Distress Risk, Bargaining Power, and Stock Returns*

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Abstract

We develop and test an agency-based contingent claims model that features debt renegotiation for cross-sectional stock returns. Our model performs well for cross-sectional returns of portfolios formed on financial leverage, book-to-market equity, and asset growth portfolios, because the time-varying stock-cash flow sensitivity we estimate in a closed-form solution captures default risk over the business cycle. Moreover, our structural estimation overcomes the difficulty of finding empirical proxies for unobservable bargaining power at debt renegotiation and provides the first direct evidence that the bargaining power helps alleviate equity risk, particularly during recessions when default probabilities are high.

Keywords: Stock-cash flow sensitivity, debt renegotiation, bargaining power, structural estimation, financial leverage, default probability, implied-state GMM
JEL Classification: G12, G13, G33

Equity is a residual claim contingent on a firm's assets that generate operating cash flows. Equity holders with bargaining power are able to receive a fraction of assets at bankruptcy.[1] Using this fundamental insight, we build an agency-based contingent claims model that features debt renegotiation for cross-sectional stock returns. In the model, excess stock returns are excess cash flow rates scaled by the sensitivities of stocks to cash flows. The sensitivities are determined by dividend payout and bargaining power because both of them affect the amount of cash flows accruing to equity holders. We test the model via a variant of implied state generalized method of moments. Our model performs well in explaining the cross-sectional returns for portfolios formed on market leverage, book-to-market equity, and asset growth rate. The reasonable performance of our model can be attributed to our innovative structural estimation for risk premiums and the stock-cash flow sensitivities that capture cross-sectional and time series variation in default risk.

All the three sets of portfolios are related to default risk. The first set is portfolios formed on market leverage, which are are natural choices because equity is a residual claim on operating cash flows after contractual debt payments. Fama and French (1992) show the positive relation between market leverage and stock returns. Ferguson and Shockley (2003) link the leverage with financial distress and show their implications for cross-sectional stock returns. Our second set of testing portfolios is book-to-market portfolios. Gomes and Schmid (2010) show that value firms have accumulated more debt and book assets during their expansions and exhibit lower growth rates than growth firms do. Choi (2013) provides empirical evidence that the value premium is driven by financial leverage instead of operating leverage. The last set is asset growth portfolios documented by Cooper, Gulen, and Schill (2008). They find that firms with low-asset growth rates outperform their counterparts with high-growth rates by 8% per year for value-weighted portfolios and 20% per year for equal-weighted portfolios. Avramov, Jostova, and Philipov (2007) relate this premium to default risk.

Our model outperforms the capital asset pricing model (CAPM), and the Fama–French three-factor model (Fama and French 1992), and the q-factor model (Hou et al. 2015) because the default-risk related portfolios suits our contingent claims model. For the market leverage portfolios, the pricing error of the high-minus-low (H–L) portfolio is 1.61% per year, much lower than 12.59% in the CAPM, 3.32% in the Fama–French model, and 1.88% in the q-factor model. The mean absolute error (m.a.e.) across the five portfolios is 0.80% per year, compared with 8.93% in the CAPM, 3.62% in the Fama–French model, and 1.88% in the

[1]A number of empirical papers find evidence that equity holders recover a considerable fraction of assets at bankruptcy, including Gilson, John, and Lang (1990), Franks and Torous (1989), and Asquith, Gertner, and Scharfstein (1994). Roberts and Sufi (2009) find that renegotiation also occurs before debt maturities and is partially controlled by the contractual assignment of bargaining power.

q-factor model. For the book-to-market portfolios, the pricing error of the H–L portfolio in our model is 1.79% per year, which is substantially lower than 15.31% in the CAPM, 7.65% in the Fama–French model and 7.33% in the q-factor model. For the asset growth portfolios, the m.a.e. in our model is 2.09% per year, which is considerably lower than 9.17% in the CAPM, 4.24% in the Fama–French model, and 2.90% in the q-factor model. In short, our model performs best for the leverage portfolios, followed by the book-to-market portfolios, and then the asset growth portfolios.

We then explore the economic mechanism behind the model's good fit, and have three new insights. First, our results show that stock returns increase with the risk premium of the operating cash flows. We provide a closed-form solution to show that the cash flow risk premium in our model is driven by default risk, because it is determined by the difference in the risk-neutral and physical default probabilities. It is well known that, for a risk-averse agent, the risk-neutral probability of default is higher than the objective probability. Therefore, the difference between these two probabilities is positively related to default risk. Empirically, we estimate the risk premium of cash flows as the difference between the actual rate and the risk-neutral rate of cash flows. The latent risk-neutral growth rate of cash flows is from our structural estimation, and the actual growth rate is proxied by the time series average of the observed rates of cash flows. We document that high-leverage firms, value firms, and low asset growth firms receive a greater risk premium than low-leverage firms, growth firms and high asset growth firms. However, the spreads in cash flow risk premiums between the high- and low- quantile portfolios are similar and small, about 3%, which is not big enough to explain the much larger spread in stock risk premium, about 13%, for all the three sets of portfolios. We then turn to the stock-cash flow sensitivity in our model.

Second, our structural estimation shows that the stock-cash flow sensitivity carries information on default probability over the business cycle. It is important to note that equity holders do not necessarily bear all the default risk of a firm. Indeed, by renegotiating with debt holders strategically, they are able to shift the risk to debt holders and make themselves less sensitive to the default risk. Equity risk premium they demand is based on their exposure to the default risk, which is proxied by the time-varying stock-cash flow sensitivity. We calculate the sensitivity based on a closed-form solution from our parsimonious model and find that stocks are more sensitive to the changing cash flows in bad times when default probabilities are high. Our key finding is that the spread in the stock-cash flow sensitivities, instead of the spread in default premium, is able to explain a large portion of cross-sectional variation in stock returns for the market leverage and book-to-market portfolios, but a relatively small fraction for asset growth portfolios. The modest performance of asset growth portfolios relative to other two sets of portfolios can be attributed to the small spread in risk-neutral default probability and therefore the small spread in the sensitivity.

Third, our counterfactual estimation demonstrates that the unobservable bargaining power significantly alleviates equity risk, proxied by stock-cash flow sensitivity, because equity holders with bargaining power can recover receive a fraction of firm value at bankruptcy. The structural estimate of bargaining power from a sample of 15 portfolios is 0.58, which is economically and statistically significant. Our structural model allows us to use a counterfactual parameter value to examine the changes in pricing errors, default probability and stock-cash flow sensitivity. For example, by setting bargaining power to zero, we find that the equity risk significantly increases for portfolios with high default probability, such as high-leverage and value portfolios. For the high-leverage portfolio, the stock-cash flow sensitivity increases from 1.63 to 2.12 by 0.49, and the increase is 0.36 in expansions and 0.89 in recessions, respectively. For the value portfolio, the sensitivity increases from 1.54 to 1.85 by 0.31, and the increase is 0.22 in expansions and 0.63 in recessions. Therefore, the increases in the stock-cash flow sensitivities indicate that the bargaining power significantly alleviates the equity risk, particularly in recessions.

Our work is related to three strands of the literature. The first strand is on the pricing of default risk. The empirical evidence on the default or distress risk premium is mixed.[2] A recent study by Friewald, Wagner, and Zechner (2014) points out the potential problem for obtaining the mixed evidence is that the aforementioned papers use the physical default probability but omit the risk-neutral probability. They estimate the default risk premium from CDS spreads, and then show that stock returns increase with the estimated premium. We complement their study by emphasizing the risk-neutral default probability, instead of the physical default probability alone, in evaluating risk premium from stock returns. However, we differ from Friewald et al. (2014) in three perspectives. First, we estimate the risk premium from stock returns, instead of CDS spreads. Second, we deliver an analytical solution to explicitly connect the default probability with risk premium for our model that emphasizes debt renegotiation. Third, we find that the variation in the stock-cash flow sensitivities is more important than that in the risk premiums to explain the cross-section of stock returns in our comparative static study. Additionally, in the same spirit of Almeida and Philippon (2007) that use the risk-neutral probability to estimate the expected distress costs, we use it to calculate the expected value of recovered value for equity holders in the stock-cash flow sensitivity.

The second strand is the emerging literature using agency-based models to study cross-

[2]For examples, Vassalou and Xing (2004) use the Merton (1974) model and document the positive relation between the physical default probability and stock returns. Dichev (1998), Griffin and Lemmon (2002) and Campbell, Hilscher, and Szilagyi (2008) find the negative relation between them.

sectional stock returns. Most of the dynamic models use investment and financing frictions to explain the asset pricing (Berk, Green, and Naik 1999; Gomes 2001; Bhamra, Kuehn, and Strebulaev 2010). Recently, Favara, Schroth, and Valta (2011), Valta (2014) and Hackbarth, Haselmann, and Schoenherr (2015) deliberately abstract from investment and financing policies and applies debt renegotiation to studying stock returns. We follow them and focus on the bargaining game between equity and debt holders. Different from them that need good empirical proxies for the strength of bargaining power at renegotiation in their regression analysis, we directly estimate the strength of bargaining power from stock returns using structural estimation. Indeed, our estimate of bargaining power, 0.58, from a sample of 15 portfolios is economically and statistically significant, therefore providing direct support for this strand of agency-based models. We further demonstrate the significant impacts from bargaining power on equity risk.

The third strand of the literature uses structural estimation to quantify the performance of the dynamic models. Structural models of capital structure have received a lot of attention recently (e.g., Leland 1994; Goldstein, Ju, and Leland (2001); Hennessy and Whited 2005; Hennessy and Whited 2007; Strebulaev 2007). Strebulaev and Whited (2011) review the dynamic models and structural estimation in capital structure and investments. For example, Cochrane (1996) use GMM to study the implications of neoclassical investment model for stock returns. Compared with their discrete-time models, our continuous-time model of default risk faces the well-known difficulty in estimating the latent variables, such as the risk-neutral growth rate and volatility of the underlying asset or cash flow process. The IS-GMM procedure we adapt overcomes this difficulty. We contribute to this literature by providing a new estimation method for the continuous-time models.

The remainder of this paper proceeds as follows. Section 1 presents the agency-based contingent claims model. Section 2 explains the empirical specifications and procedures. Section 3 describes the data and empirical measures. Section 4 adapts IS-GMM to estimate the model and then examines the underlying mechanism in the stock-cash flow sensitivity. Section 5 concludes the paper.

1 A Contingent Claims Model of Stock Returns

We start by developing a standard contingent claims model and then discuss how to take the model to the data.

1.1 Model

Consider an economy with a large number of firms, indexed by subscript i. Following Hennessy and Tserlukevich (2008), we assume that *productivity-adjusted* capital assets, K_{it}, for a firm, i, are governed by the following stochastic differential equation:

$$\frac{dK_{it}}{K_{it}} = \hat{\mu}_i dt + \sigma_i d\hat{W}_{it}, \tag{1}$$

where $\hat{\mu}_i$ is the expected growth rate, σ_i is the instantaneous volatility parameter, and $\hat{W}_{it}$ is a standard Brownian motion. The expected growth rate of productive assets, $\hat{\mu}_i = \delta_i - \xi_i$, where δ_i is the investment rate and ξ_i is the depreciation rate. While the accumulation of assets is determined by the capital investment and deprecation, but not necessarily all the existing capitals are actively producing goods.

Given a "AK" production technology (e.g., Cox, Ingersoll, and Ross 1985), the *productive* assets generate operating cash flows, X_{it}, at a constant rate of $A_i > 0$, i.e., $X_{it} = A_i K_{it}$.[3] Because cash flows are proportional to capital assets, they have the same lognormal dynamics. Hence, the observable rates of cash flows, $r_{it}^X \equiv dX_{it}/X_{it}$, are as follows:

$$\frac{dX_{it}}{X_{it}} = \hat{\mu}_i dt + \sigma_i d\hat{W}_{it}. \tag{2}$$

The cash flows are expected to grow at the same rate, $\hat{\mu}_i$, as the assets. The counterpart of $\hat{\mu}_i$ under the risk-neutral probability measure is $\mu_i = \hat{\mu}_i - \lambda_i$, where λ_i is the risk premium.

At time 0, firm i chooses its optimal capital structure by issuing a perpetual bond of B_i with a coupon payment of C_i. The cash flows are taxed at an effective rate, τ_{eff}. At any date t, the firm first uses the operating cash flows to pay coupons and taxes, and receives a net income, $NI_{it} = (X_{it} - C_i)(1 - \tau_{eff})$. Then, it distributes a fraction θ of the net income back to equity holders as dividends, i.e., $D_{it} = \theta NI_{it}$, and uses the rest to make an investment of $\delta_i K_{it}$. In the spirit of Cochrane (1996), we assume the dividend-net income ratio, θ, is the same across all the firms.[4]

The firm has an option to default, which leads to either immediate liquidation or debt renegotiation. Upon liquidation, debt holders take over the remaining assets and liquidate them at a fractional cost of α. Renegotiation incurs a constant fraction $\kappa < \alpha$ of the assets. Because liquidation is more costly than renegotiation, debt holders are willing to renegotiate

[3] The "AK" technology is a special case of the Cobb-Douglas production function with constant returns to scale.

[4] In our empirical implementation, we first follow Liu, Whited, and Zhang (2009) and estimate different θ separately for three individual sets of portfolios, and then restrict θ to be equalized across all the sets of portfolios.

with equity holders. Renegotiation surplus $\alpha - \kappa > 0$ is then shared between equity and debt holders. Equity holders are able to extract a fraction η of the surplus, with $\eta \leq 1$ denoting their bargaining power.

Equity holders determine an optimal bankruptcy threshold X_{iB} to maximize the equity value $E_{it}(X_{it})$ that leads to the following conditions:

$$E_{it}(X_{iB}) = \eta(\alpha - \kappa)\frac{X_{iB}(1-\tau_{eff})}{r - \mu_i}, \tag{3}$$

$$\frac{\partial E_{it}}{\partial X_{it}}\Big|_{X_{it}=X_{iB}} = \eta(\alpha - \kappa)\frac{(1-\tau_{eff})}{r - \mu_i}, \tag{4}$$

where r is the risk-free rate. Equation (3) is the value-matching condition, which states the equity holders' payoff in renegotiation. Equation (4) is the standard smooth-pasting condition that enables equity holders to choose the optimal X_{iB} to exercise their bankruptcy option (Harrison 1985; Leland 1994).

In Proposition 1 we derive instantaneous stock returns, r_{it}^M, implied by our contingent claims model.

Proposition 1 *For $X_{it} \geq X_{iB}$, the instantaneous stock return r_{it}^M of firm, i, at time t is*

$$r_{it}^M = rdt + \epsilon_{it}(r_{it}^X - \mu_i dt), \tag{5}$$

and the instantaneous stock volatility

$$\sigma_{it}^M = \epsilon_{it}\sigma_i, \tag{6}$$

where ϵ_{it} is the sensitivity of stock to cash flows:

$$\begin{aligned} \epsilon_{it} =& \frac{X_{it}\partial E_{it}}{E_{it}\partial X_{it}} \\ =& 1 + \underbrace{\frac{C_i/r}{E_{it}}\theta(1-\tau_{eff})}_{\textit{Financial leverage (+)}} - \underbrace{\frac{(1-\omega_i)}{E_{it}}\left[\frac{C_i}{r}\theta + \frac{X_{iB}}{r-\mu_i}(\eta(\alpha-\kappa)-\theta)\right](1-\tau_{eff})\pi_{it}}_{\textit{Option to go bankrupt (+)}}, \end{aligned} \tag{7}$$

and E_{it} is the equity value

$$E_{it} = \left[\left(\frac{X_{it}}{r-\mu_i} - \frac{C_i}{r}\right)\theta + (\frac{C_i}{r}\theta + \frac{X_{iB}}{r-\mu_i}(\eta(\alpha-\kappa)-\theta))\pi_{it}\right](1-\tau_{eff}). \tag{8}$$

where $\pi_{it} \equiv (\frac{X_{it}}{X_{iB}})^{\omega_i}$ is the risk-neutral default probability, and $\omega_i < 0$ is given in equation

(A12) *of the Appendix. The optimal bankruptcy threshold is given by*

$$X_B = \frac{\theta\omega(C/r)}{(\omega-1)} \frac{r-\mu}{\theta - \eta(\alpha-\kappa)}. \tag{9}$$

Proof: See the Appendix.

Equation (5) states that the model-predicted stock return r_{it}^M is the risk-free rate rdt plus an excess cash flow rate, $r_{it}^X - \mu_i dt$, scaled by the stock-cash flow sensitivity ϵ_{it}. The expected excess cash flow rate is the risk premium of cash flow rates, i.e., $\mathbb{E}(r_{it}^X - \mu_i dt) = \lambda_i dt$. Moreover, as shown in equation (6), the instantaneous stock return volatility σ_{it}^M is the cash flow volatility amplified by the time-varying sensitivity. While the underlying cash flow volatility σ_i is constant, σ_{it}^M is changing over time depending on the sensitivity ϵ_{it}.

