0.750	0.813	0.693	R-squared	0.310	0.361	0.428

Partial R^2

Panel C: Levels				Panel D: Changes			
	Dependent Variable: $\log cs_{i,t}$				Dependent Variable: $\Delta \log cs_{i,t}$		
	low cs	mid cs	high cs		low cs	mid cs	high cs
$\log \mathring{\sigma}_{i,t}$	0.000	0.000	0.000	$\Delta \log \mathring{\sigma}_{i,t}$	0.000	0.000	0.001
$\log[MA/ME]_{i,t}$	0.038	0.048	0.246	$\Delta \log[MA/ME]_{i,t}$	0.001	0.009	0.063

Table XII
Investment, Asset Volatility, and Leverage

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on asset volatility ($\log \sigma_{i,t-1}$) and leverage ($\log[MA/ME]_{i,t-1}$) at firm-quarter level from 1984 to 2018. Columns 4-6 use subsamples sorted by terciles on credit spreads. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$						
	(1) all	(2) all	(3) all	(4) low cs	(5) mid cs	(6) high cs	(7) all
$\log \sigma_{i,t-1}$	0.266***		0.034*	0.109***	0.009	0.002	0.069***
	(16.16)		(1.82)	(5.58)	(0.33)	(0.08)	(3.66)
$\log[MA/ME]_{i,t-1}$		-0.520***	-0.498***	-0.479***	-0.540***	-0.465***	-0.410***
		(-20.93)	(-17.62)	(-7.53)	(-12.32)	(-13.28)	(-11.28)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓
Controls							✓
Observations	48080	47686	47686	15275	15294	14326	31220
R-squared	0.125	0.167	0.168	0.178	0.171	0.147	0.230

Table XIII
Risk-Shifting

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on implied asset volatility ($\log\widehat{\sigma}_{i,t-1}$) and leverage ($\log[MA/ME]_{i,t-1}$) at firm-quarter level from 1984 to 2018. Column 1 uses a subsample with firms whose credit spreads are below 100 basis points. Columns 2-7 use subsamples with firms whose credit spreads are above 200, 300, ..., 600 basis points, respectively. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$						
	(1) $cs < 100$	(2) $cs \geq 100$	(3) $cs \geq 200$	(4) $cs \geq 300$	(5) $cs \geq 400$	(6) $cs \geq 500$	(7) $cs \geq 600$
$\log\widehat{\sigma}_{i,t-1}$	0.073	0.015	-0.087*	-0.124**	-0.142*	-0.245**	-0.250*
	(0.83)	(0.34)	(-1.69)	(-2.07)	(-1.96)	(-2.31)	(-1.67)
$\log[MA/ME]_{i,t-1}$	-0.431*	-0.536***	-0.577***	-0.601***	-0.580***	-0.581***	-0.679***
	(-1.77)	(-10.00)	(-9.59)	(-9.94)	(-9.10)	(-7.26)	(-6.08)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	1912	13625	7916	5362	3438	2006	1114
R-squared	0.244	0.248	0.264	0.264	0.275	0.303	0.374

Table XIV
Investment, Asset Volatility, Credit Spreads and Tobin's q

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on asset volatility ($\log \sigma_{i,t-1}$), credit spreads ($\log cs_{i,t-1}$), and Tobin's q ($\log q_{i,t-1}$) at firm-quarter level from 1984 to 2018. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

Panel A: Without controls

	Dependent Variable: $\log[I/K]_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log \sigma_{i,t-1}$	0.266***		0.233***			0.190***
	(16.16)		(14.04)			(10.20)
$\log cs_{i,t-1}$		-0.271***	-0.243***		-0.176***	-0.168***
		(-13.32)	(-12.24)		(-7.75)	(-7.61)
$\log q_{i,t-1}$				0.209***	0.177***	0.149***
				(15.27)	(12.74)	(10.64)
Firm FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Observations	48080	48655	48080	35902	35902	35558
R-squared	0.125	0.132	0.150	0.157	0.169	0.180

Panel B: With controls

	Dependent Variable: $\log[I/K]_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log \sigma_{i,t-1}$	0.244***		0.226***			0.191***
	(13.55)		(12.51)			(10.53)
$\log cs_{i,t-1}$		-0.195***	-0.176***		-0.156***	-0.152***
		(-9.48)	(-8.81)		(-7.37)	(-7.53)
$\log q_{i,t-1}$				0.154***	0.124***	0.090***
				(11.13)	(9.10)	(6.65)
Firm FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	33658	33993	33658	31741	31741	31447
R-squared	0.201	0.197	0.214	0.200	0.209	0.221

Table XV
Investment, Equity Volatility, and Asset Volatility for Firms without Observable Credit Spreads

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on equity volatility ($\log \sigma^e_{i,t-1}$), asset volatility ($\log \sigma_{i,t-1}$), and distance-to-default ($DD_{i,t-1}$) at firm-quarter level from 1984 to 2018 for firms without observable credit spreads. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$			
	(1)	(2)	(3)	(4)
$\log \sigma^e_{i,t-1}$	-0.187***		-0.114***	
	(-4.68)		(-6.86)	
$\log \sigma^e_{i,t-1} \times DD_{i,t-1}$	0.076***		0.044***	
	(11.39)		(14.80)	
$\log \sigma_{i,t-1}$		0.358***		0.231***
		(25.75)		(16.97)
$DD_{i,t-1}$	0.150***	0.082***	0.087***	0.047***
	(7.30)	(12.62)	(14.11)	(17.42)
Firm FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Controls			✓	✓
Observations	234963	233948	103473	103269
R-squared	0.073	0.081	0.159	0.162

Appendices

A Data and Definitions

This section discusses the data sources used for the empirical analysis and the construction of variables.

Data Collection We use S&P's Compustat quarterly database from 1984:Q1 to 2018:Q4. We exclude firms in the financial sector (SIC code 6000 to 6999) and utility sector (SIC code 4900 to 4949); firms not in the panel for at least 3 years; and observations with missing investment rate or equity volatility and with negative sales. We use daily returns from the Center for Research in Security Prices (CRSP) database. Implied volatilities are from OptionMetrics data starting in 1996. Bond prices come from the Lehman/Warga (1984-2005) and ICE databases (1997-2018). These selection criteria yield 1,407 unique firms with 48,672 firm-quarter observations. To ensure that our results are not driven by extreme values, we trim every regression variable at the 1st and 99th percentiles. We provide summary statistics in Table I and describe how we construct our key variables below.

Investment We define the investment rate as capital expenditures in quarter t scaled by net property, plant, and equipment in quarter $t-1$.

Equity Volatility Total equity volatility σ^e is defined as the standard deviation of equity returns and is given by

$$\sigma_{i,t}^e = \sqrt{\frac{1}{D_t}\sum_{d=1}^{D_t}\left(r_{i,t_d} - \frac{1}{D_t}\sum_{d=1}^{D_t} r_{i,t_d}\right)^2}. \tag{27}$$

Idiosyncratic equity volatility $\widetilde{\sigma}^e$ is constructed in two steps. For each firm i and fiscal quarter t, we extract daily idiosyncratic equity returns using the Carhart (1997) four-factor model:

$$r_{i,t_d} - r^f_{t_d} = \alpha_i + \boldsymbol{\beta}'_i \mathbf{f}_{t_d} + u_{i,t_d}, \tag{28}$$

where $t_d = 1, ..., D_t$ denotes trading days in the quarter. In equation (28), r_{i,t_d} is the daily equity return, $r^f_{t_d}$ is the risk-free rate, and $\boldsymbol{f}_{t_d}$ are the factors. We obtain the OLS residuals $\hat{u}_{i,t_d}$ by running the regression in equation (28) and define idiosyncratic equity volatility as the standard deviation of these residuals. The idiosyncratic equity volatility of firm i in quarter t is given by

$$\widetilde{\sigma}^e_{i,t} = \sqrt{\frac{1}{D_t} \sum_{d=1}^{D_t} \left(\hat{u}_{i,t_d} - \frac{1}{D_t} \sum_{d=1}^{D_t} \hat{u}_{i,t_d} \right)^2}. \tag{29}$$

We only keep observations for quarters with more than 30 trading days ($D_t > 30$).

In addition to realized equity volatility measures, we use an implied equity volatility measure implied by at-the-money 30-day-forward put options equity volatility from OptionMetrics, denoted by $\hat{\sigma}^e$.

Credit Spreads We follow Gilchrist and Zakrajšek (2012) to compute bond-level credit spreads. First, we construct a theoretical risk-free bond that exactly replicates the promised cash flows. Suppose at time t a bond i of firm k promises cash flows $\{C(s), s = 1, 2, ..., S\}$, which are paid in time $\{t_s, s = 1, 2, ...S\}$ from today. We can calculate the price of the corresponding risk-free bond by discounting the promised cash flows as follows:

$$p^f_{i,t}[k] = \sum_{s=1}^{S} C(s) \exp\left(-y^T_t[t_s] t_s\right), \tag{30}$$

where $y^T_t[t_s]$ is the continuously compounded zero-coupon Treasury yield for time horizon t_s at time t from Gürkaynak, Sack, and Wright (2007).

Then we convert bond prices to yields [48] and define the credit spread of an individual bond as the difference between the yield of the actual bond and the yield of the corresponding risk-free bond: $cs_{i,t}[k] = y_{i,t}[k] - y^f_{i,t}[k]$. We then compute the

[48] From bond price p, we first compute yield-to-maturity as $YTM = \frac{CP+(FV-p)/M}{(FV+p)/2}$, where CP denotes annual coupon, FV denotes face value, and M denotes the maturity of the bond. Then we define yield y as the effective annual yield $y = \left(1 + \frac{YTM}{2}\right)^2 - 1$.

credit spread of a firm i in quarter t as the quarterly average of the credit spreads of all bonds issued by that firm: $cs_{i,t} = \frac{1}{3}\sum_{m=t_1}^{t_3} \frac{1}{N_{i,m}^k} \sum_{k=1}^{N_{i,m}^k} cs_{i,m}[k]$, where t_n is the nth month of quarter t and $N_{i,m}^k$ is the number of bonds of firm i in month m.

Firm-level Leverage Firm-level leverage is defined as the ratio of the market value of assets to the market value of equity: $[MA/ME]_{i,t} = \frac{MA_{i,t}}{ME_{i,t}}$. Market value of equity ($ME_{i,t}$) is the product of share price and number of shares outstanding. Market value of assets ($MA_{i,t}$) is built as the book value of assets plus market value of equity minus the book value of equity. Following Davies, Fama, and French (2000), the book value of equity is defined as the book value of stockholders' equity plus balance sheet deferred taxes and investment tax credit, minus the book value of preferred stock. Depending on availability, we use the redemption, liquidation, or par value (in that order) for the book value of preferred stock. If this procedure generates missing values, we measure stockholders' equity as the book value of common equity plus par value of preferred stock, or the book value of assets minus total liabilities.

