Contingent-Claim-Based Expected Stock Returns*

Zhiyao Chen
ICMA Centre
University of Reading

Ilya A. Strebulaev
Graduate School of Business
Stanford University and NBER

*We thank Harjoat Bhamra, Chris Brooks, Wayne Ferson, Vito Gala, Andrea Gamba, João Gomes, Patrick Gagliardini, Chris Hennessy, Chris Juilliard, Nan Li, Rajnish Mehra, Stefan Nagel, Stavros Panageas, Marcel Prokopczuk, Michael Roberts, Ravindra Sastry, Stephan Siegel, Neal Stoughton, Yuri Tserlukevich, Kathy Yuan, Jeffrey Zwiebel and participants at the ASU Sonoran 2013 Winter Finance Conference, the European Financial Associations 2013 annual meetings and the American Financial Associations 2014 annual meetings for their helpful comments. Zhiyao Chen: ICMA Centre, University of Reading, UK, email: n.chen@icmacentre.ac.uk; Ilya A. Strebulaev: Graduate School of Business, Stanford University, and NBER, email: istrebulaev@stanford.edu.

Contingent-Claim-Based Expected Stock Returns

Abstract

We develop and test a parsimonious contingent claims model for cross-sectional returns of stock portfolios formed on market leverage, book-to-market equity, asset growth rate, and equity size. Since stocks are residual claims on firms' assets that generate operating cash flows, stock returns are cash flow rates scaled by the sensitivities of stocks to cash flows. Our model performs well because the stock-cash flow sensitivities contain economic information. Value stocks, high-leverage stocks and low-asset-growth stocks are more sensitive to cash flows than growth stocks, low-leverage stocks and high-asset-growth stocks, particularly in recessions when default probabilities are high.

Keywords: Stock-cash flow sensitivity, structural estimation, implied-state GMM, financial leverage, default probability, asset pricing anomalies
JEL Classification: G12, G13, G33

1 Introduction

Equity is a residual claim contingent on a firm's assets that generate operating cash flows. Using this fundamental insight, we build a parsimonious contingent claims model for cross-sectional stock returns under a no-arbitrage condition. In the model, stock returns are cash flow rates scaled by the sensitivities of stocks to cash flows. We test the model via a variant of implied state generalized method of moments. Our model outperforms the capital asset pricing model (CAPM) and the Fama–French three-factor model in explaining stock returns of portfolios formed on market leverage, book-to-market equity, asset growth rate, and equity size.[1] The better performance of our model can be attributed to our innovative structural estimation of the stock-cash flow sensitivities that capture cross-sectional variation in financial leverage as well as variation in default probabilities over the business cycle.

Inspired by Schaefer and Strebulaev (2008), who successfully use a simple structural model to explain bond returns, we develop and test a simple contingent claims model for cross-sectional stock returns. It has only one state variable and two policy parameters related to dividend payout and default policies that determine the stock-cash flow sensitivities. The only state variable is observable cash flows. Our choice of one observable state variable follows Cochrane (1996), who essentially uses observable investment returns as the main state variable. Similarly, we infer the underlying market movement from firms' operating cash flows instead of looking for unobservable market returns. We also explicitly model the dividend payout and default policies that affect the amount of cash flows accruing to stock holders and therefore the stock-cash flow sensitivities.

[1]While the market leverage premium, value premium and size premium are long well-known, Cooper, Gulen, and Schill (2008) recently 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.

We adapt implied-state generalized method of moments (IS-GMM) proposed by Pan (2002) to test the model for four sets of equal-weighted portfolios. All the portfolios considered 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. We take book-to-market and asset growth portfolios as our next two sets of testing 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. Avramov, Chordia, Jostova, and Philipov (2013) empirically document that value premium and asset growth premium associate with financial distress risk. The last set is size portfolios. Griffin and Lemmon (2002) and Vassalou and Xing (2004) document that size premium is more significant in firms with high default risk.

Our model performs well in explaining the cross-sectional returns for all the sets of portfolios. For the financial leverage portfolios, the pricing error of the high-minus-low (H–L) portfolio is 0.65% per year, substantially lower than 12.39% in the CAPM and 3.19% in the Fama–French model. The mean absolute error (m.a.e.) across the five portfolios is 0.87% per year, compared with 7.03% in the CAPM and 3.72% in the Fama–French model. For the book-to-market portfolios, the pricing error of the H–L portfolio in our model is 1.95% per year, lower than 15.00% in the CAPM and 7.38% in the Fama–French model. For the asset growth portfolios, the m.a.e. in our model is 1.60% per year, which is considerably lower than 7.28% in the CAPM and 4.26% in the Fama–French model. For the size portfolios, the pricing error of the small-minus-big (S–B) portfolio in our model is −0.08% per year, which is much lower than 8.03% in the CAPM and 2.81% in the Fama–French model.

We then explore the economic mechanism behind the model's good fit. Our model results in the closed-form solution for the time-varying stock-cash flow sensitivity. We therefore first estimate the two policy parameters and back out the latent risk-neutral rate and volatility and then use them to calculate the time based on a closed-form solution from our parsimonious model. Our analysis demonstrates that the spread in the stock-cash flow sensitivities is able to explain a large portion of cross-sectional variation in stock returns for the market leverage, book-to-market and asset growth portfolios, while the spread in the cash flow rates plays an important role for the size portfolios. We also find that stocks are more sensitive to the changing cash flows in bad times when default probabilities are high. More important, the counter-cyclical spread in stock-cash flow sensitivity is a manifestation of the cross-sectional difference in default probabilities over the business cycle.