The stock-cash flow sensitivity ϵ_{it} in equation (7) plays an important role in connecting the expected stock return, r_{it}^M, with the cash flow rates, r_{it}^X. It consists of three components. The first one is the cash flow sensitivity, which is normalized to one. The second component is the well-known financial leverage effect, because C_i/r is equivalent to the value of a perpetual risk-free bond. The dividend–net income ratio, θ, amplifies this financial leverage effect. Intuitively, equity holders leverage up their positions by issuing more debt. The greater fraction θ equity holders can claim from their leveraged position, the more sensitive their claims are to the fluctuating cash flows. To illustrate the impact of θ on the stock-cash flow sensitivity, we calibrate this model using standard parameter values. Panel A of Figure 1 shows that, consistent with this intuition, the stock-cash flow sensitivity significantly increases with the dividend–net income ratio.

The option to go bankrupt gives rise to the last component of equation (7). The strategic default policy, X_{iB}, is affected by equity holders' bargaining power η at bankruptcy. The higher η, the more asset value equity holders can extract through debt renegotiation. Therefore, their claim becomes less sensitive to the decline in cash flows at bankruptcy and has less exposure to downside risk.[5] Consistent with this reasoning, stock-cash flow sensitivity declines monotonically with bargaining power, as shown in Panel B of Figure 1.

Note that the stock-cash flow sensitivity does not necessarily decrease with the risk-neutral probability of default, $\pi_{it} \equiv (X_{it}/X_{iB})^{\omega_i}$. Their relationship depends on the relative effect of financial leverage and the option to default. Consider two opposite cases: one when the firm is very healthy and another when the firm is distressed. In the first case,

[5] Equity holders with greater bargaining power are willing to file for bankruptcy earlier than their counterparts with relatively lower bargaining power. Garlappi and Yan (2011) show that the bargaining power helps us understand the hump-shaped relationship between default probability and cross-sectional stock returns. Favara et al. (2011) provide international evidence regarding the negative impact of bargaining power on equity risk.

X_{it} is very large and a decrease in its value only slightly increases the likelihood of default. However, at the same time, it increases the financial leverage component by decreasing its denominator, E_{it}. Because the small increase in π_{it} is negligible for the healthy firms, the increase in financial leverage dominates and therefore boosts the stock-cash flow sensitivity. Therefore, the higher default probability appears to be positively associated with the stock-cash flow sensitivity for the healthy firms. In the second case, X_{it} is close to the default boundary. The put option to go bankrupt becomes more valuable to the distressed firms when π_{it} increases. As a result, stocks with this embedded put option become less sensitive to the decrease in cash flows. Hence, the negative effect of the default option dominates the positive effect of leverage, resulting in a negative association between π_{it} and ϵ_{it} among the distressed firms. Consistent with this intuition, Garlappi and Yan (2011) identify an inverted U-shaped relationship between π_{it} and ϵ_{it}.

1.2 Default-related risk premium

To establish the link between the default risk premium with the default probability as in Duffie and Singleton (2012), we simplify our model and consider a special case where the risk-neutral growth rate is close to the risk-free rate. The following corollary connect the instantaneous stock return with default risk.

Corollary 1 *If the risk-neutral rate $\mu_i \to r$, the instantaneous stock return r^M_{it} of firm, i, at time t for $X_{it} \geq X_{iB}$ is*

$$\begin{aligned} r^M_{it} =& rdt + \epsilon_{it}\left(\lambda_i dt + \sigma_i d\hat{W}_{it}\right), \qquad (10)\\ =& rdt + \epsilon_{it}\left[\left(\frac{log(\pi_{it}) - log(\hat{\pi}_{it})}{log(X_{it}) - log(X_{iB})} + 1\right)\frac{\sigma_i^2}{2}dt + \sigma_i d\hat{W}_{it}\right]. \qquad (11)\end{aligned}$$

where $\hat{\pi}_{it} \equiv (\frac{X_{it}}{X_{iB}})^{\hat{\omega}_i}$ is the physical (actual) default probability, and $\hat{\omega}_i < 0$ is defined in the Appendix.

Under the simplified assumption, we explicitly shows that the risk premium of the underlying cash flows is given by $[(log(\pi_{it}) - log(\hat{\pi}_{it}))/(log(X_{it}) - log(X_{iB})) + 1]\sigma_i^2/2$ and is indeed related to the default risk. It is intuitive that the risk-neutral probability of default exceeds its actual proability for a risk-averse agent, i.e., $log(\pi_{it}) - log(\hat{\pi}_{it})$. Combined with the condition of $X_{it} \geq X_{iB}$, the model implies a positive risk premium λ_i. We call λ_i the default-related risk premium in this framework, because the default risk is not the only driving force of this risk premium.

2 Empirical Design and Specification

2.1 Overview

To take the model to the data, we need to estimate the risk premium of the cash flow rates, $\lambda_i dt$, which can be modeled in the standard asset pricing frameworks. In the CAPM,

$$\lambda_i dt = \beta_i^X \mathbb{E}(r_t^m - rdt), \tag{12}$$

where β_i^X is the market beta of cash flows and r_t^m is the market return. Favara et al. (2011) assume the same β_i^X across all the stocks and label ϵ_{it} the stock market beta. We do not estimate β_i^X because the market return r_t^m is unobservable (Roll, 1977) and different estimation windows and data frequencies could result in lower estimation power. Rather, we directly use the observable operating cash flows as our state variable and assume that they capture the market movement. This approach is similar to Cochrane (1996), who infers real macroeconomic shocks from firms' investment returns.

We test the equality between the observed stock returns, r_{it+1}^S, and the predicted returns from our contingent claim model, r_{it+1}^M, at the portfolio level as follows:

$$\mathbb{E}[r_{it+1}^S - r_{it+1}^M] = 0, \tag{13}$$

where $\mathbb{E}[.]$ is an unconditional mean operator and $\mathbb{E}_t[.]$ is a conditional mean operator for a time series. We adapt IS-GMM to test the model.[6]

Assume that the model holds for each time t. To construct the predicted return r_{it+1}^M in equation (5), we take constant values of the market-wide variables from recent studies (e.g., Carlson, Fisher, and Giammarino 2004; Morellec, Nikolov, and Schrhoff 2012), including r, α, κ, and τ_{eff}, and obtain the firm- and time- specific variablessuch as X_{it}, C_i, and E_{it} from the data.[7]

The latent parameters, μ_i and σ_i, and, the two policy parameters, θ and η, are to be estimated. We first discuss the procedure of how to back out the risk-neutral rate μ_i and the cash flow volatility σ_i in Section 2.2 and then present our adapted IS-GMM procedure on how to estimate θ and η in Section 2.3. Because we use the first moment of stock returns to estimate the two policy parameters and use their second moment to back out the implied cash flow volatility, we essentially jointly match the first and second moments of stock returns.

[6]The consistency and asymptotic normality of the IS-GMM estimators can be found in the Appendix of Pan (2002).

[7]We take the coupon (or its associated debt) exogenously, because it is well known that a simple structural model is not able to generate a low financial leverage observed in the data (Huang and Huang, 2003).

2.2 Unobservable risk-neutral cash flow rate and volatility

The parameters of cash flows, μ_i and σ_i, are not observable. Using the IS-GMM procedure proposed by Pan (2002), we back out μ_i and σ_i from the observable market capitalization S_{it} and stock return volatility σ_{it}^S. In her IS-GMM procedure, the latent stock return volatility is the second time-varying state variable in the European stock option model. In contrast, both the latent risk-neutral rate and volatility of cash flows are constant in our American option framework. The constant parameters enable us to obtain the closed-form solution for the optimal default threshold for the American option of going into bankruptcy. Our procedure is also in the spirit of the commonly used Moody's KMV method of credit risk (Crosbie and Bohn, 2003). See e.g., Vassalou and Xing (2004); Bharath and Shumway (2008); Davydenko and Strebulaev (2007).

Before finding the true values of θ and η, we initialize a pair of trial values for them in each IS-GMM iteration loop, which we discuss further in the next section. Combining the trivial values with the information set $\Theta_{it} = (X_{it}, C_{it}, S_{it}, \sigma_{it}^S, r, \alpha, \kappa, \tau_{eff})$, we solve the following system of two equations for the two unknowns, $\mu_i(\theta, \eta, \Theta_{it})$ and $\sigma_i(\theta, \eta, \Theta_{it})$:

$$\overline{S_{it}} = \overline{E_{it}}; \tag{14}$$

$$\overline{\sigma_{it}^S} = \overline{\sigma_{it}^M}. \tag{15}$$

Equation (14) states that the average of observed equity values equals that of predicted equity values, and equation (15) shows the average of the observed volatility of stock returns equals that of predicted volatility. In an early version, we estimate equity value and volatility year by year and obtain time-varying cash flow rate and volatility. The results estimating the time-varying rate and volatility are qualitatively similar. S_{it} and σ_{it}^S and obtained from the data, while E_{it} and σ_{it}^M are calculated from equations (8) and (6). Therefore, by combining equation (13) with (15), we effectively jointly test both first and second moments of stock returns.

2.3 IS-GMM framework

Given the implied μ_i and σ_i for each period t, the discrete-time version of the predict return from equation (5) is:

$$r_{it+1}^M = r\Delta t + \epsilon_{it+1}\left(\frac{\Delta X_{it+1}}{X_{it}} - \mu_i \Delta t\right), \tag{16}$$

where ϵ_{it+1} is the expected stock-cash flow sensitivity of $t+1$ given the information up to the end of June of each year t.

We test the model at the annual frequency ($\Delta t = 1$). Our results hold when we test the model at the quarterly frequency and are reported in the Internet Appendix. In addition to potential specification errors, this discretization might suffer from measurement errors (Lo 1986).[8] However, we can still test the weak condition of equations (13) as in Cochrane (1991) and Liu et al. (2009). Our results in the Internet Appendix show that our main results still hold when the model is tested at the quarterly frequency.

Denote $\mathbf{b} \equiv [\theta, \eta]'$. The pricing error for each portfolio i at time t is:

$$e_{it}^M(\mathbf{b}, \Theta_{it}) \equiv e_{it}^M(\mathbf{b}, \Theta_{it}, \mu_i(\mathbf{b}, \Theta_{it}), \sigma_i(\mathbf{b}, \Theta_{it})) = r_{it+1}^S - r_{it+1}^M \tag{17}$$

and the expected pricing error for each portfolio, i, is:

$$\begin{aligned} e_i^M &= \mathbb{E}[e_{it}^M(\mathbf{b}, \Theta_{it})] \\ &= \mathbb{E}[r_{it+1}^S - r_{it+1}^M] \\ &= \mathbb{E}[r_{it+1}^S - (r + \epsilon_{it+1}(r_{it+1}^X - \mu_i))]. \end{aligned} \tag{18}$$

The sample moments of pricing errors are $\mathbf{g}_T = [e_1^M ... e_n^M]'$, where n is the number of testing portfolios. If the model is correctly specified and empirical measures are accurate, $\mathbf{g}_T$ converges to zero for an infinite sample size. Both measurement and specification errors contribute to the expected pricing errors. Under the weak condition of equation (13), the objective of the IS-GMM procedure is to choose a parameter vector, $\mathbf{b}$, to minimize a weighted sum of squared errors (Pan 2002):

$$J_T = \mathbf{g}_T' \mathbf{W} \mathbf{g}_T, \tag{19}$$

$$\text{s.t. } 0 < \theta \leq 1, \tag{20}$$

$$0 < \eta \leq 1, \tag{21}$$

where $\mathbf{W}$ is a positive-definite symmetric weighting matrix. Until the optimal parameter vector $\mathbf{b} \equiv [\theta, \eta]'$ is found, both μ_i and σ_i are recalculated for each trial set of $\mathbf{b}$ in the IS-GMM optimization loops. Following Cochrane (1991), we choose an identity matrix $\mathbf{W} = \mathbf{I}$ in one-stage IS-GMM. By weighting the pricing errors from individual portfolios equally, the identity-weighting matrix preserves the economic structure of the testing assets (Cochrane 1996).[9]

In summary, we back out μ_i and σ_i from observable stock price and stock return volatility

[8]For instance, equity is a convex function of underlying cash flows. The aggregation of cash flows at the portfolio level may induce a upward bias in equation valuation.

[9]A robustness check using two-stage IS-GMM is provided in the Internet Appendix.

and estimate the optimal values of θ and η using the following IS-GMM procedure:

1. A trial set of $\mathbf{b}_0 \equiv [\theta, \eta]'$ is initialized.

2. Given the initial values of $\mathbf{b}_0$ and information set of Θ_{it}, the expected μ_i and σ_i are solved from the system of equations (14) and (15) for each portfolio-year observation.

3. Given $\mathbf{b}_0$ and Θ_{it} as well as the implied $\mu_i(\mathbf{b}_0, \Theta_{it})$ and $\sigma_i(\mathbf{b}_0, \Theta_{it})$, ϵ_{it+1} and r^M_{it+1} are calculated based on equation (16), respectively.

4. The pricing error e^M_i for each portfolio is obtained from (18) and the objective value J_T in equation (19) across all the portfolios is calculated.

5. Repeat from Step 1 until the optimal vector $\mathbf{b} \equiv [\theta, \eta]'$ is found that minimizes J_T.

3 Data

We use daily and monthly stock returns from the Center for Research in Security Prices (CRSP), as well as the Compustat annual industrial files from 1964 to 2010. We exclude firms from the financial (SIC codes 6000 – 6999) and utility (SIC codes 4900 – 4999) sectors and include all the common stocks listed on the NYSE, AMEX, and NASDAQ with CRSP codes 10 or 11. For the Compustat data, we restrict the sample to firm-year observations with non-missing values for operating income, debt, and total assets and with positive total assets and debt. The three Fama–French factors are from Kenneth French's website. We follow Hou, Xue, and Zhang (2015) and construct the four q-factors for the investment-based asset pricing model, such as the market factor, a size factor, an investment factor, and a return on equity factor. Because of the limited availability of quarterly accounting data, the four q-factors are from 1972 to 2010.

3.1 Variable measurement and parameter values

For the market-wide variables, the effective tax rate τ_{eff} is set to 15%, the expected liquidation cost $\alpha = 0.45$, the renegotiation cost $\kappa = 0$, and the after-tax annual risk-free rate $r = 3.6\%$.[10]

[10] Andrade and Kaplan (1998) consider 31 distressed firms and find the costs of financial distress to be 10% – 20% of firm value. Korteweg (2010) finds bankruptcy costs amount to 15%–30%. Davydenko, Strebulaev, and Zhao (2012) find that the cost of default is 21.7% of the market value of assets. Different from the above papers, Glover (2015) argues that the bankruptcy costs estimated from defaulted firms are potentially downward biased because those firms are likely to have smaller costs of bankruptcy and endogenously choose high levels of debt, resulting in a high likelihood of default. He uses SMM to estimate a structural model and shows that average firms are expected to lose 45% of firm value at bankruptcy.

We follow Fama and French (1995) and Liu et al. (2009) and aggregate firm-specific characteristics to portfolio-level characteristics. The most important state variable in this study is the operating cash flows X_{it}. Following Glover (2015), we use operating income after depreciation (Compustat item OIADP) to proxy for the operating cash flows. The operating income observations are trimmed at the upper and lower one-percentiles to eliminate outliers and eradicate errors. S_{it} is the observed equity value (price per share times the number of shares outstanding) and coupon C_{it} is the total interest expenses (item XINT).[11] X_{it}, S_{it}, and C_{it} in year t are aggregated for all the firms in portfolio i formed in June of year t, while σ_{it}^S is the annualized standard deviation of daily returns of the stock portfolios from the beginning of July of year $t-1$ to the end of June of year t. r_{t+1}^X is the percentage change of the aggregate operating cash flows from year t to year $t+1$.

We use the observed operating income to proxy for X_{it}, and the updated, current coupon payment C_{it} at time t to proxy for C_i. The empirical counterpart of E_{it} is the observed equity market capitalization S_{it}, and the counterpart of σ_{it}^M is the annualized standard deviation of the past one-year daily returns σ_{it}^S.

3.2 Testing portfolios

We employ three sets of testing portfolios: five market leverage portfolios, five book-to-market portfolios, and five asset growth portfolios. We choose five portfolios for each asset pricing anomaly to ensure that the simultaneous equations (15) and (14) are solvable for all portfolio-year observations. We follow Liu et al. (2009) and Fama (1998) and use equal-weighted portfolios because these portfolios are more difficult to be explained by asset pricing models.

We follow Fama and French (1992) and construct stock portfolios with NYSE breakpoints for every set of portfolios. Based on the ranking variables calculated at the end of year $t-1$, we first sort firms into quintiles and then form equal-weighted portfolios at the end of each June of year t. Then, we rebalance them each June. Raw returns of equal-weighted portfolios are computed from the beginning of July of year t to the end of June of year $t+1$.

We use standard procedures to calculate ranking variables and form stock portfolios (Fama and French 1992, 1993). The first ranking variable is market leverage, which is calculated as book debt for the fiscal year ending in calendar year $t-1$ divided by the sum of book debt and market equity (ME) at the end of December of year $t-1$. Book debt is the sum of short-term debt (Computstat item DLC) and long-term debt (item DLTT). ME is price per share (CRSP item PRC) times the number of shares outstanding (item SHROUT).

[11]We use the most updated coupon payments instead of the fixed coupon payment.