Return on equity, Tangibility, Sales, Income, and Tobin's q Return on equity is the cumulative equity return realized over a quarter. Tangibility is property, plant, and equipment divided by total assets. Sales and income ratios are given by sales and operating income before depreciation divided by lagged property, plant, and equipment. Following Erickson and Whited (2012), we construct the numerator of Tobin's q as book debt plus market value of equity minus book assets, and the denominator is capital stock.

Asset Volatility and Distance to Default For our main measure of asset volatility, we first delever equity returns with the firm's leverage to obtain asset returns according to $r_{i,t}^a = \frac{r_{i,t}}{[MA/ME]_{i,t-1}}$. Note that we generate leverage $[MA/ME]_{i,t}$ at daily frequency by using daily equity prices. The asset volatility $\sigma_{i,t}$ is defined as the standard deviation of asset returns and is given by

$$\sigma_{i,t} = \sqrt{\frac{1}{D_t}\sum_{d=1}^{D_t}\left(r_{i,t_d}^a - \frac{1}{D_t}\sum_{d=1}^{D_t} r_{i,t_d}^a\right)^2}. \tag{31}$$

To construct the idiosyncratic asset volatility, we follow the same procedures used to generate idiosyncratic equity volatility—that is, we first obtain idiosyncratic asset returns using the classic Carhart (1997) four-factor model:

$$r^a_{i,t_d} - r^f_{t_d} = \alpha_i + \boldsymbol{\beta}'_i \mathbf{f}_{t_d} + u^a_{i,t_d}, \tag{32}$$

and then construct idiosyncratic asset volatility as the standard deviation of the idiosyncratic asset returns:

$$\widetilde{\sigma}_{i,t} = \sqrt{\frac{1}{D_t} \sum_{d=1}^{D_t} \left(\hat{u}^a_{i,t_d} - \frac{1}{D_t} \sum_{d=1}^{D_t} \hat{u}^a_{i,t_d} \right)^2}. \tag{33}$$

We also construct the measure of firm-level asset volatility based on Merton's (1974) model, denoted by $\mathring{\sigma}$. Asset value V and asset volatility $\mathring{\sigma}$ can be obtained from a two-equation system as follows:

$$E = VN(d_1) - e^{-rT} BN(d_2) \tag{34}$$

$$\sigma_E = \left(\frac{V}{E} \right) N(d_1) \mathring{\sigma} \tag{35}$$

where

$$d_1 = \frac{\ln(V/B) + (r + 0.5\mathring{\sigma}^2)T}{\mathring{\sigma}\sqrt{T}}, \quad d_2 = d_1 - \mathring{\sigma}\sqrt{T}.$$

Inputs for the two-equation system are (i) market value of equity E, measured by the product of stock price and the number of shares outstanding; (ii) equity volatility σ_E, measured by the annualized realized volatility of daily stock returns in each month; (iii) face value of debt B, measured as the sum of the firm's current liabilities and one-half of its long-term liabilities; (iv) debt maturity (forecasting horizon) $T = 1$; and (v) risk-free rate r, measured by the annualized monthly return on 90-day Treasury bills.

Instead of solving this two-equation system directly, we implement the iterative procedure proposed by Bharath and Shumway (2008).[49] We linearly interpolate the quarterly value of debt to a daily frequency and estimate asset value at daily frequency. With the time series of daily asset returns we can calculate the asset volatility, which is defined as the standard deviation of asset returns according to

[49] Gilchrist and Zakrajšek (2012) also adopt this iterative procedure.

Equation (31). This is how we obtain the asset volatility derived from Merton's model ($\mathring{\sigma}_{i,t}$).

In addition to this realized asset volatility measure, we also use an implied asset volatility measure. Implied asset volatility ($\widehat{\sigma}_{i,t}$) is constructed as delevered implied equity volatility—that is, implied equity volatility times the market value of equity divided by the market value of assets.

Also, after we obtain the asset value V and total asset volatility σ_V, the distance to default (DD) can easily be computed according to the following equation:

$$DD = \frac{\ln(V/B) + (\mu - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}.$$

We also construct the measure of firm-level asset volatility using a reduced-form regression of the log of equity volatility on the log of firm level leverage:

$$\log \sigma_{i,t}^e = \beta \log[MA/ME]_{i,t} + \eta_i + \lambda_t + \epsilon_{i,t}. \tag{36}$$

We use the residuals obtained from this regression as the log of the residual asset volatility, denoted by $\log \sigma_{i,t}^{\varepsilon}$.

Fair Value Spreads We use a proprietary data set from Moody's on its public firm expected default frequency (EDF) metric, which is an equity-based measure of a firm's probability of default. The core model used to generate the EDF metric belongs to the class of option-pricing based, structural credit risk models pioneered by Black and Scholes (1973) and Merton (1974). The Vasicek-Kealhofer (VK) model summarizes information on asset volatility, the market value of assets, and the default point in one metric—the distance to default (DD)—and then maps the DD to obtain the EDF metric. The DD-to-EDF mapping step uses the empirical distribution of DD and frequency of realized defaults. Nazeran and Dwyer (2015) provide a detailed description of their methodology. Most important for our purpose, the EDF credit risk measure relies only on equity market inputs and does not contain bond market information.

Using the EDF credit risk measure, we construct a cumulative EDF (CEDF) over T years by assuming a flat term structure—that is, $CEDF_T = 1 - (1 - EDF)^T$. Then we convert our physical measure of default probabilities (CEDF) to risk-neutral default probabilities (CQDF) using the following equation:

$$CQDF_T = N\left[N^{-1}\left(CEDF_T\right) + \lambda\rho\sqrt{T}\right],$$

where N is the cumulative distribution function for the standard normal distribution, λ is the market Sharpe ratio, and ρ is the correlation between the underlying asset returns and market returns. Given this risk-neutral default probability measure, the spread of a zero-coupon bond with duration T can be computed as

$$\hat{cs} = -\frac{1}{T}\log(1 - CQDF_T \cdot LGD),$$

where LGD stands for the risk-neutral expected loss given default. We follow Moody's convention and set $T = 5$, $LGD = 60\%$, $\lambda = 0.546$, and $\rho = \sqrt{0.3}$ to build our "fair value spread" measure $\hat{cs}$. We successfully match $39,925$ fair value spreads with our firm-quarter observations.

Instrumental Variables We follow the instrumental variables strategy of Alfaro, Bloom, and Lin (2018). First, we estimate sensitivities to energy, currencies, treasuries, and policy at industry level as the factor loadings of a regression of a firm's daily stock return on the price growth of energy and 7 currencies, return on treasury bonds, and changes in daily policy uncertainty from Baker, Bloom, and Davis (2016). That is, for firm i in industry j, sensitivity β_j^c is estimated as follows:

$$r_{i,t} = \alpha_j + \sum_c \beta_j^c \cdot r_t^c + \varepsilon_{i,t},$$

where $r_{i,t}$ is the daily risk-adjusted return on firm i, r_t^c is the change in the price of commodity c, and α_j is industry j's intercept.

Risk-adjusted returns $r_{i,t}$ are the residuals from running firm-level time-series regressions of daily CRSP stock returns on the Carhart (1997) four-factor asset-pricing model. We estimate risk-adjusted returns and sensitivity β_j^c yearly using the same 10-year window.

Next, for these 10 aggregate market price shocks (oil, 7 currencies, treasuries, and policy), we multiply the absolute value of their time-varying sensitivities $|\beta_j^c|$ by their implied volatilities σ_t^c. This provides 10 instruments for lagged equity volatility, as follows:

$$z^c_{i,t-1} = |\beta^c_j| \cdot \sigma^c_{t-1}.$$

To instrument for asset volatility, we first generate risk-adjusted asset returns $r^a_{i,t}$ as the residuals of regressing firms' *unlevered* equity returns on the Carhart factors. We construct asset volatility as the standard deviation of $r^a_{i,t}$, and estimate the sensitivities of asset returns to the 10 aggregate market price shocks by estimating the following equation:

$$r^a_{i,t} = \alpha_j + \sum_c \beta^{c,a}_j \cdot r^c_t + \varepsilon_{i,t}.$$

Then we construct instruments for lagged asset volatility:

$$z^{c,a}_{i,t-1} = |\beta^{c,a}_j| \cdot \sigma^c_{t-1}.$$

Online Appendix

A Additional Robustness Checks

In this appendix, we provide several robustness checks for the results discussed above and show that they yield similar results.

Table OA I in the main text presents summary statistics for all variables used in this appendix.

Table OA II and Table OA III are robustness checks for Table II and Table VI using an alternative measure for investment rate, respectively.

In Table OA IV, we replicate Table II and regress investment rate on total asset volatility and credit spreads, but using a restricted sample of firms with an observable implied asset volatility. The idea is to use the same sample and compare the estimation results of using implied asset volatility versus realized total asset volatility. By comparing the results in Table OA IV with those in Table III, we show that the coefficient on asset volatility increases by 50% by using implied asset volatility instead of realized asset volatility. This yields support that it is the expectation of future volatility that impacts the investment rate.

We also provide robustness checks for the results in Table II by using different measures of asset volatility. We show the results using idiosyncratic asset volatility, asset volatility derived from Merton's model, and the residual of equity volatility regressed on firm leverage in Table OA V, Table OA VI, and Table OA VII, respectively.

Table OA VIII is a robustness check for results in Table IV using leads and lags of implied asset volatility instead of realized asset volatility.

We present the empirical relationship between investment and changes in implied asset volatility in Table OA IX. The coefficient on the change is negative and the coefficient on the level is positive when both the levels of and changes in the asset volatility are included in the regression.

Table OA X and Table OA XI provide robustness checks for results in Table VI using idiosyncratic equity volatility and implied equity volatility, respectively. Table OA XII is a robustness check for the results in Table VII using implied equity volatility. Table OA XIII is a robustness check for the results in Table IX, in which we use industry-level regressors—constructed as the average of all firms in the same industry, excluding the firm itself—instead of using the firm's asset volatility and leverage directly.

Table OA XIV is a robustness check for the results in Table XII using implied asset volatility instead of realized asset volatility and Table OA XV is a robustness check for the results in Table XIII using realized asset volatility instead of implied asset volatility.

Table OA I
Summary Statistics of Firm-quarter Variables

This table documents the summary statistics of our firm-quarter variables. See Appendix A for a detailed variable description.