Our work is related to several strands of the literature. First, structural models of capital structure have received a lot of attention recently (See e.g., Goldstein, Ju, and Leland (2001), Strebulaev (2007), Chen (2009), Morellec, Nikolov, and Schurhoff (2008), Hennessy and Whited (2005), and Hennessy and Whited (2007)). Our model is based on Fan and Sundaresan (2000) and Davydenko and Strebulaev (2007) that study the impact of renegotiation between equity and debt holders on capital structure choice and bond pricing. We extend their models to examine cross-sectional stock returns. The second strand is the emerging literature using dynamic models to study cross-sectional stock returns (See e.g., Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003), Gomes and Schmid (2010), Bhamra, Kuehn, and Strebulaev (2010) and Kogan and Papanikolaou (2010)). While they use calibration to evaluate their model performance, we use IS-GMM that incorporates all the information from data without generating artificial data sets.

The third strand of the literature quantifies the performance of the dynamic models. Because of the complexity of the dynamic models, most research either employs reduced-form regressions to test model predictions or uses calibration and simulated method of moments (SMM) to evaluate the structural model performance.[2] Cochrane (1996) and Liu, Whited, and Zhang (2009) develop neoclassical investment models and use generalized method of moments to study the model implications for stock returns. Compared with the discrete-time investment models, our continuous-time model of default risk faces the well-known difficulty in estimating the latent variables. The IS-GMM procedure we adapt overcomes this difficulty and provides a new perspective for the continuous-time contingent claims models.

The remainder of this paper proceeds as follows. Section 2 presents the parsimonious contingent claim model. Section 3 explains the empirical specifications and procedures. Section 4 describes the data and the empirical measures. Section 5 adapts IS-GMM to estimate the model and examines the time series of stock-cash flow sensitivity and default probability. Section 6 concludes the paper.

2 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.

[2]Recent works that use linear regressions include Garlappi and Yan (2011) and Favara, Schroth, and Valta (2011). Carlson, Fisher, and Giammarino (2004) and Hennessy and Whited (2005) use SMM to simulate a firm's dynamic paths, generate artificial data sets and match certain selected moments.

2.1 Model

Consider an economy with a large number of firms, indexed by subscript i. Assets that generate cash flows are traded continuously in arbitrage-free markets. Under a physical probability measure, the observable operating rate of cash flows r_{it}^X for a firm, i, is governed by

$$r_{it}^X \equiv \frac{dX_{it}}{X_{it}} = \hat{\mu}_i dt + \sigma_i d\hat{W}_t, \tag{1}$$

where X_{it} is cash flows, $\hat{\mu}_i$ is an expected growth rate of the cash flows, σ_i is an instantaneous volatility parameter, and $\hat{W}_{it}$ is a standard Brownian motion. 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, the 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 of τ_{eff}. At any date t, the firm first uses the operating cash flows to pay coupon and taxes, and then distributes a fraction θ of its net income, $(X_{it} - C_i)(1 - \tau_{eff})$, back to its equity holders, where $\theta \leq 1$ is the dividend–net income ratio. The remainder of the net income is used for capital investments, cash retention, etc. The final payoff that accrues to equity holders is thus the dividend, $D_{it} = \theta(X_{it} - C_i)(1 - \tau_{eff})$.

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 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 $S_{it}(X_{it})$ that leads to the following conditions:

$$S_{it}(X_{iB}) = \eta(\alpha - \kappa)\frac{X_{iB}}{r - \mu_i}, \tag{2}$$

$$\frac{\partial S_{it}}{\partial X_{it}}\bigg|_{X_{it}=X_{iB}} = \eta(\alpha - \kappa)\frac{1}{r - \mu_i}, \tag{3}$$

where r is the risk-free rate. Equation (2) is the value-matching condition, which states the equity holders' payoff in renegotiation. Equation (3) is the standard smooth-pasting condition that enables equity holders to choose the optimal X_{iB} to exercise their bankruptcy option.[3]

The next proposition derives instantaneous stock returns r_{it}^M implied by this contingent claims model.

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

$$r_{it}^M = rdt + \epsilon_{it}(r_{it}^X - \mu_i dt), \tag{4}$$

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

$$\begin{aligned}\epsilon_{it} =& \frac{X_{it}\partial S_{it}}{S_{it}\partial X_{it}} \\ =& 1 + \underbrace{\frac{C_i/r}{S_{it}}\theta(1-\tau_{eff})}_{\textit{Financial leverage (+)}} - \underbrace{\frac{(1-\omega_i)}{S_{it}}\left[\frac{C_i}{r}\theta + \frac{X_{iB}}{r-\mu_i}(\eta(\alpha-\kappa)-\theta)\right](1-\tau_{eff})\pi_{it}}_{\textit{Option to go bankrupt (+)}},\end{aligned} \tag{5}$$

where $\pi_{it} \equiv (\frac{X_{it}}{X_{iB}})^{\omega_i}$ is the risk-neutral default probability and S_{it} is the equity value

$$S_{it} = \left[\left(\frac{X_{it}}{r-\mu_i} - \frac{C_i}{r}\right)\theta + (\frac{C_i}{r}\theta + \frac{X_{iB}}{r-\mu_i}(\eta(\alpha-\kappa)-\theta))\pi_{it}\right](1-\tau_{eff}). \tag{6}$$

[3] See Harrison (1985) and Leland (1994).

The optimal bankruptcy threshold X_{iB} and $\omega_i < 0$ are given in Appendix A.

Proof: See Appendix A.