Book-to-market equity (BE/ME) ratio is the variable of interest for the second set of portfolios. The ratio is calculated as book equity (BE) of the fiscal year ending in calendar year $t-1$ divided by the ME at the end of December of year $t-1$. The BE is the book value of equity (Computstat item CEQ) plus balance sheet deferred taxes (item TXDB) and investment tax credit (ITCB, if available), minus the book value of preferred stock. Depending on availability, we use redemption (item PSTKRV), liquidation (item RSTKL), or par value (item PSTK) in that order to estimate the book value of preferred stock. Observations with negative BE/ME are excluded.

The third variable considered is the asset growth rate for the asset growth portfolios. Following Cooper et al. (2008), the asset growth rate is the percentage change in total assets (Compustat item AT). The growth rate for year $t-1$ is the percentage change from the fiscal year ending in calendar year $t-2$ to the fiscal year ending in calendar year $t-1$.

3.3 Timing alignment

To match the observed stock returns r^S_{it+1} with the returns r^M_{it+1} predicted from our model, we follow Liu et al. (2009) and align the inputs with the observed stock returns in Figure 2. The only difference is that we need to incorporate the KMV procedure into the timing alignment.

To calculate the model-predicted returns, r^M_{it+1}, we need to obtain the operating cash flow rate, r^X_{it+1}, and estimate the expected stock-cash flow sensitivity, ϵ_{it+1} . First, to calculate r^X_{it+1}, we use the operating income X_{it} reported at the end of year t and year $t+1$ because operating incomes are realized over the course of a year. Therefore, r^X_{it+1} largely matches with r^S_{it+1} as in Liu et al. (2009). It is important to note that r^X_{it+1} is not the ranking variable so that we do not need to lag it. Instead, we test the instantaneous and contemporaneous no-arbitrage relationship between cash flows and stocks. Our results are qualitatively the same even if we lag r^X_{it+1} by three months.

Second, to estimate ϵ_{it+1}, we use the KMV procedure to obtain the expected μ_i and σ_i. The stock price S_{it} for calculating the equity value is at the end of June of year t and the stock return volatility σ^S_{it} is the annualized standard deviation of daily returns of the stock portfolios from the beginning of July of year $t-1$ to the end of June of year t. All the accounting variables used for the KMV procedure, including X_{it} and C_{it}, are at the end of year t.

In the Fama–French portfolio approach, the set of firms in a portfolio formed in year t is fixed from July of year t to June of year $t+1$ for each portfolio. The stock composition changes only at the end of June of year $t+1$ when the portfolios are rebalanced. Hence, we keep the same set of firms in the portfolio in the formation year t until the rebalancing year

$t + 1$.

4 Empirical Results

We start with verifying pricing errors in traditional models and presenting summary statistics for our model inputs. Then, we adapt IS-GMM to perform a structural estimation. We use the counterfactual parameter value to examine the importance of bargaining power and conduct comparative statics analysis to identify crucial factors. Lastly, we attempt to examine the stock-cash flow sensitivity over the business cycle.

4.1 Pricing errors from alternative models

We first confirm the well-known pricing errors in our data. Table 1 reports the averages of annualized monthly returns in percentages for equal-weighted quintile portfolios and for the high-minus-low (H–L) and small-minus-big (S–B) hedge portfolios. The pricing errors, such as e^C from the CAPM, e^{FF} from the Fama–French three-factor model, and e^q from the q-factor model, are estimated by regressing the time series of portfolio returns on the market factor, the three Fama–French factors, and the four q-factors.

Market leverage portfolio: Panel A shows that stocks with a high market leverage earn 13.23% per year more than stocks with low leverage. The pricing error of the H–L portfolio for the CAPM is 12.59% (t = 4.21) and decreases to 3.32% (t = 1.56) for the Fama–French model. The m.a.e. is 8.93% per year for the CAPM and decreases to 3.62% for the Fama–French model. These two decreases in pricing errors are consistent with the conclusion of Fama and French (1992) that the book-to-market factor is able to explain the cross-sectional returns of the market leverage portfolios. Similarly, the pricing error of the H–L portfolio and m.a.e. decrease to 1.88% (t = 0.54) and 1.88%, respectively, for the q-factor model.

BE/ME portfolios: The average returns in Panel B monotonically increase with the book-to-market ratio from 12.99% to 27.44% per year. After controlling for the market factor, the H–L portfolio earns 15.31% (t = 5.95) per year and the m.a.e. is 8.79%. The performance of the Fama–French model improves because the pricing error of the H–L portfolio decreases to 7.65% (t = 3.87) and the m.a.e. declines to 3.83%. The q-factor model shows a comparable performance to the Fama–French model. The pricing error of the H–L portfolio is 7.33% (t = 2.46) and the m.a.e. drops to 2.19%.

Asset growth portfolios: As shown in Panel C, high-growth firms earn 12.26% lower stock returns per year than low-growth firms.[12] This finding cannot be explained by the standard

[12] The difference is smaller than the difference of 20% per year documented by Cooper et al. (2008) because

CAPM, the Fama–French model and the q-theory of investment. The errors of the H–L portfolio from the CAPM, the Fama–French model and the q-factor model are -11.91% ($t = -6.29$), -10.50% ($t = -4.87$) and -8.67% ($t = -3.25$), respectively. The m.a.e.'s for asset growth portfolios are the greatest among all three sets of testing portfolios. The m.a.e. is 9.17% for the CAPM, 4.24% for the Fama–French model, and 2.90% for the q-factor model. The largest deviation, 10.90%, for the q-factor model is due to the low-growth portfolio.

Overall, we confirm the well-documented pricing errors from the alternative models in our data sample. The newly proposed q-factor model generally performs better than the traditional CAPM and the Fama–French model.

4.2 Summary statistics of model inputs and portfolio characteristics

In Table 2 we summarize main inputs and portfolio characteristics for the three sets of quintile portfolios. It reports the time series averages of earnings–price ratios, $\overline{X_{it}/S_{it}}$, and interest coverage ratios, $\overline{X_{it}/C_{it}}$. The latter measures the financial health of the firms and provides preliminary information about the financial leverage effect in the stock-cash flow sensitivity, as shown in the second component of equation (7).

Market leverage portfolios: Unlike the monotonically increasing stock returns across the market leverage portfolios, both the times series average of cash flow rates r^X_{it+1} and their correlations with the stock returns r^S_{it+1} are slightly U-shaped. Additionally, while $\overline{X_{it}/S_{it}}$ increases from 0.09 to 0.23, $\overline{X_{it}/C_{it}}$ dramatically declines from 21.00 to 2.12, implying that high-leverage firms have difficulties covering their interest expenses. The stock volatility $\overline{\sigma^S_{it}}$ is slightly U-shaped as well.

BE/ME portfolios: Similar to the market leverage portfolios, both r^X_{it+1} and $corr(r^X_{it+1}, r^S_{it+1})$ are slightly U-shaped. The *unconditional* correlation coefficient, $corr(r^X_{it+1}, r^S_{it+1})$, of the second quintile portfolio is negative, but its magnitude is small and statistically insignificant. The weak *unconditional* correlation between the cash flows rate and stock returns is not against the model, because our model connect cash flows rate with stock returns via the *conditional*, time-varying stock-cash flow sensitivity. The magnitude of the increase in $\overline{X_{it}/S_{it}}$ across the BE/ME portfolios is comparable to that across the market leverage portfolios too. $\overline{X_{it}/C_{it}}$ for the BE/ME portfolios declines from 9.77 to 3.14 and the decrease is considerably smaller than that in the market leverage portfolios.

Asset growth portfolios: The decrease in the earnings-price ratios across the asset growth portfolios is the opposite to the increases in the BE/ME portfolios, because low-growth

our sample requires positive debt and has other restrictions as well.

firms are more likely to be value firms with larger equity-in-place. The spread in the interest coverage ratios between the low-growth firms and the high-growth firms is only 1.67, the smallest difference among the three sets of portfolios.

Taken together, the cash flow rates changes with the ranking variables in the same direction as the average stock returns for all three sets of portfolios. The magnitude of the changes in the average cash flow rates is considerably smaller than that in the average stock returns, and the stock volatility is slightly U-shaped. Moreover, the spread in the interest coverage ratios is the greatest for the market leverage portfolios; it is the smallest for the asset growth portfolios.

4.3 Model estimation

Within the IS-GMM framework, we first estimate two parameters, dividend–net income ratio θ and shareholder bargaining power η for the three sets of portfolios separately. Then, we impose stricter condition and jointly estimate all the three sets of portfolios, because they are internally consistent. Firms with high book-to-market equity have accumulated more debt and therefore have more leverage; they have also exercised their growth options and exhibit lower growth rates.

Panel A of Table 3 reports the parameter estimates and χ^2 statistics for model fitness when we match the predicted returns with the observed returns, as in equation (13). As shown in Panel A, the estimates of dividend-net income ratio θ are 0.75, 0.63, and 0.80 for market leverage, book-to-market equity, and asset growth portfolios, respectively. Given an average price–earning ratio of 15 from the data, the estimated dividend–net income estimates suggest a dividend payout ratio of 0.04 to 0.06, consistent with the data. Their respective t-statistics indicate that the estimates are statistically significant at a 95% confidence level. This estimated value of η is 0.57, 0.44 and 0.00, for market leverage, book-to-market equity, and asset growth portfolios, respectively. Finally, when we pool all the three sets of portfolios together, the estimates of θ and η in the last column are 0.74 and 0.58, respectively. The estimate of 0.58 for η is close to the value of 0.5 chosen by Morellec et al. (2012) and the 0.6 assumed in Favara et al. (2011) in a Nash-bargaining game.

The χ^2 statistic, which tests whether all the model errors are jointly zero, gives an overall evaluation of model performance. For the sample of individual set of portfolios, the degrees of freedom (d.f.) are three because the number of moments (or portfolios) is five and the number of parameters is two. For the sample of all the three sets of portfolios, the d.f. is 13 because the number of moments (or portfolios) is 15 and the number of parameters is still two. The p-values of the χ^2 tests indicate that the model cannot be rejected for all three sets of testing portfolios, with a modest performance for the set of asset growth portfolios.

Panels B and C present the implied risk-neutral growth rate μ_i, and risk premium λ_i, respectively. The results on the left hand side of these two panels are from the estimation using individual set of portfolios, and those on the right hand side are using all the three sets of portfolios jointly. Because these two sets of results are almost identical, we discuss the estimates using the individual set of portfolios.

The risk-neutral rate μ_i does not contain information on the riskiness of the underlying operating cash flows, and is negatively correlated with the stocks returns according to equation (5). Note that the risk-neutral rate is not the risk-free rate, and can be different across assets. As shown in Panel B, all the μ_i's are all small and close to zero, consistent with the results obtained by Glover (2015). μ_i decreases by 1.08%, 1.16%, and 0.04% per year for the leverage, BE/ME and asset growth portfolios, respectively. These small spreads indicate that the large cross-sectional differences in stock returns are unlikely driven by the small differences in these risk-neutral rates.

To gain some insight into default-related risk premium as shown in Corollary 1, we use $\mathbb{E}(r_{it}^X)$ to approximate $\hat{\mu}_i$ and calculate the risk premium $\lambda_i = \mathbb{E}(r_{it}^X) - mu_i$. Panel C shows that the default-related risk premium of underlying cash flow increases in financial leverage and BE/ME, but declines in asset growth rate, suggesting that the underlying assets of firms with high leverage, BE/ME and low asset growth have greater exposure to default risk. Note that although this risk premium of the underlying assets is moving the same direction as stock returns along the ranking variable, their spread is only about 3%, which is not big enough to explain the large spread in stock returns for the three sets of stock portfolios.

Panel D reports the implied cash flow volatility σ_i. For the leverage portfolios, it declines significantly from 25.58% to 17.20%, confirming our conventional wisdom that firms with low operating risk have better access to debt markets and therefore have greater financial leverage. The same declining pattern applies to the BE/ME portfolios, because value firms accumulate debt during their expansion. However, the implied volatility increases slightly by 3.41% for asset growth portfolios.

Overall, our contingent claims model performs well for all the individual set of portfolios, with the modest performance for the set of asset growth portfolios. The relatively weak statistical significance could be attributed to our small data sample. Additionally, it is well-known that the consistent one-stage IS-GMM estimation gives relatively weaker statistical performance, compared to the efficient two-stage IS-GMM estimation shown in the Internet Appendix that delivers much higher t-statistics for the parameter estimates.

Because the estimates of θ, η, μ_i and σ_i using individual sets of portfolios are almost identical to those using all the three sets of portfolios, we opt to report the results using the parameter values estimated from the sample consisting of all the three sets of portfolios for the rest of the main text. Our unreported results using individual sets are slightly better.

4.4 Pricing errors from our contingent claims model

Using the joint estimates of θ, η, μ_i, and σ_i for the sample of three sets of portfolios in Table 3, we construct the model predicted returns r^M_{it+1} as in equation (16) and calculate the expected pricing error e^M_i as in equation (17) for each individual portfolio. Panel A of Table 4 reports the pricing errors from our model and compares the errors with those from the alternative models. Although we evaluate the traditional models with standard ordinary least squares (OLS) regression, we can compare the models because OLS is essentially the same as one-stage GMM with an identity-weighting matrix in our structural estimation. However, we are not able to compare the models.

Market leverage portfolios: The first row shows that the pricing errors vary from -1.54% to 1.07% per year. Additionally, the pricing error of the H–L portfolio is 1.61% ($t = 1.01$), which is not statistically significant. This error is smaller than 12.59% from the CAPM, 3.32% from the Fama–French model, and 1.88% from the q-factor model in Table 1. Figure 3 visually illustrates the model fitness and pricing errors. We plot the average predicted returns against their realized returns for the contingent claims model, the CAPM, and the Fama–French model. If a model fits the data perfectly, all the predicted returns should lie on the 45-degree line. As shown in the scatter plot in Panel A, the predicted average returns from the contingent claims model reside on the 45-degree line. In contrast, the predicted returns from the CAPM in Panel B are almost flat. Panel C shows that none of the predicted returns from the Fama–French model lie on the 45-degree line. Although the predicted returns from the q-factor model in Panel D show some improvement, the q-factor model has difficulty in capturing the deviation of the high-leverage portfolio.

BE/ME portfolios: From the third row of Table 4, the H–L portfolio has a pricing error of 1.79% per year, which is smaller than 15.31% in the CAPM, 7.65% in the Fama–French model, and 7.33% in the q-factor model. This error from our model is mostly due to the large deviation of -2.37% for the growth portfolio. The small error of -0.58% in the value portfolio implies that our model is able to capture the default risk associated with value firms. The m.a.e. is 1.21% per year, much lower than 8.79% from the CAPM, 3.83% from the Fama–French model, and 2.19% from the q-factor model. Figure 4 provides a visual confirmation. As shown in Panel A, the largest deviation from the 45-degree line is the growth portfolio. In Panel B, the predicted returns from the CAPM are almost horizontal. The Fama–French model in Panel C and the q-factor model in Panel D perform better, but they are not able to predict the returns of the value portfolio.

Asset growth portfolios: The difference in the pricing errors between the high- and low-growth portfolios is -5.97% per year, which is much less than -11.91% from the CAPM, -10.50% from the Fama–French model, and -8.67% from the q-factor model in Table 1. Panel A of Figure 5 shows that the average predicted returns generally align with the realized returns. The predicted returns for the low- and high-asset growth portfolios are slightly out of line. In sharp contrast, the predicted returns from the CAPM and the Fama–French model are almost flat. Although the q-factor model improves significantly, it fails to predict the average stock return of the low-growth rate portfolio.

In summary, our model outperforms the alternative models for the default-risk related portfolios.[13] Our model performs best for the market leverage portfolios and the BE/ME portfolios, and predicts the expected returns of value firms well. Although the model performs modestly for the asset growth portfolios, it delivers a much better fit than the CAPM, the Fama–French three-factor model, and the q-factor model.

4.5 Cross-sectional properties of default probabilities and stock-cash flow sensitivities from our fitted model

The sensitivity ϵ_{it+1} from our method is a structural estimate instead of a reduced-form estimate from rolling regressions in other studies. Given the *optimal* estimates of θ and η, we obtain the implied risk-neutral rate μ_i and cash flow volatility σ_i by solving equations (14) and (15) for each portfolio. Then, we calculate the risk-neutral probability $\pi_{it} = (X_{it}/X_{iB})_i^{\omega}$ and the stock-cash flow sensitivity ϵ_{it+1} according to equation (7).[14]

The means of the risk-neural default probability are reported in Panels B of Table 4. For the leverage portfolios, the default probability increases by 36.62%from 10.62% for the lowest leverage portfolio to 47.24% for the highest leverage portfolio. For the BE/ME portfolios,

[13]Note that the pricing errors in the q-factor model are for the sample period of 1972 to 2010 because of the limited quarterly data for constructing the factors. Without re-estimating our contingent claims model for this specific period and using the estimates from Table 3, the H–L portfolio's pricing errors (m.a.e.) from our model are –0.19% (1.34%) for the market leverage portfolios, 3.20% (1.21%) for the BE/ME portfolios, and –5.63% (1.78%) for the asset growth portfolios, respectively, for the same period of 1972 to 2010. Overall, they are still smaller than those from the q-factor model in Table 1.