	Method	Coverage	N	Mean	SD	Min	Max
Credit spreads cs	GZ spread as in Gilchrist and Zakrajšek (2012)	1984-2018	48685	295.89	239.82	8.73	1912.25
Fair value spreads $\widehat{cs}$	Computed using Moody's EDF measure	1984-2018	39219	160.18	252.36	9.15	1821.42
Equity volatility σ^e	Computed using realized equity returns	1984-2018	48685	0.35	0.19	0.07	2.26
Implied equity volatility $\widehat{\sigma}^e$	Implied by at-the-money 30-day forward put options	1996-2018	21304	0.34	0.15	0.12	1.58
Idiosyncratic equity volatility $\widetilde{\sigma}^e$	Computed using realized idiosyncratic equity returns	1984-2018	48483	0.28	0.16	0.06	2.04
Asset volatility σ	Deleveraged by firm-level leverage	1984-2018	48053	0.18	0.09	0.02	1.06
Implied asset volatility $\widehat{\sigma}$	Deleveraged by firm-level leverage	1996-2018	21187	0.19	0.08	0.03	0.78
Merton's asset volatility $\mathring{\sigma}$	Deleveraged using a Merton approach	1984-2018	45923	0.23	0.12	0.04	1.67
Residual asset volatility $\log \sigma^\varepsilon$	Deleveraged using reduced-form regressions	1984-2018	47103	-0.00	0.35	-1.11	1.16
Idiosyncratic asset volatility $\widetilde{\sigma}$	Deleveraged by firm-level leverage	1984-2018	48034	0.14	0.07	0.01	0.77
Distance-to-default DD	Merton DD as in Bharath and Shumway (2008)	1984-2018	46400	5.86	3.25	-1.90	24.51
Market leverage $[MA/ME]$	Market value of assets divided by market value of equity	1984-2018	48091	2.23	1.72	1.04	50.47
Investment ratio $[I/K]$	Capital expenditures (Capx) divided by net PP&E	1984-2018	48685	0.05	0.03	-0.07	0.49
Alternative investment ratio $[\widehat{I}/\widetilde{K}]$	(Capx+30% SG&A+R&D)/(net PP&E+intangible assets)	1984-2018	47257	0.03	0.02	-0.07	1.03
Return on equity	Cumulative return realized over the quarter	1984-2018	47932	0.15	0.50	-0.97	16.73
Tangibility ratio	Capital stock divided by total assets	1984-2018	38451	0.69	0.40	0.02	3.98
Sales ratio	Sales divided by capital	1984-2018	47960	1.52	2.81	0.03	49.88
Income ratio	Operating income divided by capital	1984-2018	45323	0.20	0.32	-3.33	6.34
Tobin's q	Market value divided by replacement value of capital stock	1984-2018	36461	2.49	3.79	-1.37	63.86

Table OA II

Alternative Measure for Investment, Asset Volatility, and Credit Spreads

This table presents panel regressions of an alternative measure of investment rate ($\log[\widetilde{I}/\widetilde{K}]_{i,t}$) on asset volatility ($\log \sigma_{i,t-1}$) and credit spreads ($\log cs_{i,t-1}$) at firm-quarter level from 1984 to 2018. The alternative measure of investment rate is defined as capital expenditures plus R&D and 30% of SG&A, divided by the lagged sum of net PP&E and intangible capital. Columns 4-6 use subsamples sorted by terciles every quarter on credit spreads. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	all	all	all	low cs	mid cs	high cs	all
$\log \sigma_{i,t-1}$	0.210***		0.182***	0.186***	0.177***	0.143***	0.148***
	(13.63)		(11.77)	(8.66)	(7.77)	(6.44)	(8.37)
$\log cs_{i,t-1}$		-0.237***	-0.217***	-0.136***	-0.233***	-0.278***	-0.169***
		(-13.78)	(-12.88)	(-4.35)	(-6.01)	(-8.68)	(-8.59)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓
Controls							✓
Observations	46687	46687	46687	15236	14959	13963	30843
R-squared	0.126	0.139	0.157	0.162	0.157	0.130	0.197

Table OA III

Alternative Measure for Investment, Equity Volatility, and Credit Spreads

This table presents panel regressions of an alternative measure of investment rate ($\log[\widetilde{I}/\widetilde{K}]_{i,t}$) on equity volatility ($\log \sigma^e_{i,t-1}$) and credit spreads ($\log cs_{i,t-1}$) at firm-quarter level from 1984 to 2018. The alternative measure of investment rate is defined as capital expenditures plus R&D and 30% of SG&A, divided by the lagged sum of gross PP&E and intangible capital. Columns 4-6 use subsamples sorted by terciles every quarter on credit spreads. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$							
	(1) all	(2) all	(3) all	(4) low cs	(5) mid cs	(6) high cs	(7) all	(8) all
$\log \sigma^e_{i,t-1}$	-0.095***		0.005	0.106***	0.039	-0.066***	0.566***	0.416***
	(-5.36)		(0.32)	(5.48)	(1.51)	(-2.81)	(8.71)	(5.83)
$\log cs_{i,t-1}$		-0.239***	-0.240***	-0.154***	-0.255***	-0.298***	-0.351***	-0.260***
		(-13.92)	(-14.03)	(-4.97)	(-6.70)	(-9.14)	(-17.43)	(-10.55)
$\log \sigma^e_{i,t-1} \times \log cs_{i,t-1}$							-0.101***	-0.068***
							(-8.68)	(-5.29)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls								✓
Observations	47245	47245	47245	15303	15111	14278	47245	31131
R-squared	0.106	0.140	0.140	0.146	0.143	0.122	0.145	0.189

Table OA IV
Investment, Asset Volatility, and Credit Spreads in Restricted Sample

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on asset volatility ($\log \sigma_{i,t-1}$) and credit spreads ($\log cs_{i,t-1}$) at firm-quarter level from 1984 to 2018. We restrict the sample of firms to firms with observable implied asset volatility. Columns 4-6 use subsamples sorted by terciles every quarter on credit spreads. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$						
	(1) all	(2) all	(3) all	(4) low cs	(5) mid cs	(6) high cs	(7) all
$\log \sigma_{i,t-1}$	0.206***		0.192***	0.189***	0.172***	0.131***	0.145***
	(8.74)		(8.46)	(6.21)	(4.69)	(2.85)	(5.87)
$\log cs_{i,t-1}$		-0.331***	-0.323***	-0.172***	-0.353***	-0.622***	-0.171***
		(-10.66)	(-10.50)	(-3.61)	(-5.29)	(-7.17)	(-5.62)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓
Controls							✓
Observations	21340	21340	21340	8598	7081	4704	14688
R-squared	0.116	0.142	0.154	0.155	0.141	0.155	0.237

Table OA V
Investment, Idiosyncratic Asset Volatility, and Credit Spreads

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on idiosyncratic asset volatility ($\log \widetilde{\sigma}_{i,t-1}$) and credit spreads ($\log cs_{i,t-1}$) at firm-quarter level from 1984 to 2018. Columns 4-6 use subsamples sorted by terciles every quarter on credit spreads. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$						
	(1) all	(2) all	(3) all	(4) low cs	(5) mid cs	(6) high cs	(7) all
$\log \widetilde{\sigma}_{i,t-1}$	0.231***		0.206***	0.176***	0.160***	0.196***	0.169***
	(15.23)		(13.69)	(9.69)	(7.75)	(7.75)	(10.76)
$\log cs_{i,t-1}$		-0.269***	-0.251***	-0.121***	-0.282***	-0.401***	-0.156***
		(-13.25)	(-12.61)	(-3.36)	(-6.26)	(-9.83)	(-7.67)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓
Controls							✓
Observations	48068	48068	48068	15509	15329	14414	31469
R-squared	0.120	0.132	0.147	0.158	0.145	0.129	0.220

Table OA VI
Investment, Merton Asset Volatility, and Credit Spreads

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on asset volatility derived from Merton's model ($\log \mathring{\sigma}_{i,t-1}$) and credit spreads ($\log cs_{i,t-1}$) at firm-quarter level from 1984 to 2018. Columns 4-6 use subsamples sorted by terciles every quarter on credit spreads. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$						
	(1) all	(2) all	(3) all	(4) low cs	(5) mid cs	(6) high cs	(7) all
$\log \mathring{\sigma}_{i,t-1}$	0.128***		0.140***	0.183***	0.119***	0.126***	0.107***
	(7.83)		(8.78)	(8.77)	(5.03)	(4.82)	(6.29)
$\log cs_{i,t-1}$		-0.261***	-0.266***	-0.126***	-0.281***	-0.447***	-0.157***
		(-12.73)	(-13.14)	(-3.45)	(-6.37)	(-10.21)	(-7.41)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓
Controls							✓
Observations	45846	45846	45846	15024	14682	13728	30205
R-squared	0.106	0.130	0.137	0.155	0.135	0.122	0.214

Table OA VII
Investment, Residual Asset Volatility, and Credit Spreads

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on residual asset volatility ($\log\sigma^{\varepsilon}_{i,t-1}$) and credit spreads ($\log cs_{i,t-1}$) at firm-quarter level from 1984 to 2018. Residual asset volatility is the residual of realized idiosyncratic equity volatility on leverage. For each column, we obtain $\log\sigma^{\varepsilon}_{i,t}$ from the regression of the log of idiosyncratic equity volatility on the log of firm-level leverage, controlling for the same set of control variables that are used in the regression model of that column. Columns 4-6 use subsamples sorted by terciles every quarter on credit spreads. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$						
	(1) all	(2) all	(3) all	(4) low cs	(5) mid cs	(6) high cs	(7) all
$\log\sigma^{\varepsilon}_{i,t-1}$	0.009		0.038**	0.150***	0.026	-0.037	0.068***
	(0.47)		(2.20)	(6.94)	(0.97)	(-1.23)	(3.54)
$\log cs_{i,t-1}$		-0.270***	-0.269***	-0.113***	-0.296***	-0.439***	-0.152***
		(-13.39)	(-13.21)	(-3.01)	(-6.48)	(-10.33)	(-7.28)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓
Controls							✓
Observations	47429	47429	47436	15206	15193	14229	31012
R-squared	0.100	0.132	0.132	0.149	0.138	0.117	0.210

Table OA VIII

Investment, Credit Spreads, and Leads and Lags of Implied Asset Volatility

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on credit spreads ($\log cs_{i,t-1}$) and different lags and leads of implied asset volatility ($\log \widehat{\sigma}_{i,t+\tau}, \tau = -4, ..., 4$) at firm-quarter level from 1984 to 2018. Implied asset volatility is deleveraged equity volatility implied from options. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$	
	(1)	(2)
$\log cs_{i,t-1}$	-0.314***	-0.185***
	(-9.67)	(-5.73)
$\log \widehat{\sigma}_{i,t-4}$	0.085***	0.067**
	(3.02)	(2.12)
$\log \widehat{\sigma}_{i,t-3}$	0.084***	0.065**
	(3.35)	(2.00)
$\log \widehat{\sigma}_{i,t-2}$	0.066**	0.022
	(2.47)	(0.79)
$\log \widehat{\sigma}_{i,t-1}$	0.152***	0.130***
	(5.93)	(3.74)
$\log \widehat{\sigma}_{i,t}$	0.011	-0.006
	(0.45)	(-0.22)
$\log \widehat{\sigma}_{i,t+1}$	0.045**	0.035
	(2.01)	(1.26)
$\log \widehat{\sigma}_{i,t+2}$	-0.059**	-0.052*
	(-2.42)	(-1.77)
$\log \widehat{\sigma}_{i,t+3}$	0.063**	0.069**
	(2.52)	(2.21)
$\log \widehat{\sigma}_{i,t+4}$	-0.042	-0.054*
	(-1.46)	(-1.72)
Firm FE	✓	✓
Time FE	✓	✓
Controls		✓
Observations	17365	12092
R-squared	0.171	0.242