Equation (4) 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., $\mathbb{E}(r_{it}^X - \mu_i dt) = \lambda_i dt$.

The stock-cash flow sensitivity ϵ_{it} in equation (5) plays an important role in characterizing the no-arbitrage relation between the expected stock return r_{it}^M and the cash flow rate 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 under 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 (5). 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.[4] Consistent with this

[4]Equity holders with greater bargaining power are willing to file for bankruptcy earlier than their counterparts with relatively lower 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

reasoning, the stock-cash flow sensitivity declines monotonically with the bargaining power, as shown in Panel B of Figure 1.

It is worth noting 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 firm is distressed. In the first case, X_{it} must be 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 S_{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 distress, 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, stock values become less sensitive to the variation in cash flows for constant leverage. Hence, the negative effect of the option of default 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) find the inverted U-shaped relationship between π_{it} and ϵ_{it}.

2.2 Taking the Model to the Data

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

$$\lambda_i dt = \beta_i^X \mathbb{E}(r_t^m - rdt), \tag{7}$$

bargaining power on equity risk.

where β_i^X is the market beta of cash flows X_{it} and r_t^m is the market return. Garlappi and Yan (2011), and 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 both because the market return r_t^m is unobservable (Roll, 1977) and because 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.

Recently, in a structural equilibrium model, Bhamra et al. (2010) embed the contingent-claims-based capital structure model into the consumption-based asset pricing framework and derive the following result for the risk premium

$$\lambda_i dt = \mathbb{E}(r_{it}^X - \mu_i dt) = \gamma \rho_i \sigma_i \sigma_c dt, \tag{8}$$

where γ is the relative risk aversion of an Epstein-Zin-Weil agent, ρ_i is the correlation coefficient between cash flows X_{it} and aggregate consumption, and σ_c is the volatility of aggregate consumption growth rate. However, we face the same difficulties in observing the true consumption changes and estimating ρ_i.

3 Empirical Specification and Design

We test the equality between the observed stock returns, r_{it+1}^S, and the predicted returns from our contingent claim model, $r_{it+1}^M \equiv \mathbb{E}_t[r_{it+1}^M]$, at the portfolio level as follows:

$$\mathbb{E}[r_{it+1}^S - \mathbb{E}_t[r_{it+1}^M]] = 0, \tag{9}$$

where $\mathbb{E}[.]$ is an unconditional mean operator and $\mathbb{E}_t[.]$ is a conditional one for a time series. We adapt implied state generalized method of moments (IS-GMM) to test the model.

Assume that the model holds for each time t. To construct the predicted return r^M_{it+1} in equation (4), we obtain the values of the firm- and time- specific variables from the data, such as X_{it}, S_{it} and C_{it}, and take constant values of the market-wide variables from recent studies, including r, α, κ and τ_{eff}. We assume that the observed coupon payment C_i at time t is the optimal and add subscript t for it.[5]

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 3.1 and then present our adapted IS-GMM procedure on how to estimate θ and η in Section 3.2.

3.1 Latent Risk-Neutral Cash Flow Rate and Volatility

The latent parameters of cash flows, μ_i and σ_i, are not observable. Using the observable stock price and stock return volatility, we adapt the IS-GMM procedure proposed by Pan (2002) to back out μ_i and σ_i.[6] 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

[5]Note that C_{it} is not an additional state variable, because given X_{it} the coupon is an outcome of the optimization problem for equity holders. The derivation of the optimal coupon can be found in Leland (1994) and Goldstein et al. (2001).

[6]The consistency and asymptotic normality of the IS-GMM estimators can be found in the Appendix of Pan (2002). Alternative choices is maximum likelihood method (MLM) proposed by Duan (1994) for European stock options.

used KMV method of credit risk (Crosbie and Bohn, 2003).[7]

To back out the expected $\mu_{it+1} \equiv \mathbb{E}_t[\mu_{it+1}]$ and $\sigma_{it+1} \equiv \mathbb{E}_t[\sigma_{it+1}]$ for operating cash flows, we need the historical stock price S_{it} and stock volatility σ_{it}^S up to time t. We use the past one-year daily returns of stock portfolios to estimate σ_{it}^S.

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 will elaborate in the next section. Combining the trivial values with the information set $\Theta_{it} = (X_{it}, S_{it}, C_{it}, \sigma_{it}^S, r, \alpha, \kappa, \tau_{eff})$ up to time t, we solve the following system of two equations for the two unknowns, $\mu_{it+1}(\theta, \eta, \Theta_{it})$ and $\sigma_{it+1}(\theta, \eta, \Theta_{it})$:

$$\sigma_{it}^S = \mathbb{E}_t[\sigma_{it+1}\epsilon_{it+1}] \equiv \sigma_{it+1}\epsilon_{it+1}; \tag{10}$$

$$S_{it} = \left[\left(\frac{X_{it}}{r-\mu_{it+1}} - \frac{C_{it}}{r}\right)\theta + \left(\frac{C_{it}}{r}\theta + \frac{X_{iB}}{r-\mu_{it+1}}(\eta(\alpha-\kappa)-\theta)\right)\left(\frac{X_{it}}{X_{iB}}\right)^{\omega_{it+1}}\right](1-\tau_{eff}), \tag{11}$$

where the expected stock-cash flow sensitivity is

$$\epsilon_{it+1} = 1 + \frac{C_{it}/r}{S_{it}}\theta(1-\tau_{eff}) + \frac{(\omega_{it+1}-1)}{S_{it}}\left[\frac{C_{it}}{r}\theta + \frac{X_{iB}}{r-\mu_{it+1}}(\eta(\alpha-\kappa)-\theta)\right](1-\tau_{eff})\left(\frac{X_{it}}{X_{iB}}\right)^{\omega_{it+1}}, \tag{12}$$

and ω_{it+1} is the negative root of the following equation:

$$\frac{1}{2}(\sigma_{it+1}^X)^2\omega_{it+1}(\omega_{it+1}-1) + \mu_{it+1}\omega_{it+1} - r = 0. \tag{13}$$

Equation (10) is implied by Ito's lemma. Equation (11) derives the equity value S_{it}, defined in equation (6), given the information set Θ_{it}.