[14]The reasons we consider the risk-neutral probability are as follows. First, it is the risk-neutral default probability, instead of the objective probability, that determines the stock-cash flow sensitivity. Similar to Almeida and Philippon (2007) that use the risk-adjusted default probability for calculating expected distress costs, we use the risk-neutral default probability for the expected value of the put option of going bankrupt, the third component of the sensitivity; Second, the physical default probability and the risk-neutral probability are monotonically associated (Garlappi and Yan, 2011). Third, we do not back out the objective expected rate of cash flows, $\hat{\mu}_i$, in our IS-GMM estimation and the instantaneous realized cash flow rate r_{it}^X observed from the data is not the expected one and is noisy.

the increase in π_{it} is 23.05%. For the asset growth portfolios, the difference in π_{it} between the low- and high-asset growth portfolios is only 5.13%, the smallest among the three sets of portfolios. Overall, the magnitude is consistent with the findings by Almeida and Philippon (2007) that the risk-neutral probabilities ranges from 1.65% for AAA bonds to 62.48% for B bonds with a 10-year maturity.[15]

Panels C of Table 4 reports the means of the stock-cash flow sensitivity. For the leverage portfolios, firms with more debt have a higher stock-cash flow sensitivity, as shown in the increasing means of ϵ_{it} along the market leverage. For the BE/ME portfolios, the pattern and magnitude of ϵ_{it} are very similar to those for the leverage portfolios. These similarities are a manifestation of the portfolio characteristics in Table 1. Because investment and debt financing are positively correlated, firms with relatively more book assets and fewer growth opportunities have higher financial leverages, which in turn result in high default probability and stock-cash flow sensitivity. For the asset growth portfolios, the difference in the stock-cash flow sensitivity is 0.14, only about one fifth of 0.57 in the leverage portfolios.

When comparing the default probability and stock-cash flow sensitivity across different sets of portfolios, we have two main observations. First, while the spread in default probability between the high and low quintile portfolios is the largest in leverage portfolios, it is the smallest in asset growth firms. Second, the spread in the sensitivity is sizable in the market leverage portfolios and BE/ME portfolios but is much smaller in the asset growth portfolios. Through a comparative statics analysis in Section 4.7, we further show that the cross-sectional spread in the sensitivities is the key to understanding the value, leverage and asset growth premiums.

4.6 Importance of bargaining power

Before examining the crucial role of the stock-cash flow sensitivity in stock returns, we investigate the model specification first because the sensitivity is largely determined by the two policy parameters. For the dividend-net income ratio, most of the capital structure models assume firms distribute all the residuals back to equity holders as dividends, i.e., $\theta = 1$. This is not necessarily true because it is likely that firms might use the residuals of operating cash flows to make investments. For the parameter of bargaining power, it is commonly assumed in the capital structure literature there is no renegotiation and equity holders simply walk away and receive nothing at bankruptcy, i.e., $\eta = 0$. However, empirical studies, including Gilson et al. (1990), Franks and Torous (1989), and Asquith et al. (1994), find that equity holders recover a considerable fraction of assets at bankruptcy.

[15] We follow the literature and model a perpetual bond. Therefore, we compare the expected default probability of our perpetual bond to those of 10-year bonds reported by Almeida and Philippon (2007).

To demonstrate the importance of bargaining power in modeling the stock-cash flow sensitivity, we use the counterfactual parameter value and examine the changes in pricing errors, default probabilities and sensitivities. Specifically, we set the bargaining power parameter $\eta = 0$, while keeping the estimates of all the other parameters from the fitted model in Table 3. We repeat the same procedure for the dividend-net income ratio and the results in the Internet Appendix show that the change of θ has only small effects on the stock-cash flow sensitivity.

Panel A of Table 5 reports the expected errors. Compared with those in Table 4, the m.a.e. increases from 0.80 to 2.13 for the set of leverage portfolios, and from 1.21 to 2.92 for the set of BE/ME portfolios. The significant increase in the m.a.e. is largely due to the mispricing for the high-leverage portfolio and the value portfolio. However, the m.a.e. decrease slightly from 2.09 to 1.90 for the asset growth portfolio, because we set $\eta = 0$, which is the same as the optimal estimate for the individual set of asset growth portfolios in the third column of Panel A in Table 3.

Without debt renegotiation, equity holders receive nothing at bankruptcy and have incentives to delay bankruptcy, which results in a low *endogenous* default probability. Compared with their counterparts in Table 4, the risk-neutral default probabilities and their difference between the high- and low quintile portfolios in Panel B are smaller, particularly for the high-leverage portfolio and the value portfolio.

The stock-cash flow sensitivities in Panel C increase overall. This is consistent with the implication from Panel B of Figure 1 that equity holders expose greater downside risk when they have no bargaining power, i.e., $\eta = 0$, to recover anything at bankruptcy. Particularly, the stock-cash flow sensitivity increases to 2.12 from 1.63 (in Panel C of Table 4) for high-leverage firms and increases to 1.85 from 1.54 for value firms, when their default probabilities are very high. This sharp contrast demonstrates that, for firms with high default probabilities, equity holders' bargaining power can effectively reduce the equity risk, proxied by the sensitivity of stock to cash flows.

In summary, by using the counterfactual parameter value to remove bargaining power, a realistic feature in our model, we demonstrate that bargain power can effectively protect equity holders from downside risk when the likelihood to default is very high.

4.7 Pricing errors from comparative statics analysis

Given the reasonably good performance of our contingent claims model, we follow Liu et al. (2009) and perform a comparative statics analysis to identify the most important factor in the model. We first set an input to its cross-sectional average for each year. We then use the joint parameter estimates from the sample of all the three sets of portfolios in Table 3 to recalculate the expected stock return according to equations (5) and (7), while keeping all other inputs unchanged. A large increase in the expected pricing errors or m.a.e. implies that this certain input is important in explaining the cross-sectional stock returns.

Aside from the state variable, operating cash flows X_{it}, the main inputs in our model include historical stock return volatility σ_{it}^S, coupon C_{it} and equity value S_{it}. We set them to their cross-sectional average each year, and need to use the new inputs and the parameter estimates to recalculate μ_i and σ_i before we construct ϵ_{it+1} and r_{it+1}^M. For C_{it} and S_{it}, rather than fixing them to their cross-sectional averages, we set $S_{it} = X_{it}/(\widetilde{X_{it}/S_{it}})$ and $C_{it} = X_{it}/(\widetilde{X_{it}/C_{it}})$, where $\widetilde{X_{it}/S_{it}}$ and $\widetilde{X_{it}/C_{it}}$ are the cross-sectional averages of earnings–price and interest coverage ratios, respectively.Then, we use its average and the parameter estimates from Table 3 to recalculate r_{it+1}^M, while keeping all the other model inputs the same.

Recall the stock return is the product of the risk premium λ_i and ϵ_{it+1}. To evaluate the their importance, we use their cross-sectional averages directly from the benchmark estimation without recalculating μ_i and σ_i. We use $\mathbb{E}(r_{it}^X)$ to approximate $\hat{\mu}_i$. Because $\lambda_i = \mathbb{E}(r_{it}^X) - \mu_i$ is constant for each portfolio, the cross-sectional average, $\widetilde{\lambda}_i$, is the constant across all the portfolio and over time. Because both λ_i and ϵ_{it+1} do not need to invoke recalculations of μ_i and σ_i, this exercise provides a direct comparison between the contributions of λ_i and ϵ_{it+1} to the cross-sectional variation of predicted stock returns. Table 6 reports the results.

Market leverage portfolios: In Panel A, the stock-cash flow sensitivity is the most important determinant, followed by the earnings–price ratio and risk premium λ_i. By removing the cross-sectional variation of ϵ_{it+1}, the pricing error of the H–L portfolio jumps to 10.35% per year from 1.61% per year in the benchmark model.[16] The m.a.e. increases from 0.80% to 3.57%. The effects from the cash flow rates, interest coverage ratios, and stock volatility are much smaller.

BE/ME portfolios: Similar to the market leverage portfolios, the stock-cash flow sensitivity dominates other model inputs. The lack of cross-sectional variation in ϵ_{it+1} increases the m.a.e. to 2.90% from 1.21% in the benchmark model. The effects of the risk premium and the earnings–price ratio are very similar, with the risk premium slightly better. The lowest impact is observed when the cross-sectional average of stock volatility is an input.

Asset growth portfolios: Consistent with the modest performance of our model for the asset growth portfolios shown in Table 3 and 4, the effects of eliminating the cross-sectional variations of model inputs are relatively small in Table 6. The pricing error of the H–L

[16]Admittedly, the CAPM has only one degree of freedom, while our model has two parameters to fit the 45-degree line.

portfolio in absolute value increases from 5.97% in the benchmark model to 10.63% after fixing the cross-sectional variation in λ_i. This increment is greater than the one resulting from the elimination of the cross-sectional variation in ϵ_{it+1}. Although the pricing error of the H–L portfolio suggests that λ_i is slightly more important than ϵ_{it+1}, the m.a.e. that evaluates the overall performance across all the quintile portfolios indicates the opposite inference. After fixing ϵ_{it+1} to its cross-sectional average, the m.a.e. increases from 2.09% in the benchmark model to 3.25%, which is greater than 2.57% due to fixing r^X_{it+1} to its cross-sectional average.

Overall, the cross-sectional variation in the stock-cash flow sensitivity is the most important determinant for alleviating the pricing errors for the market leverage, BE/ME market and asset growth portfolios, followed by the risk premium and the earnings–price ratio. Moreover, the cross-sectional variation of the historical stock volatility has the least impact on the expected pricing errors among all the inputs we consider.[17]

4.8 Stock-cash flow sensitivities over the business cycle

Having demonstrated the importance of the stock-cash flow sensitivity in the cross-section, we proceed to investigate its economic information content over the business cycle. More important, we use the counterfractual parameter value to demonstrate how the bargaining power can help equity holders to alleviate their downside risk.

4.8.1 Default probabilities and stock-cash flow sensitivities

We inspect default probability first and then the sensitivity, as the sensitivity is partially determined by the risk-neutral default probability.

We plot the time series of the risk-neutral probability of default and the stock-cash flow sensitivity in Figures 7 and 8, respectively. We use NBER recessions to classify the cycles. Panel A of Figure 7 shows that high-leverage firms have greater default probabilities than low-leverage firms, particularly during recessions. The highest default probability for the high-leverage portfolio is about 29% in the 1980 recession. In Panel B, BE/ME portfolios exhibit the same pattern as those of market leverage portfolios, with the two spikes of default probability for the value portfolio occurring in 1975 and 1991. This likely similarity arises because value firms accumulate debt during their investment expansions. However, as shown in Panel C, the difference in default probabilities between low- and high-growth firms is much smaller compared with that in Panels A and B.

[17] This implies that including stochastic volatility as the second state variable does not necessarily improve the model's performance.

The stock-cash flow sensitivity, ϵ_{it}, is partially determined by the risk-neutral default probability. Figure 8 shows the times series of the stock-cash flow sensitivity over the business cycle and Table 7 provides the average of the sensitivities ϵ_{it} during expansions and recessions, respectively. Consistent with the default probability in Figure 7, Panels A and B show that high-leverage and value firms are considerably more sensitive to cash flows than low-leverage and growth firms, particularly during NBER recessions. As shown in Panel C, low-growth firms are more sensitive to the business cycles. Similar to the observations in Figure 7 for the cross-sectional spread in default probabilities, Figure 8 shows that the spread in the stock-cash flow sensitivities between the high- and low-growth firms is not as significant as that in the market leverage and BE/ME portfolios.

4.8.2 Increases in stock-cash flow sensitivity when equity holders have no bargaining power

We have shown that bargaining power allows equity holders to alleviate their exposure to the cash flow risk cross-sectionally in Section 4.6. Next, we proceed to examie whether equity holders benefit more from their bargaining power in recessions than in expansions. We calculate the difference in the stock-cash flow sensitivity, $\zeta_{it} = \epsilon_{it}^{\mathrm{NoBP}} - \epsilon_{it}$, and obtain their averages during the expansions and recessions, respectively, for each portfolio.

Three observations emerge from Panel B of Table 7. First, the difference in the sensitivities ζ_{it} is very trivial for the low leverage portfolio, growth portfolio and high growth rate portfolio in both expansions and recessions, and there is no much difference in ζ_{it} between expansions and recessions for these portfolios. The negligible difference in the sensitivity indicates that bargaining power is not important for equity holders of healthy firms. Second, for the high-leverage portfolio with a high default probability, the average of ζ_{it} is 0.36 in expansions and 0.89 in recession and for the value portfolio, the sensitivity is 0.22 in expansions and 0.63 in recessions. These sharp contrasts in ζ_{it} between expansions and recessions demonstrate that the bargain power is important for equity holders of firms with a high default probability, particularly in recessions. Third, for the asset growth portfolios, the difference in the average of ζ_{it} between expansions and recessions is trivial across all the five asset growth rate portfolios, because the default probabilities of all the asset growth portfolios are small.

In summary, stocks are more sensitive to their underlying operating cash flows during recessions when default probabilities are high than they are during expansions when default probabilities are low. The large spreads in the counter-cyclical stock-cash flow sensitivities help explain the high-leverage premium, the value premium, and the asset growth premium. Lastly, equity holders' bargaining power helps alleviate their downside risk, particularly in recessions.

5 Conclusion

We develop an agency-based contingent claims model for cross-sectional stock returns. The state variable is operating cash flows and the two policy parameters are related to dividend payout and strategic default policies. We adapt IS-GMM to test the model for equal-weighted stock portfolios formed on market leverage, book-to-market equity, and asset growth rate. Our contingent claims model outperforms the CAPM, the Fama–French three-factor model, and the q-factor model in explaining the cross-sectional variation in stock returns.

The success of our model can be attributed to its ability to capture the sensitivities of stocks to their underlying operating cash flows. The stock-cash flow sensitivity is affected by dividend payout policy and shareholder bargaining power. Our counterfactual study shows that the bargaining power can significantly alleviate equity holders' exposure to downside risk, particularly in recessions.

The stock return predicted from our model is the product of the default-related risk premium and the stock-cash flow sensitivity. Our comparative static analysis shows that the cross-sectional variation in the sensitivities is more important than that in the default-related risk premiums. We find that the default probabilities and the stock-cash flow sensitivities of value stocks, high-leverage stocks, and low-asset growth stocks are greater than those of growth stocks, low-leverage stocks, and high-asset growth stocks, particularly during recessions. It is the large spread in the stock-cash flow sensitivities that helps explain the cross-sectional spreads in stock returns for the market leverage, book-to-market and asset growth portfolios.

Our work demonstrates that a simple agency-based model successfully explains the cross-sectional variation in stock returns for three sets of stock portfolios related to default risk. Admittedly, we do not intend to use this model to explain all the asset pricing anomalies. Instead, our objective is to show that the right choice of the model is important to understand certain anomalies. However, because our model deliberately abstracts from investments and financing, we are not able to directly compare our default risk-based model with the investment-based model. It is fruitful to embed our agency-based model into an investment-based framework, which allows a more direct comparison across different model within a framework. We leave this exercise to future studies.

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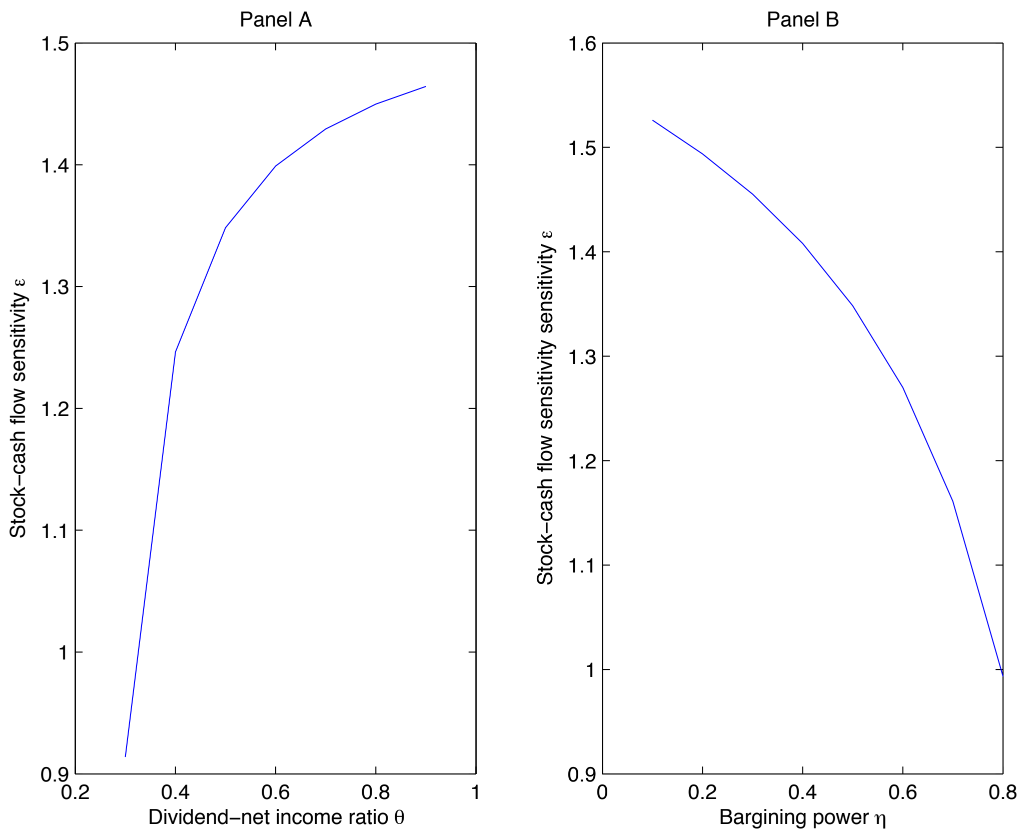
Figure 1: **Stock-cash flow sensitivity**
This figure plots the stock-cash flow sensitivity ϵ_i against dividend–net income ratio θ (in Panel A) and shareholder bargaining power η (in Panel B). Parameters are r = 3.6%, τ_{eff} = 15%, $\mu_i = 0$, $\sigma_i = 0.25$, $\alpha = 0.30$, and $\kappa = 0$. X_i is normalized to one.