Table OA IX

Investment, Levels and Changes of Implied Asset Volatility, and Credit Spreads

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on levels of implied asset volatility ($\log \widehat{\sigma}_{i,t-1}$), changes in implied asset volatility ($\Delta \log \widehat{\sigma}_{i,t-1}$), and credit spreads ($\log cs_{i,t-1}$) at firm-quarter level from 1984 to 2018. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
$\log \widehat{\sigma}_{i,t-1}$	0.355***	0.331***	0.288***		0.248***
	(9.76)	(9.25)	(9.20)		(6.04)
$\Delta \log \widehat{\sigma}_{i,t-1}$	-0.193***	-0.164***		-0.002	-0.101***
	(-7.16)	(-6.23)		(-0.11)	(-3.64)
$\log cs_{i,t-1}$		-0.314***	-0.320***	-0.327***	-0.176***
		(-10.16)	(-10.44)	(-10.55)	(-5.81)
Firm FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
Controls					✓
Observations	21100	21100	21475	21100	14554
R-squared	0.124	0.160	0.159	0.140	0.240

Table OA X

Investment, Idiosyncratic Equity Volatility, and Credit Spreads

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on idiosyncratic equity volatility ($\log \widetilde{\sigma}^{e}_{i,t-1}$) and credit spreads ($\log cs_{i,t-1}$) at firm-quarter level from 1984 to 2018. Columns 4-6 use subsamples sorted by terciles every quarter on credit spreads. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$							
	(1) all	(2) all	(3) all	(4) low cs	(5) mid cs	(6) high cs	(7) all	(8) all
$\log \widetilde{\sigma}^{e}_{i,t-1}$	-0.148***		-0.051***	0.055***	-0.039*	-0.109***	0.799***	0.596***
	(-8.73)		(-3.55)	(2.98)	(-1.93)	(-4.33)	(9.60)	(6.85)
$\log cs_{i,t-1}$		-0.271***	-0.257***	-0.134***	-0.283***	-0.405***	-0.459***	-0.307***
		(-13.32)	(-12.96)	(-3.75)	(-6.27)	(-9.61)	(-16.84)	(-10.62)
$\log \widetilde{\sigma}^{e}_{i,t-1} \times \log cs_{i,t-1}$							-0.153***	-0.107***
							(-10.18)	(-6.77)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls								✓
Observations	48477	48655	48477	15470	15473	14709	48477	31615
R-squared	0.107	0.132	0.132	0.144	0.136	0.120	0.140	0.213

Table OA XI

Investment, Implied Equity Volatility, and Credit Spreads

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on implied equity volatility ($\log \widehat{\sigma}^e_{i,t-1}$) and credit spreads ($\log cs_{i,t-1}$) at firm-quarter level from 1984 to 2018. Columns 4-6 use subsamples sorted by terciles every quarter on credit spreads. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$							
	(1) all	(2) all	(3) all	(4) low cs	(5) mid cs	(6) high cs	(7) all	(8) all
$\log \widehat{\sigma}^e_{i,t-1}$	-0.293***		-0.086**	0.117**	-0.058	-0.262***	1.205***	1.057***
	(-7.15)		(-2.03)	(2.32)	(-0.85)	(-3.65)	(7.65)	(6.22)
$\log cs_{i,t-1}$		-0.271***	-0.299***	-0.199***	-0.341***	-0.469***	-0.541***	-0.372***
		(-13.32)	(-9.10)	(-4.04)	(-4.82)	(-5.61)	(-13.33)	(-8.29)
$\log \widehat{\sigma}^e_{i,t-1} \times \log cs_{i,t-1}$							-0.229***	-0.190***
							(-8.42)	(-6.32)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls								✓
Observations	21587	48655	21587	8615	7189	4838	21587	14777
R-squared	0.117	0.132	0.143	0.145	0.135	0.146	0.155	0.238

Table OA XII

Investment, Implied Equity Volatility, and Fair Value Spreads

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on implied equity volatility ($\log \widehat{\sigma}^e_{i,t-1}$) and fair value spreads ($\log \widehat{cs}_{i,t-1}$) at firm-quarter level from 1984 to 2018. Columns 4-6 use subsamples sorted by terciles every quarter on fair value spreads. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$							
	(1) all	(2) all	(3) all	(4) low $\widehat{cs}$	(5) mid $\widehat{cs}$	(6) high $\widehat{cs}$	(7) all	(8) all
$\log \widehat{\sigma}^e_{i,t-1}$	-0.255***		0.066*	0.180***	0.081	-0.040	0.417***	0.379***
	(-5.97)		(1.71)	(3.65)	(1.29)	(-0.68)	(5.15)	(4.34)
$\log \widehat{cs}_{i,t-1}$		-0.170***	-0.197***	-0.179***	-0.129***	-0.217***	-0.275***	-0.177***
		(-16.56)	(-13.59)	(-6.00)	(-4.03)	(-7.87)	(-12.57)	(-6.62)
$\log \widehat{\sigma}^e_{i,t-1} \times \log \widehat{cs}_{i,t-1}$							-0.083***	-0.073***
							(-5.07)	(-3.74)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls								✓
Observations	20088	39213	20088	7600	6855	4764	20088	13623
R-squared	0.115	0.152	0.161	0.135	0.142	0.170	0.167	0.232

Table OA XIII

Loadings of Equity Volatility and Credit Spreads on Asset Volatility and Leverage

This table presents the loadings of equity volatility and credit spreads on asset volatility (derived from Merton's model) and leverage at firm-quarter level from 1984 to 2018. The regression specification is $\log y_{i,t} = \beta_1 \log \mathring{\sigma}_{i,t} + \beta_2 \log[MA/ME]_{i,t} + \eta_i + \lambda_t + \epsilon_{i,t}$. For a firm i in industry k at time t, we compute the industry average of log asset volatility excluding itself as $\frac{1}{N_k-1}\sum_{j\neq i}\log \mathring{\sigma}_{j,t}$ and the industry average of firm-level leverage as $\frac{1}{N_k-1}\sum_{j\neq i}\log[MA/ME]_{j,t}$. We report results for estimations in levels in Panel A and results for estimations in first differences in Panel B. All variables are standardized to have mean zero and unit variance. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels and standard errors are clustered at firm level. The panels below present the partial R^2 given time and firm fixed effects—that is, the percentage reduction in the residual sum of squares (RSS) by adding each variable in addition to time and firm fixed effects.

$$\log y_{i,t} = \beta_1 \log \mathring{\sigma}_{i,t} + \beta_2 \log[MA/ME]_{i,t} + \eta_i + \lambda_t + \epsilon_{i,t}$$

Panel A: Levels	$\log \sigma^e_{i,t}$	$\log cs_{i,t}$	Panel B: Changes	$\Delta \log \sigma^e_{i,t}$	$\Delta \log cs_{i,t}$
$\frac{1}{N_k-1}\sum_{j\neq i}\log \mathring{\sigma}_{j,t}$	0.242***	0.054	$\Delta \frac{1}{N_k-1}\sum_{j\neq i}\log \mathring{\sigma}_{j,t}$	0.125***	0.022**
	(9.64)	(1.49)		(13.41)	(2.02)
$\frac{1}{N_k-1}\sum_{j\neq i}\log[MA/ME]_{j,t}$	0.077***	0.139***	$\Delta \frac{1}{N_k-1}\sum_{j\neq i}\log[MA/ME]_{j,t}$	0.031***	0.095***
	(5.30)	(7.23)		(6.19)	(12.31)
Firm FE	✓	✓	Firm FE	✓	✓
Time FE	✓	✓	Time FE	✓	✓
Observations	45401	45401	Observations	44491	44491
R-squared	0.403	0.460	R-squared	0.173	0.298

Partial R^2

Panel C: Levels	$\log \sigma^e_{i,t}$	$\log cs_{i,t}$	Panel D: Changes	$\Delta \log \sigma^e_{i,t}$	$\Delta \log cs_{i,t}$
$\frac{1}{N_k-1}\sum_{j\neq i}\log \mathring{\sigma}_{j,t}$	0.017	0.001	$\Delta \frac{1}{N_k-1}\sum_{j\neq i}\log \mathring{\sigma}_{j,t}$	0.006	0.000
$\frac{1}{N_k-1}\sum_{j\neq i}\log[MA/ME]_{j,t}$	0.007	0.016	$\Delta \frac{1}{N_k-1}\sum_{j\neq i}\log[MA/ME]_{j,t}$	0.001	0.005

Table OA XIV
Investment, Implied Asset Volatility, and Leverage

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on implied asset volatility ($\log \widehat{\sigma}_{i,t-1}$) and leverage ($\log[MA/ME]_{i,t-1}$) at firm-quarter level from 1984 to 2018. Columns 4-6 use subsamples sorted by terciles on credit spreads. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$						
	(1) all	(2) all	(3) all	(4) low cs	(5) mid cs	(6) high cs	(7) all
$\log \widehat{\sigma}_{i,t-1}$	0.304***		-0.056	0.068	-0.019	-0.231***	0.027
	(9.55)		(-1.42)	(1.39)	(-0.29)	(-3.06)	(0.63)
$\log[MA/ME]_{i,t-1}$		-0.618***	-0.652***	-0.572***	-0.644***	-0.677***	-0.494***
		(-14.61)	(-12.75)	(-6.07)	(-7.77)	(-8.43)	(-7.17)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓
Controls							✓
Observations	21475	21296	21296	8487	7103	4755	14684
R-squared	0.122	0.173	0.174	0.169	0.159	0.179	0.246

Table OA XV
Risk-Shifting with Realized Asset Volatility

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on asset volatility ($\log \widehat{\sigma}_{i,t-1}$) and leverage ($\log[MA/ME]_{i,t-1}$) at firm-quarter level from 1984 to 2018. Column 1 uses a subsample with firms whose credit spreads are below 100 basis points. Columns 2-7 use subsamples with firms whose credit spreads are above 200, 300, ..., 600 basis points, respectively. Control variables include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$cs < 100$	$cs \geq 100$	$cs \geq 200$	$cs \geq 300$	$cs \geq 400$	$cs \geq 500$	$cs \geq 600$
$\log \sigma_{i,t-1}$	0.101***	0.072***	0.046*	0.053*	0.029	0.030	-0.009
	(3.09)	(3.20)	(1.84)	(1.73)	(0.78)	(0.69)	(-0.18)
$\log[MA/ME]_{i,t-1}$	-0.458***	-0.418***	-0.417***	-0.417***	-0.388***	-0.350***	-0.391***
	(-3.99)	(-13.11)	(-12.47)	(-11.13)	(-9.49)	(-7.73)	(-6.53)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	4759	28616	16479	11056	7252	4486	2682
R-squared	0.277	0.220	0.208	0.203	0.205	0.223	0.266

B Excess Bond Premium

In Tables VII, VIII, and Table IX, we document the relationship between fundamental default risk, credit spreads, and investment rates. We also highlight this structural relationship in our model of debt overhang and equityholders' investment incentives. Thus, our discussion emphasizes that credit spreads are in large part driven by asset volatility and leverage, while a long-standing literature finds that a nontrivial fraction of credit spreads cannot be explained by credit risk. Prior work has questioned the role of fundamental default risk in explaining changes in credit spreads (Collin-Dufresn, Goldstein, and Martin, 2001) and in explaining macroeconomic aggregates such as employment, output, and inventories (Gilchrist and Zakrajšek, 2012). Gilchrist and Zakrajšek (2012) decompose aggregate credit spreads into two components: a component that captures the movements in default risk based on fundamentals (the predicted component) and a residual component (the excess bond premium). They show that in the aggregate, the excess bond premium has substantial predictive content for future economic activity and outperforms the component of credit spreads predicted by fundamentals.