[7]See e.g., Vassalou and Xing (2004), Bharath and Shumway (2008) and Davydenko and Strebulaev (2007).

3.2 IS-GMM Framework

Given the implied μ_{it+1} and σ_{it+1} for each period t, the discrete-time version of the predict return from equation (4) is

$$r^M_{it+1} = r\Delta t + \epsilon_{it+1}\left(\frac{\Delta X_{it+1}}{X_{it}} - \mu_{it+1}\Delta t\right). \tag{14}$$

We test the model at the annual frequency ($\Delta t = 1$). From equation (14), the conditional expectation of the instantaneous contingent-claim-based return is

$$\mathbb{E}_t[r^M_{it+1}] = r + \mathbb{E}_t\left[\epsilon_{it+1}\left(\frac{\Delta X_{it+1}}{X_{it}} - \mu_{it+1}\right)\right]. \tag{15}$$

In addition to potential specification errors, this discretization might suffer from measurement errors (Lo, 1986). However, we can still test the weak condition of equations (9) as in Cochrane (1991) and Liu et al. (2009).

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

$$e^M_{it}(\mathbf{b}, \Theta_{it}) \equiv e^M_{it}(\mathbf{b}, \Theta_{it}, \mu_{it+1}(\mathbf{b}, \Theta_{it}), \sigma_{it+1}(\mathbf{b}, \Theta_{it})) = r^S_{it+1} - \mathbb{E}_t[r^M_{it+1}] \tag{16}$$

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

$$\begin{aligned} e^M_i &= \mathbb{E}[e^M_{it}(\mathbf{b}, \Theta_{it})] \\ &= \mathbb{E}[r^S_{it+1} - \mathbb{E}_t[r^M_{it+1}]] \\ &= \mathbb{E}[r^S_{it+1} - (r + \epsilon_{it+1}(r^X_{it+1} - \mu_{it+1}))]. \end{aligned} \tag{17}$$

The sample moments of pricing errors are $\mathbf{g}_T = [e^M_1 ... e^M_n]'$, 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 (9), 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):

$$J_T = \mathbf{g}_T' \mathbf{W} \mathbf{g}_T, \tag{18}$$

$$\text{s.t. } 0 < \theta \leq 1, \tag{19}$$

$$0 < \eta \leq 1, \tag{20}$$

where $\mathbf{W}$ is a positive-definite symmetric weighting matrix. Until the optimal parameter vector $\mathbf{b} \equiv [\theta, \eta]'$ is found, both μ_{it+1} and σ_{it+1} 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).[8]

In summary, we back out μ_{it+1} and σ_{it+1} 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_{it+1} and σ_{it+1} are solved from the system of equations (10) and (11) for each portfolio-year observation.

3. Given $\mathbf{b}_0$ and Θ_{it} as well as the implied $\mu_{it+1}(\mathbf{b}_0, \Theta_{it})$ and $\sigma_{it+1}(\mathbf{b}_0, \Theta_{it})$, ϵ_{it+1} and r^M_{it+1} are calculated based on equations (12) and (14) respectively.

4. The pricing error e^M_i for each portfolio is obtained from (17) and the objective value J_T in equation (18) across all the portfolios is calculated.

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

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

4 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 1963 to 2010. We exclude firms from the financial (SIC 6000 – 6999) and utility (SIC 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 Fama–French factors are obtained from Kenneth French's website.

4.1 Variable Measurement and Parameter Values

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 (2011), 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 equity value (price per share times the number of shares outstanding) and coupon C_{it} is the total interest expenses (item XINT). 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. r^X_{t+1} is the percentage change of the aggregate operating cash flows from year t to year $t+1$. For the market-wide variables, the effective tax rate τ_{eff} is set to 20%, the expected liquidation cost $\alpha = 0.30$, the renegotiation cost $\kappa = 0$, and the after-tax annual risk-free rate $r = 3.6\%$.[9]

4.2 Testing Portfolios

We employ four sets of testing portfolios: five market leverage portfolios, five book-to-market portfolios, five asset growth portfolios and five size portfolios. We choose five portfolios for each asset pricing anomaly to ensure that the simultaneous equations (10) and (11) are solvable for all portfolio-year observations. All the portfolios are equal-weighted.

We take standard procedures to calculate ranking variables and form stock portfolios (Fama and French, 1992, 1993). The first ranking variable is market leverage measured as a ratio of total debt over the sum of total debt and the market value of equity. It 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).

Book-to-market equity ratio is the second variable of interest for the BE/ME portfolios. It is the ratio of book equity (BE) of the fiscal year ending in calendar year $t-1$ over 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

[9] Andrade and Kaplan (1998) consider 31 distressed firms and find the costs of financial distress between 10% and 20% of firm value. Korteweg (2010) finds the bankruptcy costs amount to 15 to 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 (2011) argue that the bankruptcy costs estimated from defaulted firms are potentially downward biased because those firms are likely have smaller costs of bankruptcy and endogenously choose high level of debt, resulting in high likelihood of default. He uses SMM to estimate a structural model and shows that the average firms are expected to lose 45% of firm value at bankruptcy. We use the bankruptcy cost of 45% for robustness check and report the results in the Internet Appendix.