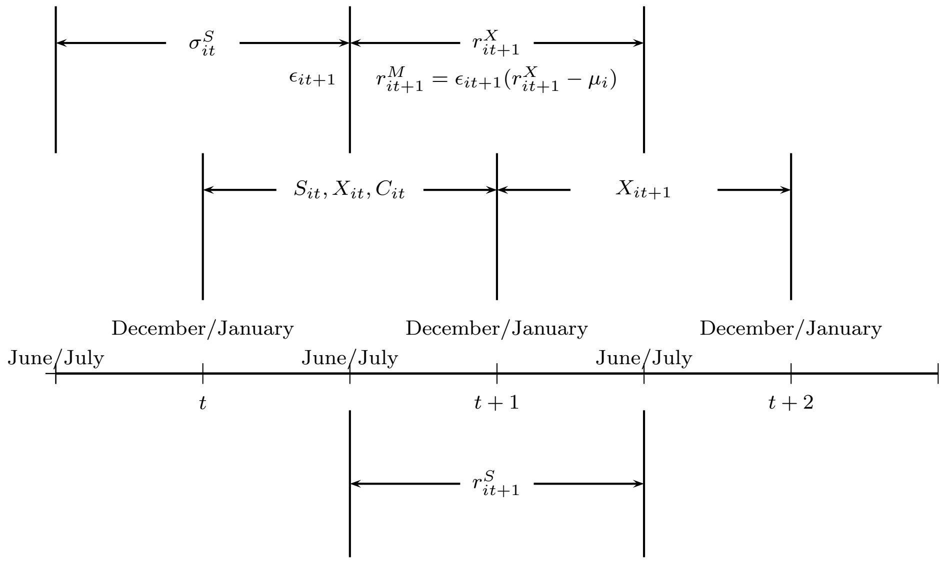


Figure 2: **Timing alignment**
This figure shows the timing alignment between model inputs and observed stock returns. r^X_{it+1} is the rate of operating cash flows and r^S_{it+1} is the return of a stock portfolio from July of year t to June of year t+1. S_{it} is the equity value at the end of June of year t, X_{it} is the operating cash flows, and C_{it} is the interest expenses at the end of year t. Stock volatility σ^S_{it} is the annualized standard deviation of the daily returns of stock portfolios from the beginning of July of year $t-1$ to the end of June of year t. ϵ_{it+1} is the expected stock-cash flow sensitivity given the information up to the end of June of each year t.

Figure 3: **Market leverage portfolios: average predicted stock returns versus average realized returns**

This figure plots the time series averages of predicted returns from the contingent claims model, the CAPM, the Fama–French model, and the investment-based q-factor model against the average realized returns. In the contingent claims model, the predicted returns are calculated based on equation (16) using the parameter estimates from the last column of Table 3. High leverage denotes the high leverage quintile and low leverage denotes the low leverage quintile.

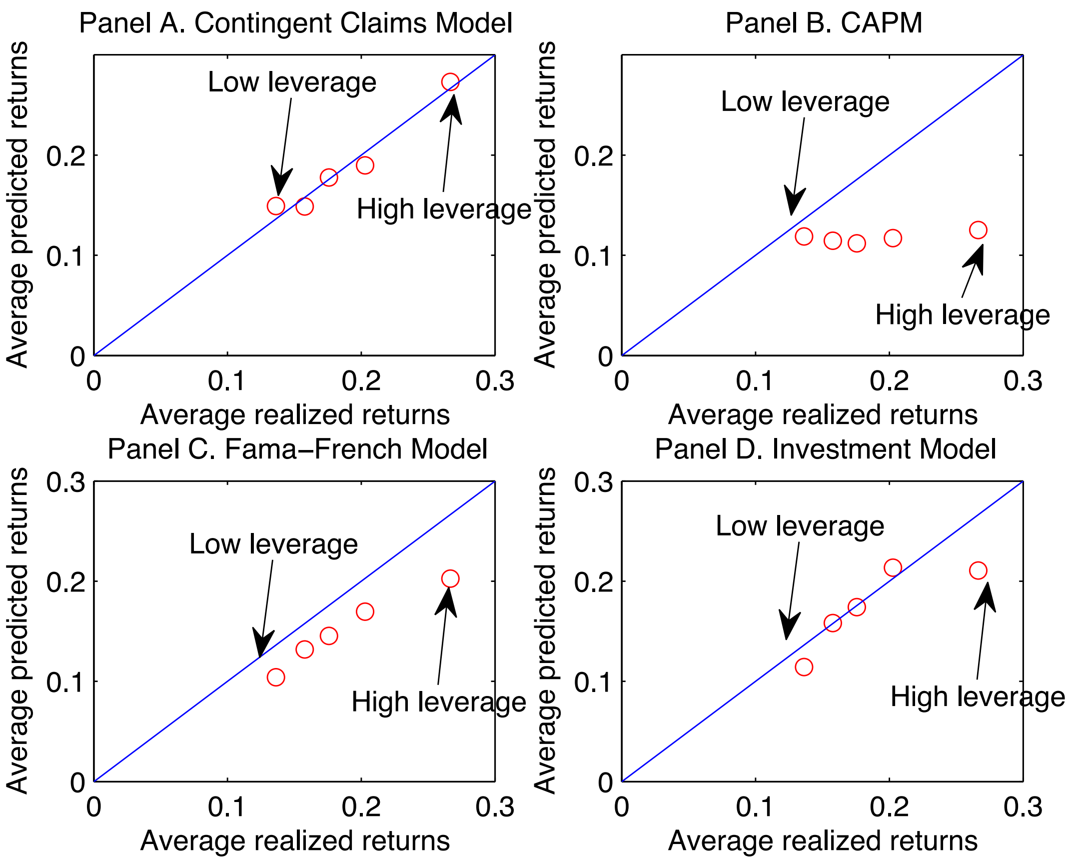


Figure 4: **BE/ME portfolios: average predicted stock returns versus average realized returns**

This figure plots the time series averages of predicted returns from the contingent claims model, the CAPM, the Fama–French model, and the investment-based q-factor model against the average realized returns. In the contingent claims model, the predicted returns are calculated based on equation (16) using the parameter estimates from the last column of Table 3. Value denotes the high BE/ME quintile and growth denotes the low BE/ME quintile.

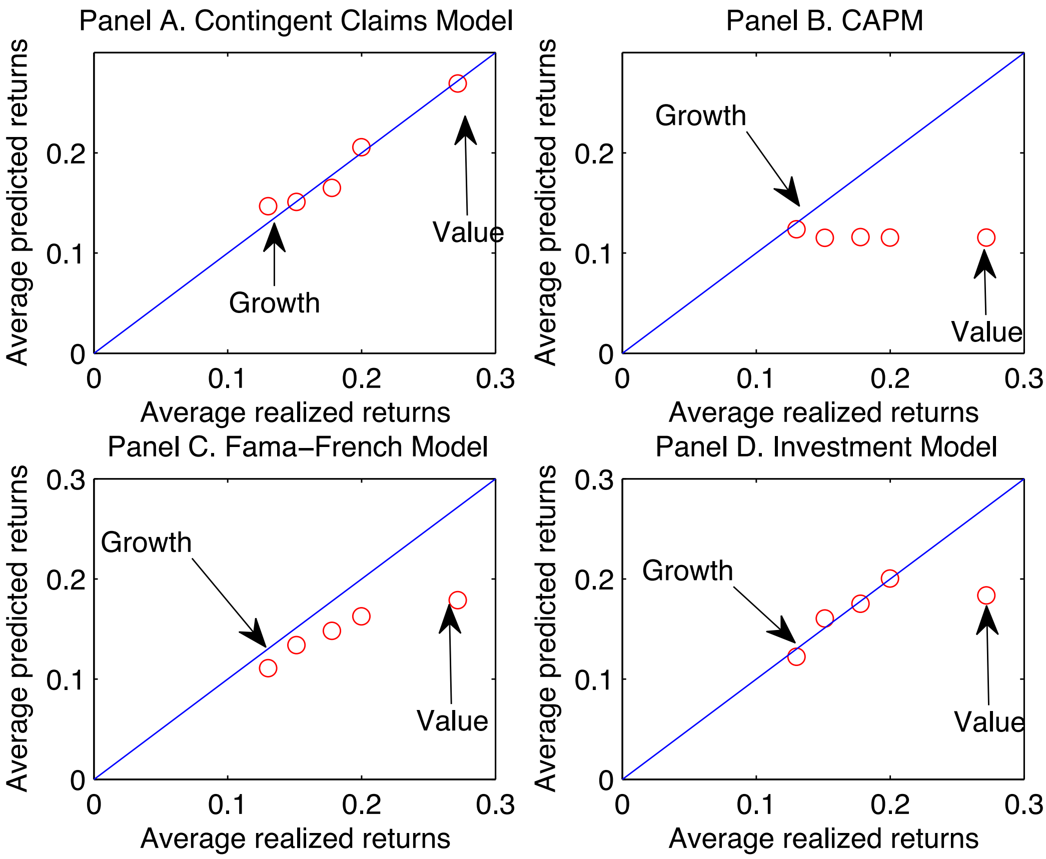


Figure 5: **Asset growth portfolios: average predicted stock returns versus average realized returns**

This figure plots the time series averages of predicted returns from the contingent claims model, the CAPM, the Fama–French model, and the investment-based q-factor model against the average realized returns. In the contingent claims model, the predicted returns are calculated based on equation (16) using the parameter estimates from the last column of Table 3. High growth denotes the high-asset growth quintile and low growth denotes the low-asset growth quintile.

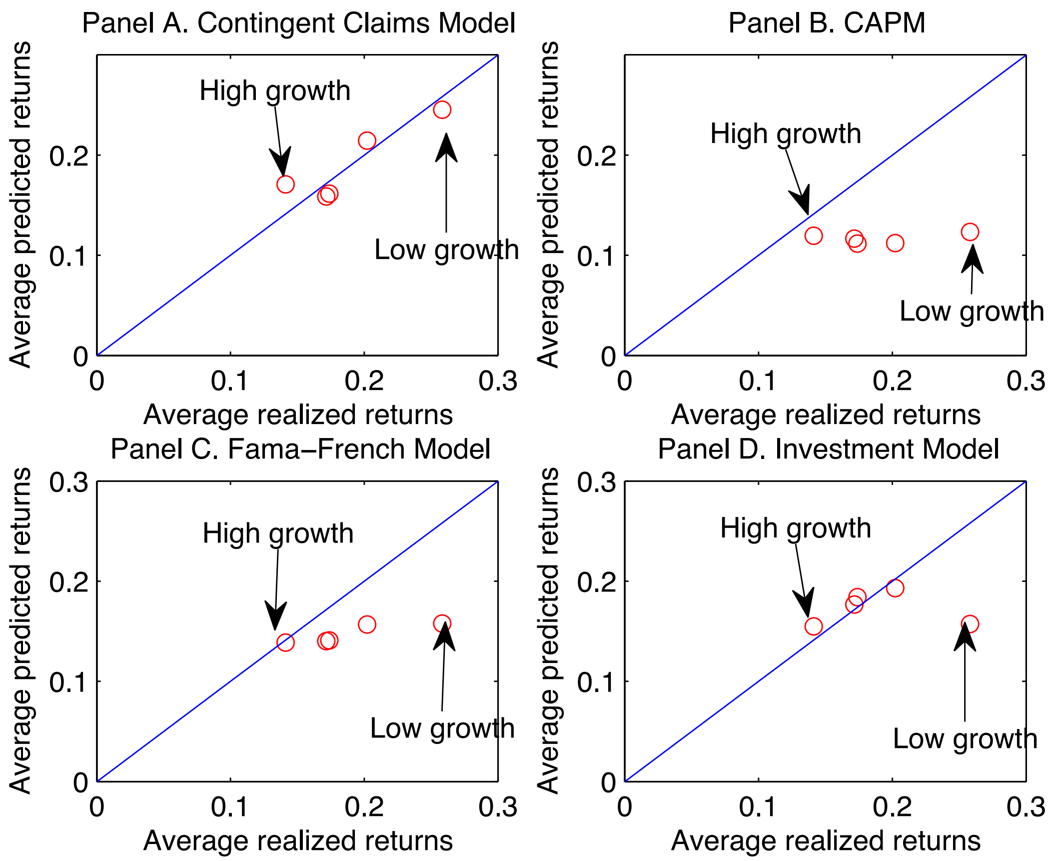


Figure 6: **All three sets of portfolios: average predicted stock returns versus average realized returns**

Each panel of this figure plots the time series averages of predicted returns from the contingent claims model, the CAPM, the Fama–French model, and the investment-based q-factor model against the average realized returns. In the contingent claims model, the predicted returns are calculated based on equation (16) using the parameter estimates from the last column of Table 3.

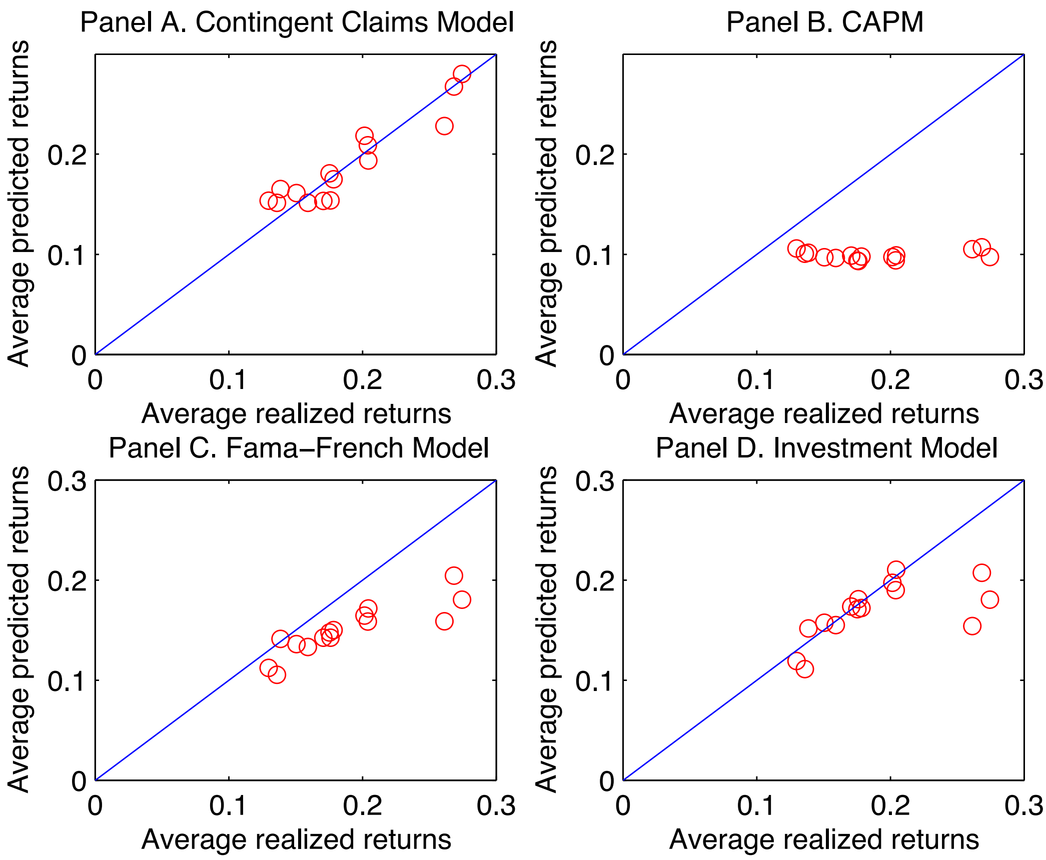


Figure 7: **Time series of risk-neutral default probability**
This figure plots time series of default probability, π_{it}, against years for the market leverage portfolios (Panel A), the book-to-market portfolios (Panel B), and the asset growth portfolios (Panel C). The shaded areas are for NBER recessions. The thick, solid lines are for the cross-sectional averages of default probabilities across all the quintile portfolios. The line with dots (–.) is for the first quintile portfolio, the line with circles (-o) for the third quintile portfolio, and the line with stars (-*) for the fifth quintile portfolio.