To further address the role of fundamentals versus residual bond market information in the context of our study, we construct firm-level excess bond spreads following Gilchrist and Zakrajšek (2012) and confirm that both credit spread components contain important information for investment. Thus, we do not question prior findings but provide evidence that the fundamental part of credit spreads explains firm-level investment rates and evidence that our main results are driven by structural relationships between our variables of interest.

First, we estimate the following panel regression:

$$\log cs_{i,m}[k] = \boldsymbol{\gamma}'\mathbf{X}_{i,m}[k] + \epsilon_{i,m}[k],$$

where the log of credit spreads on bond k issued by firm i in month m is regressed on a vector of bond-specific characteristics $\mathbf{X}_{i,m}[k]$ for bond k issued by firm i.[50] We then build firm-level quarterly excess bond premia as the quarterly average of

[50]Bond characteristics $\mathbf{X}_{i,m}[k]$ include the firm's distance-to-default; the bond's amount outstanding, duration, and coupon rate; and an indicator variable for callable bonds. It also includes the interactions of callability with these bond characteristics; firm's distance-to-default; the level, slope, and curvature of the Treasury yield curve; and the realized monthly volatility of the daily 10-year Treasury yield, which reflects the value of the call option embedded in callable bonds. Industry fixed effects and credit rating fixed effects are included as well.

the residuals for all bonds issued by the firm during that quarter: $\log(ebp_{i,q}) = \frac{1}{3}\sum_{m=q_1}^{q_3} \frac{1}{N_{i,m}^k} \sum_{k=1}^{N_{i,m}^k} \epsilon_{i,m}[k]$, where q_n is the nth month of quarter q and $N_{i,m}^k$ is the number of bonds of firm i in month m.

[Table OB I and Table OB II here.]

Table OB I replicates our main results from Table VI and shows that the fundamental part of credit spreads greatly reduces the economic significance of equity volatility in explaining investment. The excess bond premium, on the other hand, does not change (without additional controls) or slightly improves (with additional controls) the economic significance of equity volatility in explaining investment. The firm-level excess bond premium is, however, in itself a strong predictor of investment. This is consistent with the notion that an increase in the firm-level excess bond premium reflects an increase in the cost of the firm's capital and, as a result, a contraction in future investments, as emphasized by Gilchrist and Zakrajšek (2012).

Table OB II replicates our main results from Table II and shows that asset volatility is robustly positively related to firm-level investment rates when controlling for either of the two components of credit spreads—the excess bond premium or the credit spreads minus the excess bond premium.

Table OB I
Investment, Equity Volatility, and the Excess Bond Premium

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on equity volatility ($\log \sigma^e_{i,t-1}$), excess bond premium ($\log ebp_{i,t-1}$), and the predictable component of credit spreads ($\log cs_{i,t-1} - \log ebp_{i,t-1}$) at firm-quarter level from 1984 to 2018. Following Gilchrist and Zakrajšek (2012), excess bond premium $ebp_{i,t}$ is the quarterly average of the residual $\epsilon_{i,t}$ of a panel regression for credit spreads: $\log cs_{i,t} = \gamma' \mathbf{X}_{i,t} + \epsilon_{i,t}$. The vector of bond-specific characteristics $\mathbf{X}_{i,t}$ include the firm's distance-to-default; bond's amount outstanding, duration, coupon rate, industry fixed effects, and credit rating fixed effects; an indicator variable for callable bonds; the interactions of callability with these bond characteristics; the level, slope, and curvature of the Treasury yield curve; and the realized monthly volatility of the daily 10-year Treasury yield. Control variables for the regression of investment include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log \sigma^e_{i,t-1}$	-0.148***	-0.154***	-0.030	-0.037*	-0.045**	0.039*
	(-7.71)	(-7.94)	(-1.53)	(-1.87)	(-2.21)	(1.73)
$\log ebp_{i,t-1}$		-0.220***			-0.098***	
		(-10.44)			(-4.24)	
$\log cs_{i,t-1} - \log ebp_{i,t-1}$			-0.232***			-0.167***
			(-8.20)			(-5.45)
Firm FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Controls				✓	✓	✓
Observations	48655	46665	46435	31741	30527	30380
R-squared	0.106	0.116	0.117	0.200	0.203	0.207

Table OB II
Investment, Asset Volatility, and the Excess Bond Premium

This table presents panel regressions of the investment rate ($\log[I/K]_{i,t}$) on asset volatility ($\log\sigma_{i,t-1}$), excess bond premium ($\log ebp_{i,t-1}$), and the predictable component of credit spreads ($\log cs_{i,t-1} - \log ebp_{i,t-1}$) at firm-quarter level from 1984 to 2018. Following Gilchrist and Zakrajšek (2012), the excess bond premium $ebp_{i,t}$ is the quarterly average of the residual $\epsilon_{i,t}$ of a panel regression for credit spreads: $\log cs_{i,t} = \gamma'\mathbf{X}_{i,t} + \epsilon_{i,t}$. The vector of bond-specific characteristics $\mathbf{X}_{i,t}$ include the firm's distance-to-default; bond's amount outstanding, duration, coupon rate, industry fixed effects, and credit rating fixed effects; an indicator variable for callable bonds; the interactions of callability with these bond characteristics; the level, slope, and curvature of the Treasury yield curve; and the realized monthly volatility of the daily 10-year Treasury yield. Control variables for the regression of investment include quarterly return on equity, log of tangibility ratio, log of sales ratio, log of income ratio, and log of Tobin's q (all lagged by 1 quarter). See Table I and Section A for detailed variable definitions. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels. Standard errors are clustered at firm level.

	Dependent Variable: $\log[I/K]_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log\sigma_{i,t-1}$	0.266***	0.245***	0.272***	0.195***	0.188***	0.219***
	(15.60)	(13.99)	(15.92)	(10.25)	(9.62)	(11.29)
$\log ebp_{i,t-1}$		-0.158***			-0.060***	
		(-7.46)			(-2.62)	
$\log cs_{i,t-1} - \log ebp_{i,t-1}$			-0.254***			-0.187***
			(-9.93)			(-6.82)
Firm FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Controls				✓	✓	✓
Observations	45896	45896	45896	30107	30107	30107
R-squared	0.125	0.130	0.142	0.213	0.214	0.222

C Risk-Shifting

In this appendix, we attempt to reproduce the empirical findings documented in Panel A of Table II in Eisdorfer (2008), in which investment intensity is regressed on expected volatility and the coefficient on expected volatility is negative for healthy firms and positive for distressed firms. We follow Eisdorfer (2008) as closely as possible but fail to replicate the key result. Below, we describe the procedure.

Variables The dependent variable, investment intensity, is measured by the ratio of capital expenditures to PP&E at the beginning of the year. The key independent variable, *expected volatility*, is obtained by applying a GARCH $(1, 1)$ model to monthly returns of the NYSE market index from 1927 to 2002. For each calendar year, the expected volatility is measured by the 12-month-ahead forecasted volatility conditional on information available in the last month of the year before. This expected annual volatility is a linear function of the expected volatility for the next month, so it is sufficient to regress investment on expected volatility for the first month of the year. The variable that measures financial distress is Altman's Z-score[51]. Firms with Z-scores below 1.81 at the beginning of the year are classified as distressed.

Control variables include (i) firm size, which is estimated by the log of the market value of the firm's total assets; (ii) market-to-book ratio, estimated by equity market value divided by equity book value; (iii) leverage, estimated by the ratio of the book value of total debt to book value of total assets; (iv) cash flow, estimated by the ratio of operating cash flow to PP&E at the beginning of the year; (v) the NBER recession dummy variable; (vi) default spread, estimated by the Moody's BAA-AAA corporate bond yield spread; and (vii) interest rate, measured by the nominal return on 1-month Treasury bills.

Construction of the market value of assets in Eisdorfer (2008) differs from the procedure we document in our main text. Instead of using an iterative procedure, asset value is computed by directly solving the two-equation system as in Equation (34). The definitions of some input variables are also slightly different: equity volatility σ_E is measured by the realized monthly stock return volatility in the subsequent year; the face value of debt B is measured by the total liability of firms; debt maturity T

[51]Z-score is defined as 1.2 x (Working capital/Total assets)+1.4 x (Retained earnings/Total assets)+3.3 x (Earnings before interest and taxes/Total assets)+ 0.6 x (Market value of equity/Book value of total liabilities) + 0.999 x (Sales/Total assets)

is measured as $T = \frac{1}{TD}(0.5STD + 5LTD)$; and risk-free rate r is measured by the 1-year Treasury bill yield.

Sample The data are obtained from CRSP and COMPUSTAT. As in Eisdorfer (2008), we only include firms that are traded on the NYSE, AMEX, or Nasdaq, and have non-missing observations for asset value, investment intensity, and Z-score. The sample period is 1963 to 2002. According to Eisdorfer (2008), their final sample contains 52,112 firm-year observations. The sample we generated using the filters described above contains 55,462 observations (Sample I), and if we further trim every regression variables at the 1st and 99th percentiles, the regression sample contains 51,266 observations (Sample II).

Table OC I reports the results from OLS regressions of investment intensity on expected volatility for financially healthy firms and distressed firms, controlling for firm size, market-to-book ratio, leverage, cash flow, the recession dummy, the default spread, and the interest rate. Panel A presents regression results using Sample I and Panel B presents results using Sample II. In Panel A, the coefficient on expected volatility for distressed firms is negative and insignificant, which is supposed to be positive and marginally significant in Eisdorfer (2008). As documented above, we followed Eisdorfer (2008) as closely as possible but failed to generate a final sample that is exactly the same, so a possible reason for the discrepancy might be that some sample filters are not documented. In Panel B, in which we use the trimmed data, we can see that the coefficient on expected volatility is more negative and significant for distressed firms, which is actually consistent with our main results. Meanwhile, the sign and significance of other coefficients in Panel B are roughly consistent with those in Eisdorfer (2008).

Table OC I
Reproducing Panel A of Table II in Eisdorfer (2008)

This table presents results from OLS regressions of investment intensity on expected volatility for financially healthy firms and distressed firms, controlling for firm size, market-to-book ratio, leverage, cash flow,the recession dummy, the default spread, and the interest rate. Distressed firms are firms with Z-scores below 1.81 at the beginning of the year. The sample is at firm-year level from 1963 to 2002. Panel A uses Sample I, which is obtained by applying filters documented in the text of Eisdorfer (2008). Panel B uses Sample II, which is generated by further trimming investment intensity, size, market-to-book ratio, leverage, and cash flow at the 1st and 99th percentiles. Coefficients are reported with t-statistics in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels.