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 calculated as the percentage change in total assets (Compustat item AT). The growth rate for year $t-1$ is the percentage change from fiscal year ending in calendar year $t-2$ to fiscal year ending in calendar year $t-1$.

The last ranking variable is market equity (ME) for the size portfolios. The ME is obtained at the end of each December of calendar year $t-1$. The firms with a stock price lower than $5 are excluded at the portfolio formation.

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 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 $t+1$.

4.3 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.

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 worth noting 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. Second, to estimate ϵ_{it+1}, we use the KMV procedure to obtain the expected $\mu_{it+1} \equiv \mathbb{E}_t[\mu_{it+1}]$ and $\sigma_{it+1} \equiv \mathbb{E}_t[\sigma_{it+1}]$. 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 the daily returns of 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 given 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 $t+1$.

5 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 and perform comparative statics analysis to identify crucial factors. Lastly, we attempt to understand the economic driving forces behind the stock-cash flow sensitivity.

5.1 Pricing Errors from Traditional Models

We first confirm the well-known pricing errors in our data sample. Table 1 reports the averages of annualized monthly returns in percent 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 and e^{FF} from the Fama–French model, are estimated by regressing the time series of portfolio returns on the market factor and on the Fama–French three factors.

Market leverage portfolio: Panel A shows that stocks with high market leverage earn 13.03% per year more than do stocks with low leverage. The pricing error of the H–L portfolio from the CAPM is 12.39% ($t = 4.22$). This error decreases to 3.19% ($t = 1.53$) and becomes statistically insignificant for the Fama–French model. This significant drop is consistent with the conclusion of Fama and French (1992) that the book-to-market factor is capable to explain the cross-sectional returns of the market leverage portfolios. Additionally, the mean absolute errors (m.a.e.) is 7.03% per year for the CAPM and decreases to 3.72% for the Fama–French model.

BE/ME portfolios: The average returns in Panel B monotonically increase with the book-to-market ratio from 13.02% to 27.18% per year. After controlling for the market factor, the H–L portfolio earns 15.00% ($t = 5.91$) per year and the m.a.e. is 6.90%. The performance of the Fama–French model improves because the error of the H–L portfolio decreases to 7.38% ($t = 3.78$) and the m.a.e. declines to 3.93%.

Asset growth portfolios: As shown in Panel C, high-growth firms earn 11.70% lower stock returns per year than low-growth firms.[10] This finding can not be explained by the standard CAPM and the Fama–French model. The errors of the H–L portfolio from the CAPM and the Fama–French model are −11.33% ($t = -5.83$) and −9.81%

[10] The difference is smaller than the difference of 20% per year documented by Cooper et al. (2008) because our sample requires positive debt and has other restrictions.

($t = -4.42$), respectively. The m.a.e.'s for asset growth portfolios are the greatest among all the four sets of testing portfolios. The m.a.e. is 7.28% from the CAPM and 4.26% from the Fama–French model.

Size portfolios: Panel D confirms the size effect. Small firms earn 9.50% greater returns per year than big firms, even if we exclude small firms with a price lower than \$5 at the portfolio formation. The decrease in average returns with the equity size remains the same after controlling the market factor and Fama–French three factors. The errors of the small-minus-big (S–B) portfolio from the CAPM and the Fama–French model are 8.03% ($t = 2.70$) and 2.81% ($t = 2.01$), respectively. The m.a.e. is 4.11% for the CAPM and is 2.28% for the Fama–French model.

Overall, we demonstrate that the well-documented pricing errors from the traditional models are largely the same in our data sample as in the literature.

5.2 Summary Statistics of Model Inputs and Portfolio Characteristics

Table 2 summaries main inputs and portfolio characteristics for the four 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 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 (5).

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. More interestingly, the correlations between them are relatively weak. Additionally, while $\overline{X_{it}/S_{it}}$ increases from 0.09 to 0.23, $\overline{X_{it}/C_{it}}$ dramatically declines from 21.50 to 2.16, implying that high-leverage firms have difficulties covering their interest expenses. The stock volatility σ_{it}^S is slightly U-shaped.

BE/ME portfolios: Similar to the market leverage portfolios, both r_{it+1}^X and σ_{it}^S are slightly U-shaped. The magnitude of the increase in $\overline{X_{it}/S_{it}}$ across the book-to-market portfolios is comparable to that across the market leverage portfolios as well. $\overline{X_{it}/C_{it}}$ for the BE/ME portfolios declines from 10.20 to 3.46 and the decrease is considerably smaller than that in the market leverage portfolios.

Asset growth portfolios: The decrease in earnings-price ratio across the asset growth portfolios is the opposite to the increases in the book-to-market portfolios, because low-growth 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 1.87, the smallest difference among the four sets of portfolios.

Size portfolios: The decline in r_{it+1}^X is the most significant among all the four sets of portfolios. It decreases significantly from 15.65% to 8.31% per year with equity size and the difference is 7.34% per year, comparable to that in the cross-sectional stock returns of size portfolios. Moreover, the monotonic decline in σ_{it}^S is the most evident among the four sets of portfolios as well. While $\overline{X_{it}/S_{it}}$ slightly decreases, $\overline{X_{it}/C_{it}}$ increases significantly with equity size. This contrast implies that small firms face greater interest payment pressures and are more likely to become distressed. This observation is consistent with Vassalou and Xing (2004).