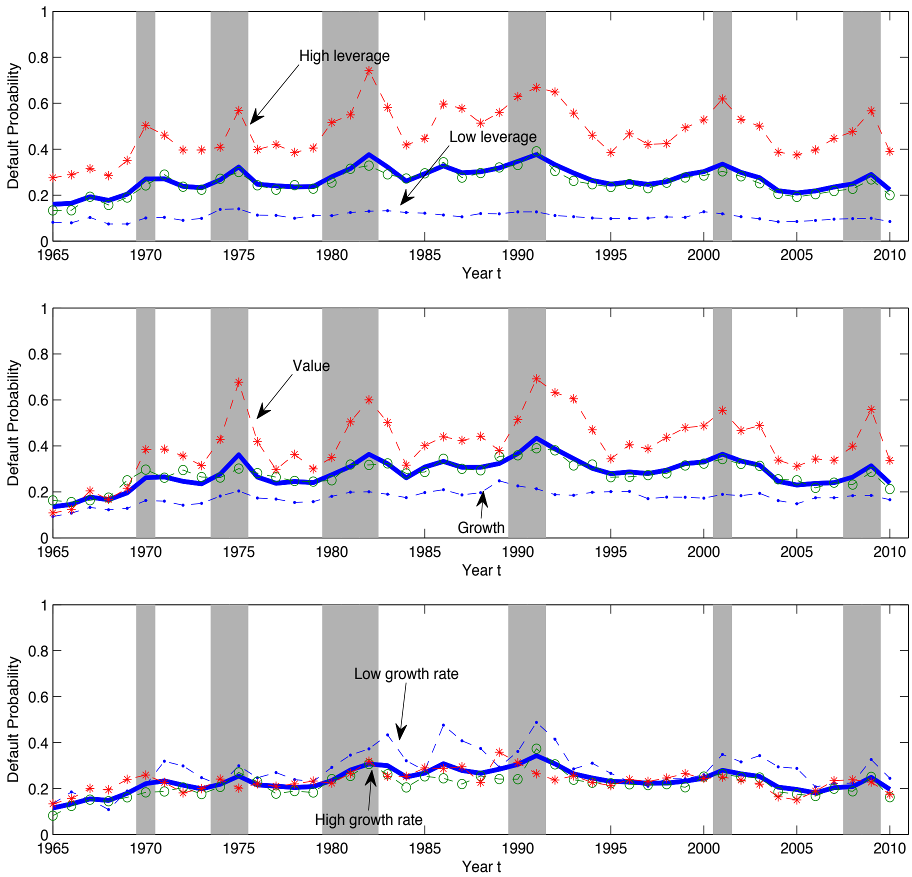


Figure 8: **Time series of stock-cash flow sensitivity**
This figure plots time series of stock-cash flow sensitivity, ϵ_{it}, against years for the market leverage portfolios (Panel A), the book-to-market portfolios (Panel B), and the asset growth portfolios (Panel C). The shaded areas are for NBER recessions. The stock-cash flow sensitivity is calculated based on equation (7) using the parameter estimates from Table 3. The thick, solid lines are for the cross-sectional averages of the stock-cash flow sensitivity across all the quintile portfolios. The line with dots (–.) is for the first quintile portfolio, the line with circles (-o) for the third quintile portfolio, and the line with stars (-*) for the fifth quintile portfolio.

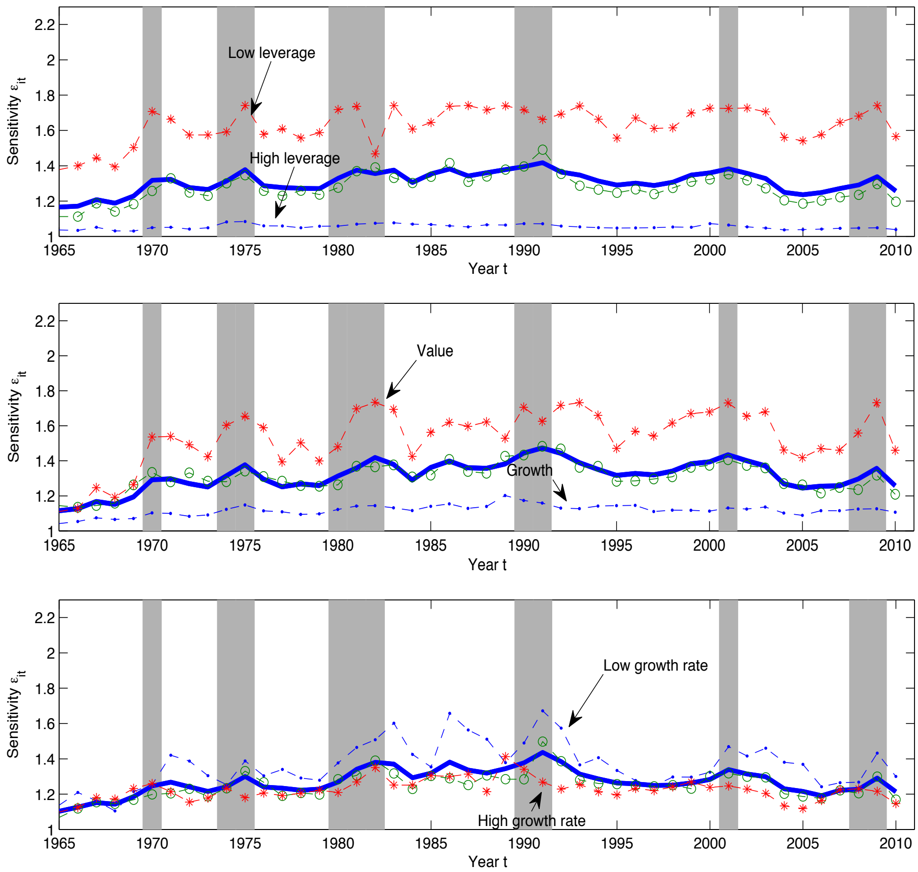


Figure 9: **Increases in stock-cash flow sensitivity when equity holders have no bargaining power**

This figure plots time series of the increase in stock-cash flow sensitivity, $\zeta_{it} = \epsilon_{it}^{\mathrm{NoBP}} - \epsilon_{it}$, against years for the market leverage portfolios (Panel A), the book-to-market portfolios (Panel B), and the asset growth portfolios (Panel C). $\epsilon_{it}^{\mathrm{NoBP}}$ is calculated by setting bargaining power $\eta = 0$. The shaded areas are for NBER recessions. The stock-cash flow sensitivity is calculated based on equation (7) using the parameter estimates from Table 3. The thick, solid lines are for the cross-sectional averages of the stock-cash flow sensitivity across all the quintile portfolios. The line with dots (–.) is for the first quintile portfolio, the line with circles (-o) for the third quintile portfolio, and the line with stars (-*) for the fifth quintile portfolio.

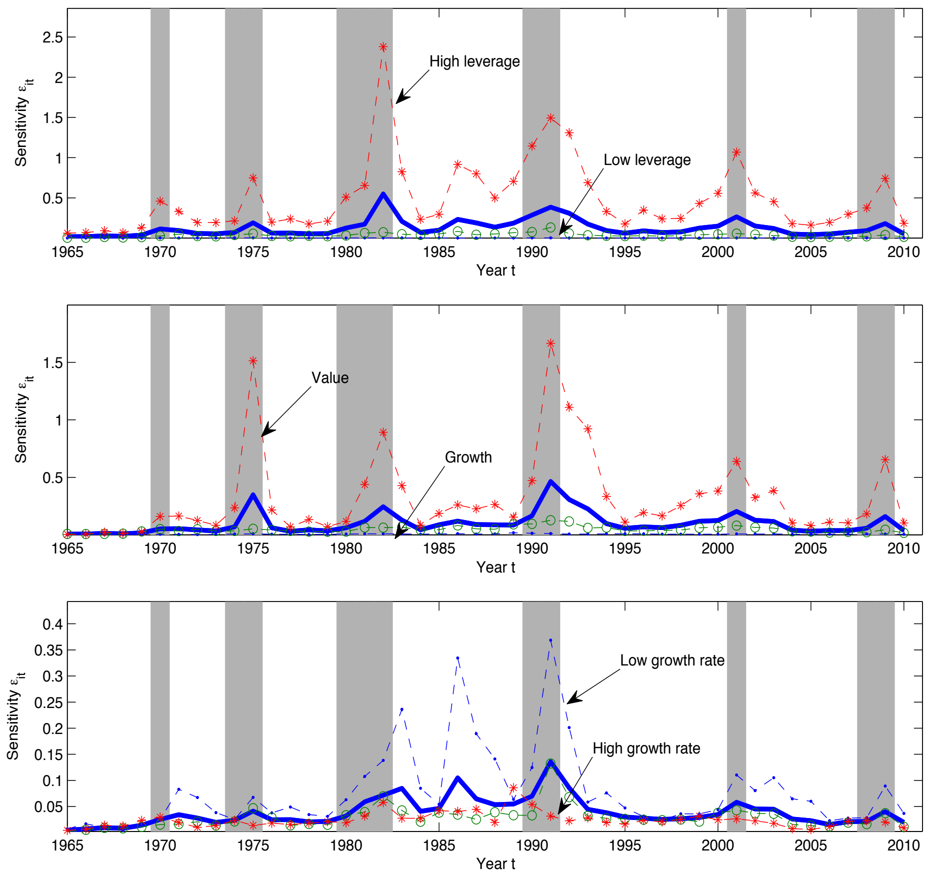


Table 1: **Pricing errors of testing portfolio returns from alternative models**
This table reports the annualized average stock return, $\overline{r^s_{it+1}}$, the pricing error from the CAPM regression, e^C_i, the pricing error from the Fama-French (FF) three-factor regression, e^{FF}_i, and the pricing error from the q-factor regression, e^q_i, for each quintile portfolio. $\overline{r^s_{it+1}}$, e^C_i, and e^{FF}_i are reported in percent. The H–L portfolio is long in the high portfolio and short in the low portfolio. The t-statistics for the pricing errors are reported in parentheses. m.a.e. is the mean absolute error in annual percent for each set of testing portfolios.

Panel A. Market Leverage Portfolios							
	Low	2	3	4	High	H–L	m.a.e.
$\overline{r^S_{it+1}}$	13.61	15.91	17.53	20.43	26.84	13.23	
e^C_i	3.54	6.29	8.17	10.54	16.13	12.59	8.93
(t)	(1.76)	(3.34)	(3.85)	(4.09)	(4.66)	(4.21)	
e^{FF}_i	3.07	2.59	2.77	3.28	6.39	3.32	3.62
(t)	(1.89)	(1.90)	(2.25)	(2.15)	(3.40)	(1.56)	
e^q_i	2.50	0.45	0.20	−0.50	5.76	1.88	1.88
(t)	1.01	0.30	0.15	−0.34	2.13	0.54	

Panel B. BE/ME Portfolios							
$\overline{r^S_{it+1}}$	12.99	15.06	17.84	20.15	27.44	14.45	
e^C_i	2.41	5.35	8.07	10.42	17.72	15.31	8.79
(t)	(1.16)	(2.85)	(3.65)	(4.20)	(5.71)	(5.95)	
e^{FF}_i	1.76	1.45	2.83	3.70	9.41	7.65	3.83
(t)	(1.16)	(1.15)	(2.07)	(2.58)	(5.03)	(3.87)	
e^q_i	0.06	−0.57	0.70	0.02	9.57	7.33	2.19
(t)	0.02	−0.43	0.47	0.02	3.89	2.46	

Panel C. Asset Growth Portfolios							
$\overline{r^S_{it+1}}$	26.13	20.40	17.60	17.07	13.87	−12.26	
e^C_i	15.63	11.01	8.27	7.20	3.72	−11.91	9.17
(t)	(5.44)	(4.71)	(4.22)	(3.65)	(1.75)	(−6.29)	
e^{FF}_i	10.26	4.54	3.36	2.83	−0.24	−10.50	4.24
(t)	(5.15)	(3.23)	(2.42)	(2.13)	(−0.18)	(−4.87)	
e^q_i	10.90	1.09	0.01	−0.84	−1.66	−8.67	2.90
(t)	4.56	0.84	0.01	−0.59	−1.01	−3.25	

Table 2: **Summary statistics of portfolio characteristics**
This table presents summary statistics for the characteristics of portfolios formed on market leverage, book-to-market equity, and asset growth rate. $\overline{r^X_{it+1}}$ is the time series average of cash flow rates in annual percent from time t to time $t+1$ after portfolios are formed at time t; $corr(r^X_{it+1}, r^S_{it+1})$ is the time series correlation coefficient between r^X_{it+1} and r^S_{it+1}; and $\overline{\sigma^S_{it}}$ is the time series average of annualized daily volatility of stock portfolio in percent calculated from one-year daily stock returns before the portfolio formation. $\overline{X_{it}/S_{it}}$ is the time series average of earnings–price ratios and $\overline{X_{it}/C_{it}}$ is the time series average of interest coverage ratios.

Panel A. Market Leverage Portfolios						
	Low	2	3	4	High	H–L
$\overline{r^X_{it+1}}$	10.36	8.44	9.41	9.35	12.41	2.05
corr(r^X_{it+1},r^S_{it+1})	0.21	0.11	0.08	0.10	0.21	0.01
$\overline{X_{it}/S_{it}}$	0.09	0.12	0.15	0.17	0.23	0.14
$\overline{X_{it}/C_{it}}$	21.00	8.74	5.62	3.71	2.12	−18.88
$\overline{\sigma^S_{it}}$	26.99	24.79	24.79	25.42	28.24	1.24

Panel B. BE/ME Portfolios						
$\overline{r^X_{it+1}}$	9.92	8.57	8.69	11.12	13.43	3.52
corr(r^X_{it+1},r^S_{it+1})	0.16	−0.02	0.04	0.20	0.21	0.05
$\overline{X_{it}/S_{it}}$	0.09	0.13	0.15	0.17	0.20	0.11
$\overline{X_{it}/C_{it}}$	9.77	6.42	5.08	4.16	3.14	−6.63
$\overline{\sigma^S_{it}}$	28.83	25.98	25.26	25.24	26.91	−1.92

Panel C. Asset Growth Portfolios						
$\overline{r^X_{it+1}}$	12.80	11.61	7.70	8.37	9.84	−2.96
corr(r^X_{it+1},r^S_{it+1})	0.20	0.14	0.03	0.11	0.03	−0.17
$\overline{X_{it}/S_{it}}$	0.14	0.14	0.13	0.12	0.11	−0.03
$\overline{X_{it}/C_{it}}$	3.87	5.21	6.40	7.15	5.54	1.67
$\overline{\sigma^S_{it}}$	27.94	23.75	23.16	24.35	28.28	0.34

Table 3: **Parameter estimates and model fitness**

This table reports the parameter estimates from one-stage IS-GMM with an identity-weighting matrix for the data over the 1965 to 2010 period. The first moment condition $\mathbb{E}[r^s_{it+1} - r^M_{it+1}] = 0$ is tested for all the quintile portfolios, in which $\mathbb{E}[.]$ is the sample mean of the series in parentheses. Panel A reports the dividend–net income ratio, θ, and the shareholder bargaining power, η. Panels B, C and D report the risk-neutral rate, μ_i, implied risk premium λ_i, and volatility σ_i, of cash flows, respectively. Their associated t-statistics are reported in parentheses. The χ^2-statistics are reported with the associated degrees of freedom (d.f.) and p-values. We first estimate the parameters for the three sets of portfolios, individually. Then, we pool all the three sets of portfolios and jointly estimate the parameters.

Panel A. Estimates of Parameter				
	Leverage	BE/ME	Asset Growth	All
θ	0.75	0.63	0.80	0.74
	(2.21)	(2.04)	(2.30)	(2.28)
η	0.57	0.44	0.00	0.58
	(2.27)	(1.22)	(0.00)	(2.32)
χ^2	2.23	2.41	7.42	9.05
d.f.	3.00	3.00	3.00	13.00
p-value	0.53	0.49	0.06	0.77

Panel B. Implied Risk-Neutral Rate $\mu_i(\%)$						
	Leverage	BE/ME	Asset Growth	Leverage	BE/ME	Asset Growth
Low	−0.63	−0.02	−1.09	−0.60	−0.62	−0.98
2	−1.57	−1.04	−1.85	−1.55	−1.76	−1.67
3	−1.94	−1.30	−2.01	−1.91	−2.03	−1.78
4	−1.94	−1.21	−1.68	−1.92	−1.90	−1.43
High	−1.71	−1.18	−1.13	−1.71	−1.86	−0.92

Panel C. Implied Risk Premium $\lambda_i(\%)$						
	Leverage	BE/ME	Asset Growth	Leverage	BE/ME	Asset Growth
Low	10.99	9.94	13.89	10.96	10.54	13.78
2	10.02	9.60	13.46	9.99	10.33	13.28
3	11.34	9.99	9.71	11.32	10.72	9.48
4	11.30	12.33	10.06	11.28	13.02	9.81
High	14.12	14.62	10.96	14.12	15.29	10.76

Panel D. Implied Volatility $\sigma_i(\%)$						
	Leverage	BE/ME	Asset Growth	Leverage	BE/ME	Asset Growth
Low	25.58	26.10	19.00	25.59	25.78	20.47
2	21.28	21.61	17.36	21.30	21.25	18.17
3	19.35	19.63	17.94	19.38	19.29	18.53
4	17.91	18.31	19.77	17.95	18.03	20.25
High	17.20	17.42	22.41	17.32	17.52	23.08

Table 4: **Pricing errors, default probability and stock-cash flow sensitivity from fitted models**

This table presents the expected pricing errors in percent in Panel A, risk-neutral default probability in Panel B, and stock-cash flow sensitivity in Panel C for each quintile portfolio from the fitted model. The model is estimated using one-stage IS-GMM with an identity-weighting matrix. We construct the predicted returns, risk-neutral default probabilities and stock-cash flow sensitivities using the parameter estimates from the sample of all the three sets of portfolios in Table 3. The expected return errors are defined as $e_i^M = \mathbb{E}[r_{it+1}^s - r_{it+1}^M]$, in which $\mathbb{E}[.]$ is the sample mean of the series in parentheses. The H denotes the highest quintile portfolio and the L denotes the lowest quintile portfolio. The H–L portfolio is long in the high portfolio and short in the low portfolio. The heteroscedasticity- and autocorrelation-consistent t-statistics for the model errors are reported in parentheses. m.a.e. is the mean absolute error for each set of testing portfolios.