	Panel A: Sample I		Panel B: Sample II	
	(1)	(2)	(3)	(4)
	Healthy Firms	Distressed Firms	Healthy Firms	Distressed Firms
Exp. volatility	-1.884**	-2.431	-1.264**	-3.684***
	(-2.21)	(-0.92)	(-2.32)	(-3.50)
Log_size	0.002***	-0.005***	-0.003***	-0.003***
	(4.17)	(-3.57)	(-7.56)	(-4.86)
Market-to-book	0.000***	0.000	0.017***	0.005***
	(3.12)	(0.07)	(46.18)	(8.15)
Leverage	-0.119***	0.010	-0.063***	0.015*
	(-20.27)	(1.04)	(-15.59)	(1.76)
Lagged cash flow	0.019***	0.002	0.086***	0.012***
	(21.91)	(1.44)	(47.36)	(4.28)
Recession	-0.016***	-0.010	-0.009***	-0.002
	(-6.48)	(-1.24)	(-6.15)	(-0.60)
Default spread	-0.853**	-1.003	-0.410*	0.770*
	(-2.54)	(-0.88)	(-1.91)	(1.66)
Interest rate	0.776***	0.481***	0.763***	0.509***
	(16.57)	(3.13)	(25.48)	(8.19)
Constant	0.185***	0.141***	0.118***	0.087***
	(37.14)	(8.69)	(35.10)	(10.58)
Observations	46179	9283	43309	7957
R-squared	0.026	0.003	0.123	0.027

D Proofs

Shareholders maximize their expected cash flow and decide when to default. Thus, the value of equity is given by

$$e = \max_{i,\underline{z}} \left\{ \mathbb{E}\Big[(iz - b)\mathbb{1}\{z \geq \underline{z}\}\Big] - \phi(i) \right\}.$$

First-order conditions for investment i and the default boundary $\underline{z}$ are given by

$$\begin{aligned} \int_{\underline{z}}^{\infty} z dF(z;\sigma) - \phi_i(i) &= 0, \\ -f(\underline{z};\sigma)(i\underline{z} - b) &= 0. \end{aligned}$$

Necessary second-order conditions for investment i and the default boundary $\underline{z}$ are given by

$$\begin{aligned} -\phi_{ii}(i) &\leq 0, \\ -f(\underline{z};\sigma)i &\leq 0, \\ \phi_{ii}(i)f(\underline{z};\sigma)i - f(\underline{z};\sigma)^2\underline{z}^2 &\geq 0. \end{aligned} \tag{37}$$

Thus, $\phi_{ii}(i)i - f(\underline{z};\sigma)\underline{z}^2 \geq 0$.

In the following sections, we derive the partial derivatives of equity with respect to (i) credit spreads and asset volatility, (ii) leverage and asset volatility, (iii) credit spreads and equity volatility, (iv) Tobin's q and asset volatility, and (v) Tobin's q and credit spreads to rationalize our empirical results.

Assume we observe $\boldsymbol{\theta}$ and want to derive the partial derivatives of $\mathbf{x}$ with respect to $\boldsymbol{\theta}$. Since $\mathbf{x}$ is the solution to a system of nonlinear equations $\boldsymbol{\mathcal{D}}(\mathbf{x},\boldsymbol{\theta})$, we need to use the multivariate implicit function theorem:

$$\frac{\partial \mathbf{x}(\boldsymbol{\theta})}{\partial \theta_k} = -\left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}),\boldsymbol{\theta})}{\partial x_j}\right]^{-1}\left[\frac{\partial \boldsymbol{\mathcal{D}}(\mathbf{x}(\boldsymbol{\theta}),\boldsymbol{\theta})}{\partial \theta_k}\right].$$

Proof of Proposition 1

If we observe cs and σ, we get

$$\boldsymbol{\mathcal{D}}(\mathbf{x},\boldsymbol{\theta}) = \begin{bmatrix} \int_{\underline{z}}^{\infty} z dF(z;\sigma) - \phi_i(i) \\ F(\underline{z};\sigma)/(1-F(\underline{z};\sigma)) - cs \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} i \\ \underline{z} \end{bmatrix}, \quad \boldsymbol{\theta} = \begin{bmatrix} cs & \sigma \end{bmatrix}.$$

We can derive the Jacobian matrix of $\boldsymbol{\mathcal{D}}(\mathbf{x},\boldsymbol{\theta})$ as

$$\left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}),\boldsymbol{\theta})}{\partial x_j}\right] = \begin{bmatrix} -\phi_{ii}(i) & -\underline{z}f(\underline{z};\sigma) \\ 0 & f(\underline{z};\sigma)/(1-F(\underline{z};\sigma))^2 \end{bmatrix}$$

and the partial derivatives as

$$\left[\frac{\partial \boldsymbol{\mathcal{D}}(\mathbf{x}(\boldsymbol{\theta}),\boldsymbol{\theta})}{\partial cs}\right] = \begin{bmatrix} 0 \\ -1 \end{bmatrix}, \qquad \left[\frac{\partial \boldsymbol{\mathcal{D}}(\mathbf{x}(\boldsymbol{\theta}),\boldsymbol{\theta})}{\partial \sigma}\right] = \begin{bmatrix} \int_{\underline{z}}^{\infty} z dF_\sigma(z;\sigma) \\ F_\sigma(\underline{z};\sigma)/(1-F(\underline{z};\sigma))^2 \end{bmatrix}.$$

To derive the comparative statics of interest, we only need two elements of $\left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}),\boldsymbol{\theta})}{\partial x_j}\right]^{-1}$. Thus, we get

$$\frac{\partial i}{\partial cs} = \left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}),\boldsymbol{\theta})}{\partial x_j}\right]^{-1}_{12} = -\frac{\underline{z}(1-F(\underline{z};\sigma))^2}{\phi_{ii}(i)} < 0$$

and

$$\begin{aligned} \frac{\partial i}{\partial \sigma} &= -\left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}),\boldsymbol{\theta})}{\partial x_j}\right]^{-1}_{11} \int_{\underline{z}}^{\infty} z dF_\sigma(z;\sigma) - \left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}),\boldsymbol{\theta})}{\partial x_j}\right]^{-1}_{12} \frac{F_\sigma(\underline{z};\sigma)}{(1-F(\underline{z};\sigma))^2} \\ &= \frac{\int_{\underline{z}}^{\infty} z dF_\sigma(z;\sigma)}{\phi_{ii}(i)} + \frac{\underline{z}(1-F(\underline{z};\sigma))^2}{\phi_{ii}(i)} \frac{F_\sigma(\underline{z};\sigma)}{(1-F(\underline{z};\sigma))^2} \\ &= \frac{\nu(\underline{z},\sigma)}{\phi_{ii}(i)} > 0. \end{aligned}$$

The sign of both partial derivatives comes directly from our assumptions.

Proof of Proposition 2

If we observe b and σ, we get

$$\frac{\partial \mathbf{x}(\boldsymbol{\theta})}{\partial \theta_k} = -\left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial x_j}\right]^{-1}\left[\frac{\partial \boldsymbol{\mathcal{D}}(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial \theta_k}\right],$$

where

$$\boldsymbol{\mathcal{D}}(\mathbf{x}, \boldsymbol{\theta}) = \begin{bmatrix} \int_{\underline{z}}^{\infty} z dF(z;\sigma) - \phi_i(i) \\ i\underline{z} - b \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} i \\ \underline{z} \end{bmatrix}, \quad \boldsymbol{\theta} = \begin{bmatrix} b & \sigma \end{bmatrix}.$$

We can derive the Jacobian matrix of $\boldsymbol{\mathcal{D}}(\mathbf{x}, \boldsymbol{\theta})$ as

$$\left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial x_j}\right] = \begin{bmatrix} -\phi_{ii}(i) & -\underline{z}f(\underline{z};\sigma) \\ \underline{z} & i \end{bmatrix}$$

and the partial derivatives as

$$\left[\frac{\partial \boldsymbol{\mathcal{D}}(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial b}\right] = \begin{bmatrix} 0 \\ -1 \end{bmatrix}, \qquad \left[\frac{\partial \boldsymbol{\mathcal{D}}(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial \sigma}\right] = \begin{bmatrix} \int_{\underline{z}}^{\infty} z dF_\sigma(z;\sigma)dz \\ 0 \end{bmatrix}.$$

To derive the comparative statics of interest, we only need two elements of $\left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial x_j}\right]^{-1}$. Thus, we can directly derive

$$\frac{\partial i}{\partial b} = \left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial x_j}\right]^{-1}_{12} = -\frac{\underline{z}f(\underline{z};\sigma)}{\phi_{ii}(i)i - \underline{z}^2 f(\underline{z};\sigma)} < 0,$$

$$\begin{aligned}
\frac{\partial i}{\partial \sigma} &= -\left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial x_j}\right]^{-1}_{11} \int_{\underline{z}}^{\infty} z dF_\sigma(z;\sigma)dz \\
&= \frac{i\int_{\underline{z}}^{\infty} z dF_\sigma(z;\sigma)dz}{\phi_{ii}(i)i - \underline{z}^2 f(\underline{z};\sigma)} \\
&= \frac{i(\nu(\underline{z},\sigma) - \underline{z}F_\sigma(\underline{z};\sigma))}{\phi_{ii}(i)i - \underline{z}^2 f(\underline{z};\sigma)}.
\end{aligned}$$

Proof of Proposition 3

If we observe cs and σ^e, we get

$$\frac{\partial \mathbf{x}(\boldsymbol{\theta})}{\partial \theta_k} = -\left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial x_j}\right]^{-1} \left[\frac{\partial \boldsymbol{\mathcal{D}}(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial \theta_k}\right],$$

where

$$\boldsymbol{\mathcal{D}}(\mathbf{x}, \boldsymbol{\theta}) = \left[\begin{array}{c} \int_{\underline{z}}^{\infty} z dF(z;\sigma) - \phi_i(i) \\ F(\underline{z};\sigma)/(1-F(\underline{z};\sigma)) - cs \\ \frac{\sigma}{\mathbb{E}[(z-\underline{z})^+]} - \sigma^e \end{array}\right], \quad \mathbf{x} = \left[\begin{array}{c} i \\ \underline{z} \\ \sigma \end{array}\right], \quad \boldsymbol{\theta} = \left[\begin{array}{cc} cs & \sigma^e \end{array}\right].$$

We can derive the Jacobian matrix of $\boldsymbol{\mathcal{D}}(\mathbf{x}, \boldsymbol{\theta})$ as

$$\left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial x_j}\right] = \left[\begin{array}{ccc} -\phi_{ii}(i) & -\underline{z} f(\underline{z};\sigma) & \int_{\underline{z}}^{\infty} z dF_\sigma(z;\sigma) \\ 0 & f(\underline{z};\sigma)/(1-F(\underline{z};\sigma))^2 & F_\sigma(\underline{z};\sigma)/(1-F(\underline{z};\sigma))^2 \\ 0 & \sigma^e_{\underline{z}} & \sigma^e_\sigma \end{array}\right]$$

where

$$\begin{aligned} \sigma^e_{\underline{z}} &= -\frac{\sigma \bar{\mu}_{\underline{z}}(\underline{z},\sigma)}{\bar{\mu}(\underline{z},\sigma)^2} = \frac{\sigma\left(1-F(\underline{z};\sigma)\right)}{\bar{\mu}(\underline{z},\sigma)^2}, \\ \sigma^e_\sigma &= \frac{\bar{\mu}(\underline{z},\sigma) - \sigma\nu(\underline{z},\sigma)}{\bar{\mu}(\underline{z},\sigma)^2} \\ \bar{\mu}(\underline{z},\sigma) &= \mathbb{E}\left[(z-\underline{z})^+\right], \end{aligned}$$

and the partial derivatives as

$$\left[\frac{\partial \boldsymbol{\mathcal{D}}(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial cs}\right] = \left[\begin{array}{c} 0 \\ -1 \\ 0 \end{array}\right], \qquad \left[\frac{\partial \boldsymbol{\mathcal{D}}(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial \sigma^e}\right] = \left[\begin{array}{c} 0 \\ 0 \\ -1 \end{array}\right].$$

To derive the comparative statics of interest, we only need two elements of $\left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}),\boldsymbol{\theta})}{\partial x_j}\right]^{-1}$.