Taken together, the average cash flow rates change with the ranking variables in the same direction as the average stock returns do for all the four sets of portfolios. Except for the size 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 but is the smallest for the asset growth portfolios.

5.3 Model Estimation

We estimate two parameters, dividend–net income ratio θ and shareholder bargaining power η within the IS-GMM framework. Table 3 reports the parameter estimates and χ^2 statistics for model fitness when matching the predicted returns with the observed returns as in equation (9). The estimates of θ are 0.56, 0.52 and 0.67 for the market leverage, book-to-market equity and asset growth portfolios, respectively. Their respective t-statistics indicate that the estimates are statistically significant at a 95% confidence level. The three sets of portfolios are internally consistent. Firms with high book-to-market equity have accumulated more debt and therefore have more leverage, and those firms also have exercised their growth options and exhibit lower growth rates. Therefore, the payout policies implied from these three sets of portfolios are very similar. In contrast, the estimate of θ for the size portfolios is only 0.24 and is statistically insignificant. The estimates of η across all the four sets of portfolios are about 0.5. This estimate is close to the one chosen by Morellec et al. (2008) and the value of 0.6 assumed in Favara et al. (2011).

The χ^2 statistic, which tests whether all the model errors are jointly zero, gives an overall evaluation of the model performance. For the four sets of portfolios, the degrees of freedom (d.f.) are three because the number of the moments (or portfolios) is five and the number of parameters is two. The p-values of the χ^2 tests indicate that the model can not be rejected for all the four sets of testing portfolios. Because the no-arbitrage condition is the only one we impose to derive the expected stock returns, the reasonable performance of our model indicates that the no-arbitrage relation between stocks and cash flows holds for our testing portfolios.

Overall, the model performs well for all the sets of testing portfolios with a modest performance for the asset growth portfolios. However, the t-statistics of the two estimates and the p-values are relatively low. The relatively weak statistical significance could be attributed to our small data sample because each testing set has only five portfolios in annual frequency. Additionally, it is well-known that the consistent one-stage IS-GMM estimation gives relatively weaker statistical performance, compared with the efficient two-stage IS-GMM estimation as shown in the Appendix.

5.4 Pricing Errors from Structural Model

Given the estimates of θ and η, we construct the contingent-claims-based returns r^M_{it+1} as in equation (14) and calculate the expected pricing error e^M_i as in equation (16) for each individual portfolio. Table 4 reports the pricing errors from our model and compares the errors with those from the traditional models. We evaluate the traditional models with standard ordinary least square (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.

Market leverage portfolios: The first row shows that the pricing errors vary from -1.29% to 1.31% per year. Additionally, the pricing error of the H–L portfolio is 0.65% ($t = 0.59$) and is not statistically significant. This error is smaller than 12.39% from the CAPM and 3.19% from the Fama–French 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 claim 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 claim model reside on the 45-degree line. In contrast, the predicted returns from the CAPM in Panel B are almost flat. Although the predicted returns from the Fama–French model in Panel C show some improvement, none of the predicted returns lie on the 45-degree line.

BE/ME portfolios: From the third row of Table 4, the H–L portfolio has a pricing error of 1.92% per year, which is smaller than 15.00% in the CAPM and 7.38% per year in the Fama–French model. This error is mostly due to the large deviation of −1.67% from the growth portfolio. The small error of 0.25% in value portfolio implies that our model is able to capture the default risk associated with value firms. The mean absolute error (m.a.e) is 0.76% per year, much lower than 6.90% from the CAPM and 3.93% from the Fama–French model. Figure 4 provides a visual confirmation. As shown in Panel A, the largest deviation from the 45-degree line is the growth portfolio. The predicted returns from the CAPM are almost horizontal in Panel B and those from the Fama–French model in Panel C are quite similar.

Asset growth portfolios: The difference in the pricing errors between the high- and low- growth portfolios is −4.25% per year, which however is much less than −11.33% from the CAPM and −9.81% from the Fama–French 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- growth portfolios are slightly out of line. In sharp contrast, the predicted returns from the CAPM and the Fama–French model are almost flat.

Size portfolios: The pricing errors range from −1.44% to 1.14%. The error of the S–B portfolio is −0.08% per year. It is evident that, in Panel A of Figure 6, the predicted returns are aligned very well with the realized stock returns, even for the portfolio of small stocks. The performance of the CAPM remains poor, as shown by the horizontal line of its predicted returns. Although the Fama–French model performs much better than the CAPM, it still fails to capture the big outlier from the small portfolio.

In summary, our model does a good job for all the sets of portfolios and outperforms the CAPM and the Fama–French model. The model performs best for the market leverage portfolios and the book-market equity portfolios, and predicts the expected returns of value firms and small firms well. Although the model performs the modest for the asset growth portfolios, it gives a much better fit than the CAPM and the Fama–French model.

5.5 Pricing Errors from Comparative Statics Analysis

Given the reasonably good performance of our model, we follow Liu et al. (2009) and perform a comparative statics analysis to identify the most important factor in our model. The procedure is as follows. We first set an input to its cross-sectional average for each year. We then use the parameter estimates to recalculate the expected stock return according to equations (4) and (5), 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 X_{it}, the main inputs of our model are r^X_{it+1},σ^S_{it}, C_{it} and S_{it}. For r^X_{it+1}, we set it to its cross-sectional average $\widetilde{r^X_{it+1}}$ each year. Then, we use its average and the parameter estimates from Table 3 to recalculate r^M_{it+1}, while keeping all the other model inputs the same.