Panel A. Expected pricing error							
	Low	2	3	4	High	H–L	m.a.e.
Market Leverage	−1.54	0.77	−0.55	1.07	0.07	1.61	0.80
	(−1.26)	(1.03)	(−0.52)	(0.78)	(0.06)	(1.01)	
BE/ME	−2.37	−1.06	0.33	−1.69	−0.58	1.79	1.21
	(−1.73)	(−1.24)	(0.29)	(−1.11)	(−0.48)	(1.42)	
Asset Growth	3.33	−0.50	2.22	1.74	−2.64	−5.97	2.09
	(1.56)	(−0.41)	(2.51)	(1.75)	(−1.36)	(−2.95)	

Panel B. Risk-neutral default probability (in %)						
	Low	2	3	4	High	H–L
Market Leverage	10.62	18.57	25.49	32.09	47.24	36.62
BE/ME	17.58	23.82	27.93	31.06	40.63	23.05
Asset Growth	28.41	24.29	21.66	19.48	23.28	−5.13

Panel C. Stock-cash flow sensitivity						
	Low	2	3	4	High	H–L
Market Leverage	1.05	1.16	1.28	1.42	1.63	0.57
BE/ME	1.12	1.22	1.31	1.40	1.54	0.42
Asset Growth	1.36	1.31	1.25	1.20	1.23	−0.14

Table 5: **Pricing errors, default probability and stock-cash flow sensitivity from the model *without bargaining power***

This table presents the expected pricing errors in percent in Panel A, risk-neutral default probability in Panel B, and stock-cash flow sensitivity in Panel C for each quintile portfolio. We construct the predicted returns, risk-neutral default probabilities and stock-cash flow sensitivities using the parameter estimates from the sample of all the three sets of portfolios in Table 3, except that we set the shareholders' bargaining power $\eta = 0$. The expected return errors are defined as $e_i^M = \mathbb{E}[r_{it+1}^s - r_{it+1}^M]$, in which $\mathbb{E}[.]$ is the sample mean of the series in parentheses. The H denotes the highest quintile portfolio and the L denotes the lowest quintile portfolio. The H–L portfolio is long in the high portfolio and short in the low portfolio. The heteroscedasticity- and autocorrelation-consistent t-statistics for the model errors are reported in parentheses. m.a.e. is the mean absolute error for each set of testing portfolios.

Panel A. Expected pricing error							
	Low	2	3	4	High	H–L	m.a.e.
Market Leverage	−1.55	0.66	−0.97	0.12	−7.34	−5.78	2.13
	(−0.67)	(0.27)	(−0.24)	(0.03)	(−2.72)	(−3.66)	
BE/ME	−2.44	−1.28	−0.12	−2.96	−7.78	−5.34	2.92
	(−0.69)	(−0.56)	(−0.03)	(−0.90)	(−4.64)	(−3.17)	
Asset Growth	2.02	−1.08	1.99	1.58	−2.84	−4.86	1.90
	(0.79)	(−0.64)	(0.79)	(0.80)	(−0.86)	(−2.13)	

Panel B. Risk-neutral default probability (in %)						
	Low	2	3	4	High	H–L
Market Leverage	9.73	16.76	22.82	28.34	41.09	31.36
BE/ME	16.13	21.59	25.07	27.43	35.63	19.49
Asset Growth	25.01	21.31	19.15	17.35	21.02	−3.99

Panel C. Stock-cash flow sensitivity						
	Low	2	3	4	High	H–L
Market Leverage	1.06	1.18	1.32	1.51	2.12	1.06
BE/ME	1.13	1.25	1.36	1.50	1.85	0.73
Asset Growth	1.44	1.35	1.28	1.22	1.25	−0.19

Table 6: **Expected pricing errors from comparative statics analysis**
This table reports the pricing errors from a comparative statics analysis. For σ_{it}^S, ϵ_{it+1}, and λ_i, we set them to their cross-sectional averages each year for each quintile portfolio. For C_{it} and S_{it}, instead of fixing them to their cross-sectional averages, we set $S_{it} = X_{it}/(\widetilde{X_{it}/S_{it}})$ and $C_{it} = X_{it}/(\widetilde{X_{it}/C_{it}})$ and recalculate μ_i and σ_i using the parameters estimates from the sample of all the three sets of portfolios in Table 3, where $\widetilde{X_{it}/S_{it}}$ and $\widetilde{X_{it}/C_{it}}$ are the cross-sectional earnings–price ratio and interest coverage ratio, respectively. Then, we reconstruct the theoretical return r_{it}^M, while keeping all the other parameters unchanged. We report the expected return errors, defined as $e_i^r = \mathbb{E}[r_{it+1}^s - r_{it+1}^M]$, and the mean absolute errors (m.a.e.) for each quintile portfolio and for the high-minus-low (H–L) hedging portfolios. The H–L portfolio is long in the high portfolio and short in the low portfolio.

Panel A. Market Leverage Portfolios							
	Low	2	3	4	High	H–L	m.a.e.
$X_{it}/\widetilde{X_{it}/S_{it}}$	−7.47	−1.63	−1.76	1.21	2.05	9.52	2.82
$X_{it}/\widetilde{X_{it}/C_{it}}$	−1.99	0.76	−0.13	1.78	1.98	3.98	1.33
$\widetilde{\sigma_{it}^S}$	−1.54	0.78	−0.52	1.09	0.04	1.58	0.79
$\widetilde{\epsilon_{it+1}}$	−3.45	1.27	1.55	4.68	6.90	10.35	3.57
$\widetilde{\lambda_i}$	−2.28	−1.24	−0.96	0.35	4.26	6.54	1.82

Panel B. BE/ME Portfolios							
$X_{it}/\widetilde{X_{it}/S_{it}}$	−7.30	−2.76	−0.18	−2.24	0.80	8.10	2.65
$X_{it}/\widetilde{X_{it}/C_{it}}$	−2.74	−1.15	0.55	−1.08	1.68	4.42	1.44
$\widetilde{\sigma_{it}^S}$	−2.40	−1.06	0.36	−1.63	−0.59	1.81	1.21
$\widetilde{\epsilon_{it+1}}$	−3.46	0.27	2.93	1.89	5.94	9.40	2.90
$\widetilde{\lambda_i}$	−3.63	−2.78	−1.01	0.25	5.95	9.59	2.73

Panel C. Asset Growth Portfolios							
$X_{it}/\widetilde{X_{it}/S_{it}}$	0.76	−3.14	1.39	−0.38	−6.09	−6.85	2.35
$X_{it}/\widetilde{X_{it}/C_{it}}$	4.83	−0.30	2.13	1.57	−2.72	−7.55	2.31
$\widetilde{\sigma_{it}^S}$	3.14	−0.43	2.27	1.76	−2.70	−5.84	2.06
$\widetilde{\epsilon_{it+1}}$	5.80	1.61	3.90	2.49	−2.46	−8.27	3.25
$\widetilde{\lambda_i}$	6.64	1.57	−0.55	−0.54	−3.99	−10.63	2.66

Table 7: **The stock-cash flow sensitivities over the business cycle**

This table presents the average of the stock-cash flow sensitivities, ϵ_{it}, during expansions and recession in Panel A. It further reports the increases in the stock-cash flow sensitivity, $\zeta_{it} = \epsilon_{it}^{\text{NoBP}} - \epsilon_{it}$, due to the lack of the bargaining power in Panel B. We construct the stock-cash flow sensitivities, ϵ_{it}, using the parameter estimates from the sample of all the three sets of portfolios in Table 3. Keeping the same parameter values as for ϵ_{it}, we construct $\epsilon_{it}^{\text{NoBP}}$ by setting the parameter of bargaining power $\eta = 0$.

Panel A. Stock-cash flow sensistivity from fitted model, ϵ_{it}						
	Leverage		BE/ME		Asset Growth	
	Expansion	Recession	Expansion	Recession	Expansion	Recession
Low	1.05	1.07	1.11	1.14	1.35	1.42
2	1.15	1.19	1.21	1.25	1.30	1.34
3	1.26	1.34	1.30	1.35	1.23	1.30
4	1.39	1.49	1.37	1.48	1.19	1.25
High	1.61	1.68	1.50	1.64	1.22	1.26

Panel B. Increase in stock-cash flow sensistivity, $\zeta_{it} = \epsilon_{it}^{\text{NoBP}} - \epsilon_{it}$						
	Expansion	Recession	Expansion	Recession	Expansion	Recession
Low	0.00	0.00	0.01	0.01	0.07	0.10
2	0.01	0.02	0.02	0.03	0.04	0.06
3	0.03	0.06	0.04	0.06	0.02	0.04
4	0.08	0.14	0.08	0.15	0.02	0.03
High	0.36	0.89	0.22	0.63	0.02	0.03

Appendix

A Proofs

A.1 Proof of Proposition 1

Define a new Brownian motion:

$$W_{it} = \hat{W}_{it} + \int_0^t \theta(s)ds, \tag{A1}$$

where $\theta = \lambda_i/\sigma_i$ is the price of risk. Girsanov's theorem states that, under a risk-neutral measure, the operating income X_{it} is governed by

$$\frac{dX_{it}}{X_{it}} = \mu_i dt + \sigma_i dW_{it}. \tag{A2}$$

For the rest of the proof, we drop the subscripts i and t for ease of notation.

Ito's lemma implies that the equity value E satisfies

$$\frac{dE}{E} = \frac{1}{E}\left(\frac{\partial E}{\partial t} + \hat{\mu}x\frac{\partial E}{\partial X} + \frac{\sigma}{2}X^2\frac{\partial^2 E}{\partial X^2}\right)dt + \frac{1}{E}X\sigma\frac{\partial E}{\partial X}\hat{W}. \tag{A3}$$

The standard non-arbitrage argument gives us the following partial differential equation (PDE):

$$\frac{\partial E}{\partial t} + \mu X\frac{\partial E}{\partial X} + \frac{\sigma^2}{2}X^2\frac{\partial^2 E}{\partial X^2} - rE + D = 0. \tag{A4}$$

Plugging equation (A4) back into equation (A3), we obtain

$$\frac{dE}{E} = \frac{1}{E}\left[(\hat{\mu} - \mu)X\frac{\partial E}{\partial X} + rE - D\right]dt + \frac{1}{E}X\sigma\frac{\partial E}{\partial X}d\hat{W}. \tag{A5}$$

Simple algebraic manipulation yields

$$\frac{dE + Ddt}{E} - rdt = \frac{1}{E}\left[(\hat{\mu} - \mu)X\frac{\partial E}{\partial X}\right]dt + \frac{1}{E}X\sigma\frac{\partial E}{\partial X}d\hat{W}, \tag{A6}$$

and

$$\frac{dE + Ddt}{E} - rdt = \frac{X}{E}\frac{\partial E}{\partial X}(\hat{\mu}dt + \sigma d\hat{W} - \mu dt). \tag{A7}$$

Hence, the relation between the stock return and the cash flow rate is established as follows:

$$\frac{dE + Ddt}{E} - rdt = \frac{X}{E}\frac{\partial E}{\partial X}\left(\frac{\partial X}{X} - \mu dt\right) = \epsilon\left(\frac{\partial X}{X} - \mu dt\right). \tag{A8}$$

Adding back the subscripts of i and t, we obtain

$$r_{it}^M = rdt + \epsilon_{it}(r_{it}^X - \mu_i dt), \tag{A9}$$

which is equation (5).

Taking conditional expectation for the second moment of equation (A7), we can easily obtain the instantaneous return volatility as follows:

$$\sigma_{it}^M = \epsilon_{it}\sigma_i. \tag{A10}$$

Next, we provide the derivation of equity value $E(X)$ and its sensitivity to cash flows X. The general solution for equity value $E(X)$ to equation (A4) is

$$E(X) = \left(\frac{X}{r-\mu} - \frac{c}{r}\right)\theta(1-\tau_{eff}) + g_1 X^{\omega} + g_2 X^{\omega'}, \tag{A11}$$

where ω and ω' are the roots of the following quadratic equation:

$$\frac{1}{2}\sigma^2\omega(\omega-1) + \mu\omega - r = 0. \tag{A12}$$

The two roots are

$$\omega = \frac{1}{2} - \frac{\mu}{\sigma^2} - \sqrt{\left(\frac{\mu}{\sigma^2} - \frac{1}{2}\right)^2 + 2\frac{r}{\sigma^2}} < 0, \tag{A13}$$

and

$$\omega' = \frac{1}{2} - \frac{\mu}{\sigma^2} + \sqrt{\left(\frac{\mu}{\sigma^2} - \frac{1}{2}\right)^2 + 2\frac{r}{\sigma^2}} > 1. \tag{A14}$$

The standard no-bubble condition, $\lim_{X\to\infty} E(X)/X < \infty$, implies $g_2 = 0$. The value-matching condition in equation (3) gives

$$g_1 = \left[\left(\frac{1}{X_B}\right)^{\omega}\left(\frac{c}{r}\theta + \frac{X_B}{r-\mu}(\eta(\alpha-\kappa)-\theta)\right)\right](1-\tau_{eff}). \tag{A15}$$

Hence, before bankruptcy $X > X_B$, equity value is

$$E = \left[\left(\frac{X}{r-\mu} - \frac{c}{r}\right)\theta + \left(\frac{c}{r}\theta + \frac{X_B}{r-\mu}(\eta(\alpha-\kappa)-\theta)\right)\left(\frac{X}{X_B}\right)^{\omega}\right](1-\tau_{eff}). \tag{A16}$$

The smooth pasting condition in equation (4) gives the optimal bankruptcy threshold

$$X_B = \frac{\theta\omega(C/r)}{(\omega-1)}\frac{r-\mu}{\theta-\eta(\alpha-\kappa)}. \tag{A17}$$

It is easy to show that X_B decreases with θ. The more dividend equity holders receive, the greater incentive they have to keep the firm alive. Hence, they delay bankruptcy if the dividend–net income ratio is high. Moreover, X_B increases with η. Intuitively, if equity holders have greater bargaining power, they are willing to file for bankruptcy earlier because they are able to extract more rent from debt holders through debt renegotiation.

The sensitivity of stocks to operating cash flows X is

$$\begin{aligned}
\epsilon =& \frac{X\partial E}{E\partial X} \\
=& \frac{1}{E}\left[\frac{\theta X}{r-\mu}(1-\tau_{eff}) + g_1\omega X^{\omega}\right] \\
=& \frac{1}{E}\left[E + \frac{c}{r}\theta(1-\tau_{eff}) - g_1 X^{\omega} + g_1\omega X^{\omega}\right] \\
=& 1 + \frac{c/r}{E}\theta(1-\tau_{eff}) + \frac{(\omega-1)}{E}g_1 X^{\omega} \\
=& 1 + \frac{c/r}{E}\theta(1-\tau_{eff}) - \frac{(1-\omega)}{E}\left[\frac{c}{r}\theta + \frac{X_B}{r-\mu}(\eta(\alpha-\kappa)-\theta)\right](1-\tau_{eff})\left(\frac{X}{X_B}\right)^{\omega}.
\end{aligned} \tag{A18}$$

Adding back the subscripts of i and t, we have have the time-varying stock-cash flow sensitivity ϵ_{it} as in equation (7) for each firm i. ■

A.2 Proof of Corollary 1

By directly applying the property of hitting time distribution of a geometric Brownian motion according to equation (11) of p.14 on Harrison (1985), we obtain the cumulative physical default probability $\hat{\pi}$ for the firm issuing a perpetual bond, i.e. $T \to \infty$.

$$\hat{\pi}_{it} = (\frac{X_{it}}{X_{iB}})^{-2(\hat{\mu}_i - 0.5\sigma_i^2)/\sigma_i^2}. \tag{A19}$$

When $\mu_i \to r$, we obtain $\omega_i \to -2r/\sigma_i^2$ from equation (A13). Therefore,

$$\pi_{it} = (\frac{X_{it}}{X_{iB}})^{\omega_i} \to (\frac{X_{it}}{X_{iB}})^{-2r/\sigma_i^2}. \tag{A20}$$

By taking logarithm of $\hat{\pi}_{it}$ and π_{it}, we can easily obtain

$$\lambda_i = \hat{\mu}_i - r = \left(\frac{log(\pi_{it}) - log(\hat{\pi}_{it})}{log(X_{it}) - log(X_{iB})} + 1 \right) \frac{\sigma_i^2}{2}. \tag{A21}$$

B GMM

Let $D = \partial \mathbf{g}_T / \partial \mathbf{b}$ and $\mathbf{S}$ be a consistent estimate of the variance-covariance matrix of the sample error $\mathbf{g}_T$. We use a standard Bartlett kernel with a window length of five to estimate $\mathbf{S}$.