Thus, we can directly derive

$$\frac{\partial i}{\partial cs} = \left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial x_j}\right]^{-1}_{12} = \frac{(1-F(\underline{z};\sigma))^2}{\phi_{ii}(i)} \frac{\int_{\underline{z}}^{\infty} z dF_\sigma(z;\sigma)\sigma^e_{\underline{z}}(\underline{z},\sigma) + \underline{z} f(\underline{z};\sigma)\sigma^e_\sigma(\underline{z},\sigma)}{F_\sigma(\underline{z};\sigma)\sigma^e_{\underline{z}}(\underline{z},\sigma) - f(\underline{z};\sigma)\sigma^e_\sigma(\underline{z},\sigma)},$$
$$= -\frac{\underline{z}(1-F(\underline{z};\sigma))^2}{\phi_{ii}(i)} \frac{\int_{\underline{z}}^{\infty} z/\underline{z} dF_\sigma(z;\sigma)\sigma^e_{\underline{z}}(\underline{z},\sigma) + f(\underline{z};\sigma)\sigma^e_\sigma(\underline{z},\sigma)}{f(\underline{z};\sigma)\sigma^e_\sigma(\underline{z},\sigma) - F_\sigma(\underline{z};\sigma)\sigma^e_{\underline{z}}(\underline{z},\sigma)}$$

and

$$\frac{\partial i}{\partial \sigma^e} = \left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial x_j}\right]^{-1}_{13} = -\frac{1}{\phi_{ii}(i)} \frac{\int_{\underline{z}}^{\infty} z dF_\sigma(z;\sigma) f(\underline{z};\sigma) + \underline{z} f(\underline{z};\sigma) F_\sigma(\underline{z};\sigma)}{F_\sigma(\underline{z};\sigma)\sigma^e_{\underline{z}}(\underline{z},\sigma) - f(\underline{z};\sigma)\sigma^e_\sigma(\underline{z},\sigma)}$$
$$= \frac{\nu(\underline{z},\sigma)}{\phi_{ii}(i)} \frac{f(\underline{z};\sigma)}{f(\underline{z};\sigma)\sigma^e_\sigma(\underline{z},\sigma) - F_\sigma(\underline{z};\sigma)\sigma^e_{\underline{z}}(\underline{z},\sigma)}.$$

Proof of Corollary 2

The value of the debt is given by

$$d = \mathbb{E}\Big[b\mathbb{1}\{z \geq b/i\}\Big].$$

Thus,

$$\frac{\partial d}{\partial \sigma} = -bF_\sigma(\underline{z};\sigma) + f(\underline{z};\sigma)\frac{b^2}{i^2}\frac{\partial i}{\partial \sigma}$$
$$= -bF_\sigma(\underline{z};\sigma) + f(\underline{z};\sigma)\frac{b^2}{i}\frac{\nu(\underline{z},\sigma) - \underline{z}F_\sigma(\underline{z};\sigma)}{\varphi(i,\underline{z},\sigma)}$$

and $\frac{\partial d}{\partial \sigma}$ has the same sign as

$$-\underline{z}F_\sigma(\underline{z};\sigma)\phi_{ii}(i)i + f(\underline{z};\sigma)\underline{z}^2\nu(\underline{z},\sigma)$$

given that $i\underline{z} = b$.

If $F_\sigma(\underline{z};\sigma) < 0$, then $\frac{\partial d}{\partial \sigma} > 0$. Since $\phi_{ii}(i)i \geq f(\underline{z};\sigma)\underline{z}^2$, if $\frac{\partial i}{\partial \sigma} < 0$, then $\frac{\partial d}{\partial \sigma} < 0$.

The marginal benefit to equity holders to increase volatility is given by

$$\frac{\partial e(b,\sigma)}{\partial \sigma} = \int_{b/i}^{\infty} (iz - b) dF_{\sigma}(z;\sigma).$$

These marginal benefits increase as leverage increases if and only if

$$\frac{\partial^2 e(b,\sigma)}{\partial \sigma \partial b} = -\int_{b/i}^{\infty} dF_{\sigma}(z;\sigma) + \int_{b/i}^{\infty} z dF_{\sigma}(z;\sigma)\frac{\partial i}{\partial b} > 0.$$

With further algebra, we get that $\frac{\partial^2 e(b,\sigma)}{\partial \sigma \partial b}$ has the opposite sign of

$$-\underline{z}F_{\sigma}(z;\sigma)\phi_{ii}(i)i + \nu(\underline{z},\sigma)\underline{z}^2 f(\underline{z};\sigma).$$

Thus, if $\frac{\partial i}{\partial \sigma} < 0$ then $\frac{\partial^2 e(b,\sigma)}{\partial \sigma \partial b} > 0$ and if $F_{\sigma}(z;\sigma) < 0$ then $\frac{\partial^2 e(b,\sigma)}{\partial \sigma \partial b} > 0$

Positive Liquidation Value

Given that the price of debt with positive liquidation value α is given by

$$D = (1 - F(\underline{z};\sigma))B + i\alpha \int_0^{\underline{z}} zK dF(z;\sigma),$$

we define credit spreads with positive liquidation value as

$$\widetilde{cs} = \frac{F(\underline{z};\sigma) - \alpha/bi \int_0^{\underline{z}} z dF(z;\sigma)}{1 - F(\underline{z};\sigma) + \alpha/bi \int_0^{\underline{z}} z dF(z;\sigma)}.$$

where $1-\alpha$ represents bankruptcy costs. For readability, we define

$$\widetilde{F}(i,\underline{z},\sigma) = F(\underline{z};\sigma) - \alpha/bi \int_0^{\underline{z}} z dF(z;\sigma).$$

Thus, we can write

$$\boldsymbol{\mathcal{D}}(\mathbf{x},\boldsymbol{\theta}) = \begin{bmatrix} \int_{\underline{z}}^{\infty} z dF(z;\sigma) - \phi_i(i) \\ \frac{\widetilde{F}(i,\underline{z},\sigma)}{1-\widetilde{F}(i,\underline{z},\sigma)} - cs \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} i \\ \underline{z} \end{bmatrix}, \quad \boldsymbol{\theta} = \begin{bmatrix} cs & \sigma \end{bmatrix}.$$

We can derive the Jacobian matrix of $\boldsymbol{\mathcal{D}}(\mathbf{x}, \boldsymbol{\theta})$ as

$$\left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial x_j}\right] = \begin{bmatrix} -\phi_{ii}(i) & -\underline{z} f(\underline{z}; \sigma) \\ -\alpha/b \int_0^{\underline{z}} z dF(z;\sigma)/(1-\widetilde{F}(i, \underline{z}, \sigma))^2 & f(\underline{z};\sigma)(1-\alpha)/(1-\widetilde{F}(i, \underline{z}, \sigma))^2 \end{bmatrix}$$

and the partial derivatives as

$$\left[\frac{\partial \boldsymbol{\mathcal{D}}(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial cs}\right] = \begin{bmatrix} 0 \\ -1 \end{bmatrix},$$
$$\left[\frac{\partial \boldsymbol{\mathcal{D}}(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial \sigma}\right] = \begin{bmatrix} \int_{\underline{z}}^{\infty} z dF_\sigma(z;\sigma) \\ \widetilde{F}_\sigma(i, \underline{z}, \sigma)/(1-\widetilde{F}(i, \underline{z}, \sigma))^2 \end{bmatrix}.$$

To derive the comparative statics of interest, we only need two elements of $\left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial x_j}\right]^{-1}$. Thus, we get

$$\frac{\partial i}{\partial cs} = \left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial x_j}\right]^{-1}_{12} = -\frac{\underline{z}(1-\widetilde{F}(i, \underline{z}, \sigma))^2}{\alpha/i \int_0^{\underline{z}} z dF(z;\sigma) + \phi_{ii}(i)(1-\alpha)} \leq 0$$

and

$$\begin{aligned}
\frac{\partial i}{\partial \sigma} &= -\left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial x_j}\right]^{-1}_{11} \int_{\underline{z}}^{\infty} z dF_\sigma(z;\sigma) - \left[\frac{\partial \mathcal{D}_i(\mathbf{x}(\boldsymbol{\theta}), \boldsymbol{\theta})}{\partial x_j}\right]^{-1}_{12} \frac{\widetilde{F}_\sigma(i, \underline{z}, \sigma)}{(1-\widetilde{F}(i, \underline{z}, \sigma))^2} \\
&= \frac{(1-\alpha)\int_{\underline{z}}^{\infty} z dF_\sigma(z;\sigma)}{\alpha/i \int_0^{\underline{z}} z dF(z;\sigma) + \phi_{ii}(i)(1-\alpha)} + \frac{\underline{z}(1-\widetilde{F}(i, \underline{z}, \sigma))^2}{\alpha/i \int_0^{\underline{z}} z dF(z;\sigma) + \phi_{ii}(i)(1-\alpha)} \frac{\widetilde{F}_\sigma(i, \underline{z}, \sigma)}{(1-\widetilde{F}(i, \underline{z}, \sigma))^2} \\
&= \frac{(1-\alpha)\int_{\underline{z}}^{\infty} z dF_\sigma(z;\sigma) + \underline{z}\widetilde{F}_\sigma(i, \underline{z}, \sigma)}{\alpha/i \int_0^{\underline{z}} z dF(z;\sigma) + \phi_{ii}(i)(1-\alpha)} \\
&= \frac{(1-\alpha)\int_{\underline{z}}^{\infty} z dF_\sigma(z;\sigma) + \underline{z} F_\sigma(\underline{z};\sigma) - \alpha \int_0^{\underline{z}} z dF_\sigma(z;\sigma)}{\alpha/i \int_0^{\underline{z}} z dF(z;\sigma) + \phi_{ii}(i)(1-\alpha)} \\
&= \frac{\nu(\underline{z}, \sigma)}{\alpha/i \int_0^{\underline{z}} z dF(z;\sigma) + \phi_{ii}(i)(1-\alpha)} \geq 0.
\end{aligned}$$

E Endogenous Leverage Dynamics

In this appendix, we extend the framework of DeMarzo and He (2020) to include an investment function. We solve numerically the Markov perfect equilibrium and confirm that our results hold in Figure 1. We refer to DeMarzo and He (2020) for proofs of the existence and uniqueness of the Markov perfect equilibrium.