We repeat the same procedure for σ^S_{it}, C_{it} and S_{it}. However, after changing their values to their cross-sectional averages, we need to use the new inputs and the parameter estimates to recalculate μ_{it+1} and σ_{it+1} before we construct ϵ_{it+1} and r^M_{it+1}. 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.

Lastly, to evaluate the importance of ϵ_{it+1}, we use its cross-sectional average directly from the benchmark estimation without recalculating μ_{it+1} and σ_{it+1}. Because both ϵ_{it+1} and r^X_{it+1} do not need to invoke the recalculations of μ_{it+1} and σ_{it+1}, this exercise provides a direct comparison between the contributions of ϵ_{it+1} and r^X_{it+1} to the cross-sectional variation of predicted stock returns. Table 5 reports the results, which will be compared with those for the benchmark model in Table 4.

Market leverage portfolios: It is evident that the stock-cash flow sensitivity is the most important determinant and the earnings–price ratio the second in Panel A. By removing the cross-sectional variation of ϵ_{it+1}, the pricing error of the H–L portfolio jumps to 10.13% per year from 0.65% per year in the benchmark model. The m.a.e. increases from 0.87% to 3.42%. 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 the other model inputs. The lack of cross-sectional variation in ϵ_{it+1}'s increases the m.a.e. to 2.97% from 0.76% in the benchmark model. 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, the effects of eliminating the cross-sectional variations of model inputs are relatively small. The pricing error of the H–L portfolio in absolute value increases from 4.25% in the benchmark model to 8.80% after fixing the cross-sectional variation in r^X_{it+1}. 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 r^X_{it+1} is slightly more important than ϵ_{it+1}, the m.a.e. that evaluates the overall performance across all the quintile portfolios suggests the opposite inference. After fixing ϵ_{it+1} to its cross-sectional average, the m.a.e. increases from 1.60% in the benchmark model to 3.05%, greater than 2.28% due to fixing r^X_{it+1} to its cross-sectional average.

Size portfolios: The cash flow rate plays a crucial role in fitting the size portfolios into the model and the stock-cash flow sensitivity the second. By fixing r^X_{it+1} to its cross-sectional average each year, the pricing error of the S–B portfolio surges to 8.17% per year from -0.08% in the benchmark estimation and the m.a.e. increases from 1.01% to 2.02%. Compared with its role in the other three portfolios, ϵ_{it+1} becomes much less important for the size portfolios. Fixing ϵ_{it+1} to its cross-sectional average each year, the pricing error increases slightly to 1.29%, which is trivial, compared with 8.17% resulting from the lack of cross-sectional variation in r^X_{it+1}. Hence, the increased pricing error caused by the stock-cash flow sensitivity for the size portfolios is much smaller than it is for the other portfolios. The difference occurs because the decreasing slope in the cash flow rates r^X_{it} is very close to that in the stock returns r^s_{it} across the size portfolios as in Tables 1 and 2. Therefore, the stock-cash flow sensitivity becomes less critical in matching the observed stock returns with the predicted returns.[11]

Simply put, while the cross-sectional variation in the stock-cash flow sensitivity is the most important determinant for alleviating the pricing errors for the market leverage, book-to-market and asset growth portfolios, the cash flow rate is the one for the size portfolios. 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. This implies that including stochastic volatility as the second state does not necessarily improve the model performance.

[11] This result is consistent with the statistically insignificant estimates of θ and η for the size portfolios in Table 3. Because these two policy parameters affect the stock returns only via the stock-cash flow sensitivity ϵ_{it}, they become less important when r^X_{it+1} is the key for stock returns of the size portfolios.

5.6 Understanding the Stock-Cash Flow Sensitivities

Given the importance of the stock-cash flow sensitivity, we proceed to investigate its economic information content. Figures 7 and 8 plot the time series of the risk-neutral probability of default and the stock-cash flow sensitivity, respectively. We use NBER recession years to classify the cycles.[12]

Panel A of Figure 7 shows that high-leverage firms have greater default probabilities than low-leverage firms, particularly in recessions. Book-to-market equity portfolios exhibit the same pattern as those of leverage portfolios but with a smaller magnitude in Panel B. 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. The difference is more evident before 1980 and then diminishes afterward. The default probabilities are almost identical across all quintile portfolios during the booms of 1980s. Similar observations apply to the size portfolios in Panel D. Small firms have greater default probability than big firms and the difference in the default probabilities is more apparent before 1982.

The stock-cash flow sensitivity ϵ_{it} is partially determined by the risk-neutral default probability. Figure 8 plots the times series of the stock-cash flow sensitivity over the business cycles. High-leverage firms are considerably more sensitive to cash flows than low-leverage firms, particularly in NBER recession years. The spread in the sensitivities between the high- and low-leverage portfolios is about 0.81 during the early 1980s and 1990s recessions. Panel B shows that the stock-cash flow sensitivities of book-to-market portfolios largely mimic those of leverage portfolios in Panel A but

[12]Additionally we provide the cross-sectional statistics for stock-cash flow sensitivities and default probabilities in Section A of the Internet Appendix.

with a slightly smaller magnitude.[13].

Similar to the observations for the difference in default probabilities, the spread in the stock-cash flow sensitivities between the high- and low-growth firms is not as significant as that in the leverage and book-to-market portfolios. As shown in Panel C, low-growth firms are more sensitive to the business cycles. Panel D shows that the spread in stock-cash flow sensitivity between the small and big portfolios is the smallest among the four sets of portfolios. The averaged spread in the sample period is 0.07 and the greatest spread is 0.14 during the 1974 recession, much smaller than those for the leverage portfolios.