The estimate of $\mathbf{b}$, denoted $\tilde{\mathbf{b}}$, is asymptotically normal-distributed as follows:

$$\tilde{\mathbf{b}} \sim \mathbf{N}(\mathbf{b}, \frac{1}{T}(\mathbf{D'WD})^{-1}\mathbf{D'WSWD}(\mathbf{D'WD})^{-1}). \tag{A1}$$

If $\mathbf{W} = \mathbf{S}^{-1}$, the GMM estimator is optimal or efficient in the sense that the variance is as small as possible.

To make statistical inferences for the pricing errors of individual portfolios or groups of pricing errors, we construct the variance-covariance matrix for the pricing errors $\mathbf{g}_T$

$$var(\mathbf{g}_T) = \frac{1}{T}[\mathbf{I} - \mathbf{D}(\mathbf{D'WD})^{-1}\mathbf{D'W}]\mathbf{S}[\mathbf{I} - \mathbf{D}(\mathbf{D'WD})^{-1}\mathbf{D'W}]'. \tag{A2}$$

To test whether all the pricing errors are jointly zero, we perform a χ^2 test as follows:

$$\mathbf{g}_T' var(\mathbf{g}_T)^{+}\mathbf{g}_T \sim \chi^2(d.f. = \#of moments - \#of parameters), \tag{A3}$$

where the superscript + denotes pesudo-inversion.

Internet Appendix

A Time series correlations between observed and model predicted returns and volatilities

Equations (5) and (6) implies that predicted stock returns and volatilities equal their observed counterparts literally at every data point. However, as pointed by Cochrane (1991), there is no such choice of parameters for which the predicted and observed returns are exactly equal at every data point in the investment-based asset pricing model. In this contingent claims model, we have matched the first moment of stock returns as in equation (13) and use the second moment of stock returns to back out the implied cash flow volatility as in equation (15). Next, we impose much stricter tests and examine the time series correlation between observed returns and volatilities and their predicted counterparts.

Panel A of Table A2 reports the contemporaneous time-series correlation coefficients between observed and predicted stock returns and their associated p-values. For the leverage quintile portfolios, the time series correlation coefficients are positive and range from 0.07 to 0.21. Their high p-values indicate that the correlation coefficients are not statistically significant, possibly due to the small sample (i.e., 46 observations for each quintile portfolio). However, when we pool all the observations of the five quintile portfolios together, the correlation between observed and model-predicted returns becomes 0.17, which is statistically significant at the 1% level. Similar observations apply to the BE/ME and asset growth portfolios.

Panel B reports the contemporaneous correlation coefficients between observed and predicted stock return volatilities. For the set of leverage portfolios, the correlation coefficients for each quintile portfolio are all positive but not statistically significant. The exception is the lowest quintile portfolio with a correlation coefficient of 0.32, which is significant at the 3% level. Moreover, by pooling the observations of all the five quintile portfolios to increase the sample size, we obtain a correlation coefficient of 0.21, which is statistically significant as well. The correlation coefficients for the book-to-market and asset growth portfolios are 0.20 and 0.23, respectively, and both of them are statistically significant.

In short, we find positive and significant contemporaneous correlations between observed returns and volatilities and their predicted counterparts. Admittedly, the contemporaneous correlation is not very high because there is no such choice of parameters for which the predicted and observed returns are exactly equal at every data point (Cochrane, 1991).

B Two-Stage IS-GMM

As Cochrane (1996) points out, while two-stage efficient IS-GMM pays more attention to statistical efficiency, one-stage consistent IS-GMM focuses on economic structure. The estimates from efficient IS-GMM could be misleading if the estimated covariance matrix of the sample moment is poorly measured. Table A3 reports the parameter estimates from a two-stage IS-GMM estimation using an inverse variance-covariance weighting matrix. The estimates of θ are greater than those from the one-stage IS-GMM estimation. The t-statistics become much greater because two-stage IS-GMM is more efficient in terms of the smaller variance. The results in Panels B and C are close to those in Table 3. Table A4 presents the pricing errors. The model performs well for all the three sets of testing portfolios. The results are very similar to those generated from the one-stage IS-GMM estimation.

C Quarterly Frequency

Table A1: **Pricing errors, default probability and stock-cash flow sensitivity from models *with fixed payout policy***

This table presents the expected pricing errors in percent in Panel A, risk-neutral default probability in Panel B, and stock-cash flow sensitivity in Panel C for each quintile portfolio from the model without renegotiation. We construct the predicted returns, risk-neutral default probabilities and stock-cash flow sensitivities using the parameter estimates from the sample of all the three sets of portfolios in Table 3, except that we set the dividend-net income ratio $\theta = 1$. The expected return errors are defined as $e_i^M = \mathbb{E}[r_{it+1}^s - r_{it+1}^M]$, in which $\mathbb{E}[.]$ is the sample mean of the series in parentheses. The H denotes the highest quintile portfolio and the L denotes the lowest quintile portfolio. The H–L portfolio is long in the high portfolio and short in the low portfolio. The heteroscedasticity- and autocorrelation-consistent t-statistics for the model errors are reported in parentheses. m.a.e. is the mean absolute error for each set of testing portfolios.

Panel A. Expected pricing error							
	Low	2	3	4	High	H–L	m.a.e.
Market Leverage	−1.54	0.74	−0.68	0.79	−1.76	−0.22	1.10
	(−0.56)	(0.32)	(−0.31)	(0.49)	(−0.96)	(−0.15)	
BE/ME	−2.39	−1.13	0.20	−2.06	−2.33	0.06	1.62
	(−0.85)	(−0.52)	(0.10)	(−0.86)	(−1.20)	(0.05)	
Asset Growth	2.95	−0.68	2.15	1.69	−2.70	−5.65	2.04
	(1.30)	(−0.56)	(1.06)	(0.76)	(−0.87)	(−2.19)	

Panel B. Default Probability (in %)						
	Low	2	3	4	High	H–L
Market Leverage	10.37	18.06	24.74	31.02	45.48	35.10
BE/ME	17.18	23.19	27.13	30.03	39.20	22.02
Asset Growth	27.44	23.44	20.94	18.88	22.64	−4.80

Panel C. Stock-cash flow sensitivity						
	Low	2	3	4	High	H–L
Market Leverage	1.06	1.17	1.29	1.44	1.75	0.70
BE/ME	1.12	1.23	1.32	1.43	1.62	0.50
Asset Growth	1.39	1.32	1.26	1.21	1.23	−0.16

Table A2: **Time Series Correlations**

This table reports the contemporaneous time-series correlations between observed stock returns r_{it}^S and predicted returns r_{it}^M in Panel A and the correlations between observed stock return volatility σ_{it}^S and predicted volatilities σ_{it}^M in Panel B. Their associated p-values are reported in parentheses. We construct the predicted returns r_{it}^M using the parameter estimates from the sample of all the three sets of portfolios in Table 3. We first assess the correlations at the individual quintile portfolio level, and report them at the first five columns. The H denotes the highest quintile portfolio and the L denotes the lowest quintile portfolio. The All denotes all the five quintile portfolios of each set.

Panel A. $corr(r_{it}^S, r_{it}^M)$						
	Low	2	3	4	High	All
Leverage	0.21	0.11	0.07	0.12	0.20	0.17
	(0.17)	(0.48)	(0.63)	(0.44)	(0.19)	(0.01)
BE/ME	0.16	−0.03	0.03	0.21	0.21	0.17
	(0.30)	(0.85)	(0.85)	(0.16)	(0.15)	(0.01)
Asset Growth	0.18	0.13	0.04	0.11	0.03	0.14
	(0.23)	(0.39)	(0.78)	(0.46)	(0.84)	(0.04)

Panel B. $corr(\sigma_{it}^S, \sigma_{it}^M)$						
Leverage	0.32	0.28	0.11	0.08	0.24	0.21
	(0.03)	(0.06)	(0.47)	(0.62)	(0.11)	(0.00)
BE/ME	0.05	0.12	0.03	0.06	0.32	0.20
	(0.72)	(0.42)	(0.85)	(0.71)	(0.03)	(0.00)
Asset Growth	0.13	−0.01	0.23	0.15	−0.02	0.23
	(0.38)	(0.96)	(0.12)	(0.33)	(0.87)	(0.00)

Table A3: **Parameter Estimates and Model Fitness from Two-Stage IS-GMM**
This table reports the parameter estimates from two-stage IS-GMM with an inverse variance-covariance weighting matrix. The first moment condition $\mathbb{E}[r^s_{it+1} - r^M_{it+1}] = 0$ is tested across all quintile portfolios, in which $\mathbb{E}[.]$ is the sample mean of the series in brackets. θ is the dividend–net income ratio and η is the shareholder bargaining power. Their associated t-statistics are reported in brackets. The χ^2-statistics are reported with the associated degrees of freedom (d.f.) and p-values.

Panel A. Estimates of Parameter				
	Leverage	BE/ME	Asset Growth	All
θ	0.98	0.70	0.86	0.76
	(3.15)	(3.51)	(3.03)	(5.96)
η	0.64	0.41	0.58	0.60
	(3.17)	(1.31)	(0.57)	(6.92)
χ^2	2.25	2.41	7.39	9.05
d.f.	3.00	3.00	3.00	13.00
p-value	0.52	0.49	0.06	0.77

Panel B. Implied Risk-Neutral Rate μ(%)						
	Leverage	BE/ME	Asset Growth	Leverage	BE/ME	Asset Growth
Low	−1.87	−0.40	−1.48	−0.70	−0.72	−1.07
2	−2.96	−1.49	−2.28	−1.66	−1.87	−1.78
3	−3.29	−1.74	−2.43	−2.02	−2.14	−1.89
4	−3.16	−1.61	−2.07	−2.03	−2.01	−1.54
High	−2.64	−1.51	−1.47	−1.81	−1.96	−1.02

Panel C. Implied Volatility σ(%)						
	Leverage	BE/ME	Asset Growth	Leverage	BE/ME	Asset Growth
Low	25.26	25.86	19.85	25.56	25.74	20.41
2	20.70	21.29	17.74	21.25	21.20	18.11
3	18.64	19.25	18.17	19.33	19.23	18.49
4	17.08	17.84	19.89	17.91	17.99	20.20
High	16.24	16.74	22.61	17.35	17.52	23.02

Table A4: **Expected Pricing Errors from Fitted Models from Two-Stage IS-GMM**
The table presents the pricing errors for each quintile portfolio from two-stage IS-GMM estimation with an inverse variance-covariance weighting matrix. The expected return errors are defined $e_i^M = \mathbb{E}[r_{it+1}^s - r_{it+1}^M]$, in which $\mathbb{E}[.]$ is the sample mean of the series in parentheses. Panel A reports the dividend–net income ratio, θ, and the shareholder bargaining power, η. Panels B and C report the risk-neutral rate, μ_i, and volatility σ_i, of cash flows, respectively. Their associated t-statistics are reported in parentheses. The χ^2-statistics are reported with the associated degrees of freedom (d.f.) and p-values. We first estimate the parameters for the three sets of portfolios, individually. Then, we pool all the three sets of portfolios and jointly estimate the parameters.

	Low	2	3	4	High	H–L	m.a.e.
Market Leverage	−1.65	0.61	−0.74	0.88	−0.05	1.61	0.79
	(−0.61)	(0.24)	(−0.20)	(0.27)	(−0.01)	(1.13)	
BE/ME	−2.50	−1.23	0.15	−1.89	−0.71	1.79	1.29
	(−0.85)	(−0.45)	(0.04)	(−0.58)	(−0.15)	(1.81)	
Asset Growth	3.15	−0.69	2.06	1.59	−2.79	−5.94	2.05
	(0.77)	(−0.23)	(0.72)	(0.59)	(−0.77)	(−2.82)	

Table A5: **Summary statistics of portfolio characteristics for quarterly data**

This table presents summary statistics for the characteristics of portfolios formed on market leverage, book-to-market equity, and asset growth rate. $\overline{r^X_{it+1}}$ is the time series average of cash flow rates in annual percent from time t to time $t+1$ after portfolios are formed at time t; $corr(r^X_{it+1}, r^S_{it+1})$ is the time series correlation coefficient between r^X_{it+1} and r^S_{it+1}; and $\overline{\sigma^S_{it}}$ is the time series average of annualized daily volatility of stock portfolio in percent calculated from one-year daily stock returns before the portfolio formation. $\overline{X_{it}/S_{it}}$ is the time series average of earnings–price ratios and $\overline{X_{it}/C_{it}}$ is the time series average of interest coverage ratios.

Panel A. Market Leverage Portfolios						
	Low	2	3	4	High	H–L
$\overline{r^X_{it+1}}$	13.45	9.21	9.45	5.55	9.48	−3.97
corr(r^X_{it+1},r^S_{it+1})	0.08	−0.03	0.10	0.01	0.13	0.05
$\overline{X_{it}/S_{it}}$	0.02	0.03	0.04	0.04	0.06	0.04
$\overline{X_{it}/C_{it}}$	23.60	8.94	5.46	3.52	1.92	−21.68
$\overline{\sigma^S_{it}}$	25.24	22.31	22.08	22.10	23.91	−1.33

Panel B. BE/ME Portfolios						
$\overline{r^X_{it+1}}$	9.88	8.54	8.70	11.13	11.87	1.99
corr(r^X_{it+1},r^S_{it+1})	−0.01	0.01	0.05	0.13	0.17	0.18
$\overline{X_{it}/S_{it}}$	0.02	0.03	0.04	0.04	0.05	0.03
$\overline{X_{it}/C_{it}}$	8.26	5.92	4.79	3.81	2.58	−5.68
$\overline{\sigma^S_{it}}$	25.86	23.62	22.82	22.59	22.48	−3.38

Panel C. Asset Growth Portfolios						
$\overline{r^X_{it+1}}$	13.65	11.69	7.66	8.98	7.43	−6.21
corr(r^X_{it+1},r^S_{it+1})	0.15	0.09	0.07	−0.03	0.00	−0.15
$\overline{X_{it}/S_{it}}$	0.03	0.04	0.03	0.03	0.03	−0.00
$\overline{X_{it}/C_{it}}$	3.29	4.80	5.94	6.94	5.13	1.84
$\overline{\sigma^S_{it}}$	23.83	22.06	21.70	22.48	25.18	1.35

Table A6: **Parameter estimates and model fitness for quarterly data**
This table reports the parameter estimates from one-stage IS-GMM with an identity-weighting matrix for the data over the 1965 to 2010 period. The first moment condition $\mathbb{E}[r^s_{it+1} - r^M_{it+1}] = 0$ is tested for all the quintile portfolios, in which $\mathbb{E}[.]$ is the sample mean of the series in parentheses. We report the dividend–net income ratio, θ, and the shareholder bargaining power, η. The χ^2-statistics are reported with the associated degrees of freedom (d.f.) and p-values. We first estimate the parameters for the three sets of portfolios, individually. Then, we pool all the three sets of portfolios and jointly estimate the parameters.

	Panel A. Estimates of Parameter			
	Leverage	BE/ME	Asset Growth	All
θ	0.93	0.67	0.81	0.79
	(2.25)	(1.84)	(2.10)	(2.09)
η	0.70	0.57	0.79	0.63
	(1.94)	(1.26)	(1.01)	(1.86)
χ^2	2.60	1.33	2.69	11.24
d.f.	3.00	3.00	3.00	13.00
p-value	0.46	0.72	0.44	0.59

Table A7: **Expected pricing errors from fitted models for quarterly data**
This table presents the pricing errors in percent for each quintile portfolio from one-stage IS-GMM with an identity-weighting matrix. We construct the predicted returns using the parameter estimates from the sample of all the three sets of portfolios in Table 3. The expected return errors are defined as $e^M_i = \mathbb{E}[r^s_{it+1} - r^M_{it+1}]$, in which $\mathbb{E}[.]$ is the sample mean of the series in parentheses. The H denotes the highest quintile portfolio and the L denotes the lowest quintile portfolio. The H–L portfolio is long in the high portfolio and short in the low portfolio. The heteroscedasticity- and autocorrelation-consistent t-statistics for the model errors are reported in parentheses. m.a.e. is the mean absolute error for each set of testing portfolios.

	Low	2	3	4	High	H–L	m.a.e.
Market Leverage	−1.83	1.45	−0.01	4.69	1.19	3.01	1.83
	(−0.80)	(0.84)	(−0.01)	(1.77)	(0.55)	(1.08)	
BE/ME	−1.08	−0.46	0.28	−3.31	−0.81	0.27	1.19
	(−0.50)	(−0.33)	(0.14)	(−1.17)	(−0.38)	(0.12)	
Asset Growth	−0.10	−3.08	2.24	0.35	0.99	1.10	1.35
	(−0.03)	(−1.31)	(1.06)	(0.21)	(0.35)	(0.28)	