We assume that agents are risk neutral with an exogenous discount rate of $r > 0$. The firm's assets-in-place generate operating cash flow at the rate of Y_t, which evolves according to a geometric Brownian motion:

$$dY_t/Y_t = \mu_t dt + \sigma dZ_t,$$

where Z_t is a standard Brownian motion. A firm has at its disposal an investment technology with adjustment costs, such that $\iota_t Y_t$ spent allows the firm to grow its capital stock by $\mu(\iota_t)Y_t dt$, where $\mu(\cdot)$ is increasing and concave. Denote by B the aggregate face value of outstanding debt that pays a constant coupon rate of $c > 0$. The firm pays corporate taxes equal to $\pi(Y_t - cF_t)$. We assume that debt takes the form of exponentially maturing coupon bonds with a constant amortization rate ξ. Equity holders control outstanding debt B_t through an endogenous issuance/repurchase policy $d\Gamma_t$ but cannot commit to a policy. Thus, evolution of the outstanding face value of debt follows

$$dB_t = d\Gamma_t - \xi B_t dt.$$

In the unique Markov equilibrium, given debt price $p(Y, B)$, the firm's issuance policy $d\Gamma_t = G_t dt$, and default time τ, maximize the market value of equity:

$$\begin{aligned} E(Y, B) = \max_{\tau, \iota_t, G_t} \mathbb{E}_t \Bigg[\int_t^\tau e^{-r(s-t)} \big[(1 - \iota_s) Y_s - \pi(Y_s - cB_s) - (c + \xi) B_s \\ + G_s p_s \big] ds \Bigg| Y_t = Y, B_t = B \Bigg]. \end{aligned}$$

Similarly, the equilibrium market price of debt must satisfy

$$p(Y, B) = \mathbb{E}_t \left[\int_t^\tau e^{-(r+\xi)} (c + \xi) ds \middle| Y_t = Y, B_t = B \right].$$

The Hamilton-Jacobi-Bellman (HJB) equation for equity holders is

$$rE(Y,B) = \max_{\iota,G}\Big[(1-\iota)Y - \pi(Y-cB) - (c+\xi)B_s \tag{38}$$
$$+ Gp(Y,B) + (G-\xi B)E_B(Y,F) + \mu(\iota)YE_Y(Y,B) + \frac{1}{2}\sigma^2Y^2E_{YY}(Y,B)\Big].$$

Thus, in equilibrium it must be that

$$p(Y,B) = -E_B(Y,B).$$

The first-order condition for the investment rate is given by

$$1 = \mu_\iota(\iota)E_Y(Y,B).$$

In the following, we define $\{\iota(Y,B), G(Y,B)\}$ as

$$\{\iota(Y,B), G(Y,B)\} = \arg\max_{\iota,G}\Big[(1-\iota)Y - \pi(Y-cB) - (c+\xi)B_s$$
$$+ Gp(Y,B) + (G-\xi B)E_B(Y,F) + \mu(\iota)YE_Y(Y,B)$$
$$+ \frac{1}{2}\sigma^2Y^2E_{YY}(Y,B)\Big].$$

In this setting with scale-invariance, the relevant measure of leverage is given by

$$y_t \equiv Y_t/B_t,$$

and the equity value function $E(Y,B)$ and debt price $p(Y,B)$ satisfy

$$E(Y,B) = E\left(Y/B,1\right) \equiv e(y)B \quad \text{and} \quad p(Y,B) = p(Y/B,1) \equiv p(y).$$

We also define the following:

$$\iota(Y,B) \equiv \iota(y) \quad \text{and} \quad G(Y,B) \equiv g(y)B.$$

Thus, we can rewrite (38) as follows:

$$(r+\xi)e(y) = \max_{\iota}\left[(1-\iota)y - \pi(y-c) - (c+\xi) + (\mu(\iota)+\xi)ye'(y) + \frac{1}{2}\sigma^2 y^2 e''(y)\right]. \tag{39}$$

The optimal default boundary is such that

$$e'(y_b) = 0.$$

The higher bound is such that

$$e'(y) = \phi y - \rho,$$

which corresponds to the value of equity without a default option. We can solve for ϕ and ρ with

$$(r+\xi)(\phi y - \rho) = \max_{\iota}\left[(1-\iota)y - \pi(y-c) - (c+\xi) + (\mu(\iota)+\xi)\phi y\right].$$

Thus,

$$\begin{aligned}
\rho &= \frac{(1-\tau)c+\xi}{r+\xi}, \\
\phi &= \frac{1-\iota^\star-\pi}{r-\mu(\iota^\star)}, \\
1 &= \mu'(\iota^\star)\phi.
\end{aligned}$$

The HJB for $p(Y,B)$ is given by

$$rp(Y,B) = c + \xi(1-p(Y,B)) + (G-\xi B)p_B(Y,B) + \mu(Y,B)Yp_Y(Y,B) + \frac{1}{2}\sigma^2 Y^2 p_{YY}(Y,B),$$

where we define $\mu(Y,B) \equiv \mu(\iota(Y,B)) \equiv \mu(y)$.

Thus, we can write the HJB for $p(y)$ as

$$rp(y) = c + \xi(1-p(y)) - (g(y)-\xi)p'(y)y + \mu(y)yp'(y) + \frac{1}{2}\sigma^2 y^2 p''(y), \tag{40}$$

where $g(y) = G(Y,B)/B$. We need $g(y)$ to be such that $p(y) = e'(y)y - e(y)$. From (39), we get

$$
\begin{aligned}
(r+\xi)e'(y)y = {} & (1-\iota(y))y - \pi y - \iota'(y)y^2 + (\mu(y)+\xi)y^2 e''(y) + (\mu(y)+\xi)ye'(y) + \mu'(y)y^2 e'(y) \\
& + \frac{1}{2}\sigma^2 y^3 e'''(y)) + \sigma^2 y^2 e''(y).
\end{aligned}
$$

Thus,

$$
\begin{aligned}
(r+\xi)(e'(y)y - e(y)) = {} & (1-\pi)c + \xi - \iota'(y)y^2 + (\mu(y)+\xi)ye''(y) + \mu'(y)y^2 e'(y) \\
& + \frac{1}{2}\sigma^2 y^2 e'''(y) + \frac{1}{2}\sigma^2 y^2 e''(y).
\end{aligned}
$$

Thus, $g(y)$ is such that

$$
\begin{aligned}
& c + \xi - (g(y) - \xi)p'(y)y + \mu(y)yp'(y) + \frac{1}{2}\sigma^2 y^2 p''(y) \\
& = (1-\pi)c + \xi - \iota'(y)y^2 + (\mu(y)+\xi)y^2 e''(y) + \mu'(y)y^2 e'(y) \\
& + \frac{1}{2}\sigma^2 y^3 e'''(y)) + \frac{1}{2}\sigma^2 y^2 e''(y).
\end{aligned}
$$

With further algebra, we get

$$
-gp'(y)y = -\pi c - \iota'(y)y^2 + \mu'(y)y^2 e'(y).
$$

Since $\mu'(\iota)e'(y) = 1$ and $\mu'(y) = \mu'(\iota)\iota'(y)$, we get

$$
g(y) = \frac{\pi c}{p'(y)y}.
$$

Plugging the solution for $g(y)$ into (40) yields

$$
(r+\xi)p(y) = (1-\pi)c + \xi + (\mu(y)+\xi)yp'(y) + \frac{1}{2}\sigma^2 y^2 p''(y).
$$

We solve numerically for the solution using ODE45 in Matlab. We use the following pseudo-algorithm.

1. Start with $y_L = 0$ and $y_H = H$, where H is a sufficiently large number.

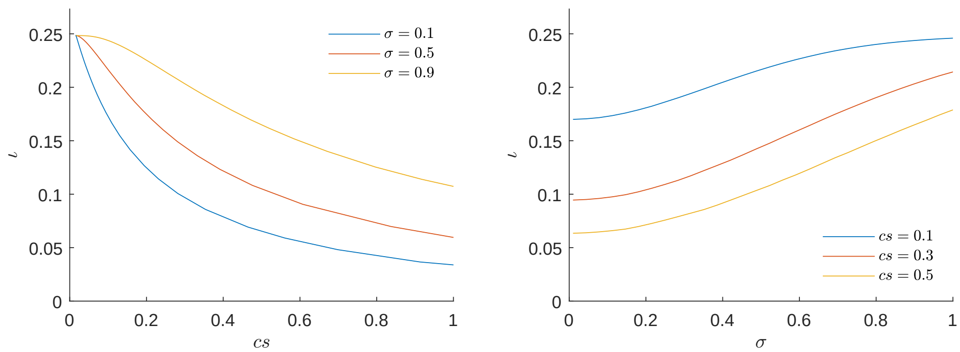

Figure 1: Optimal investment in dynamic setting with $\mu(\iota) = \frac{\log(1+\kappa\iota)}{\kappa}$, $\kappa = 100$, $r = 0.05$, $\xi = 1/8$, $c = 0.05$, $\pi = 0.3$.

2. Given $y_b = 1/2(y_L + y_H)$, $e(y_b) = 0$, and $e'(y_b) = 0$, we solve for $e(y)$ on $[y_b, y_B]$ where Y_B is a large number.

3. Check if $|e(Y_B) - (\phi y_B - \rho)| \leq \varepsilon$, where $\varepsilon > 0$ is a small number. If $e(Y_B) - (\phi y_B - \rho) > \varepsilon$, set $y_L = y_b$ and repeat 2-3. If $e(y_B) - (\phi y_B - \rho) < -\varepsilon$, set $y_H = y_b$ and repeat 2-3. Otherwise, move to 4.

4. Start with $pp_L = 0$ and $pp_H = H$, where H is a sufficiently large number.

5. Given $pp_b = 1/2(pp_L + pp_H)$, $p(y_b) = 0$, $p'(y_b) = pp_b$ we solve for $p(y)$ on $[y_b, y_B]$.

6. Check if $|p(y_B) - \rho| \leq \varepsilon$. If $p(Y_B) - \rho > \varepsilon$, set $p_H = p_b$ and repeat 2-3. If $p(y_B) - \rho < -\varepsilon$, set $pp_L = pp_b$ and repeat 4-5. Otherwise, move to 7.

7. Check if $|p'(y_b) - e''(y_b)y_b| \leq \varepsilon$. If not, increase the precision of the ODE45 solver and restart from 1.