Overall, stocks are more sensitive to their underlying operating cash flows during business recessions when default probabilities are high than they are during expansions when default probabilities are low. The large spread in the counter-cyclical stock-cash flow sensitivities helps explain the high-leverage premium, the value premium and the asset growth premium.

6 Conclusion

We develop a contingent claims model for cross-sectional stock returns. The exogenous 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 ratio, asset growth rate and market capitalization. Our model outperforms the CAPM and the Fama–French three-factor model in explaining the cross-sectional variation in stock returns. The reasonable performance of our model validates the

[13]Studies that estimate the stock-cash flow sensitivity or cash flow beta in a reduced-form find that value stocks have greater cash flow betas than growth stocks do. See e.g., Campbell and Shiller (1988), Campbell and Vuolteenaho (2004), Bansal, Dittmar, and Lundblad (2005), Hansen, Heaton, and Li (2008) and Santos and Veronesi (2010)

no-arbitrage relationship between stocks and their underlying cash flows for all the four sets of portfolios.

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 structural estimations show that, while the estimates of these two policies are economically sensible, the dividend policy is statistically more significant than the shareholder bargaining power in determining stock returns.

We make a further attempt to understand the economic driving forces behind the model. We find that 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 in 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, except for the size portfolios that rely on the spread in the cash flow rates.

Our work demonstrates that our simple contingent claims model successfully explains the cross-sectional variation in stock returns for the four sets of stock portfolios related to default risk. However, our model has difficulties matching stock returns and the U-shaped stock return volatility jointly in unreported results. Explaining these and other anomalies should be a fruitful avenue for future research.

References

Almeida, H., and T. Philippon. 2007. The Risk-Adjusted Cost of Financial Distress. *Journal of Finance* 62:2557–2586.

Andrade, G., and S. N. Kaplan. 1998. How Costly Is Financial (Not Economic) Distress? Evidence from Highly Leveraged Transactions That Became Distressed. *Journal of Finance* 53:1443–1493.

Avramov, D., T. Chordia, G. Jostova, and A. Philipov. 2013. Anomalies and financial distress. *Journal of Financial Economics* 108:139–159.

Bansal, R., R. F. Dittmar, and C. T. Lundblad. 2005. Consumption, dividends, and the cross section of equity returns. *Journal of Finance* 60:1639–1672.

Berk, J. B., R. C. Green, and V. Naik. 1999. Optimal Investment, Growth Options and Security Returns. *Journal of Finance* 54:1553 – 1607.

Bhamra, H. S., L.-A. Kuehn, and I. A. Strebulaev. 2010. The Levered Equity Risk Premium and Credit Spreads: A Unified Framework. *Review of Financial Studies* 23:645–703.

Bharath, S. T., and T. Shumway. 2008. Forecasting Default with the Merton Distance to Default Model. *Review of Financial Studies* 21:1339–1369.

Campbell, J. Y., and R. J. Shiller. 1988. The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors. *The Review of Financial Studies* 1:195–228.

Campbell, J. Y., and T. Vuolteenaho. 2004. Bad Beta, Good Beta. *American Economic Review* 94:1249–1275.

Carlson, M., A. Fisher, and R. Giammarino. 2004. Corporate Investment and Asset Price Dynamics: Implications for the Cross-Section of Returns. *Journal of Finance* 59:2577–2603.

Chen, H. 2009. Macroeconomic Conditions and the Puzzles of Credit Spreads and Capital Structure. *Journal of Finance, forthcoming* .

Cochrane, J. H. 1991. Production-Based Asset Pricing and the Link between Stock Returns and Economic Fluctuations. *Journal of Finance* 46:209–237.

Cochrane, J. H. 1996. A Cross-Sectional Test of an Investment-Based Asset Pricing Model. *Journal of Political Economy* 104:572–621.

Cooper, M. J., H. Gulen, and M. J. Schill. 2008. Asset Growth and the Cross-Section of Stock Returns. *Journal of Finance* 63:1609–1651.

Crosbie, P., and J. Bohn. 2003. Modeling default risk. *Working Paper, Moody's KMV* .

Davydenko, S. A., and I. A. Strebulaev. 2007. Strategic Actions and Credit Spreads: An Empirical Investigation. *Journal of Finance* 62:2633–2671.

Davydenko, S. A., I. A. Strebulaev, and X. Zhao. 2012. A market-based study of the cost of default. *Review of Financial Studies* 25:2959–2999.

Duan, J.-C. 1994. Maximum Likelihood Estimation Using Price Data of the Derivative Contract. *Mathematical Finance* 4:55–167.

Fama, E. F., and K. R. French. 1992. The Cross-Section of Expected Stock Returns. *Journal of Finance* 47:427–465.

Fama, E. F., and K. R. French. 1993. Common Risk Factors in the Returns on Stock and Bonds. *Journal of Financial Economics* 33:3–56.

Fama, E. F., and K. R. French. 1995. Size and Book-to-Market Factors in Earnings and Returns. *Journal of Finance* 50:131–155.

Fan, H., and S. M. Sundaresan. 2000. Debt Valuation, Renegotiation, and Optimal Dividend Policy. *Review of Financial Studies* 13:1057–1099.

Favara, G., E. Schroth, and P. Valta. 2011. Strategic Default and Equity Risk Across Countries. *Journal of Finance, Forthcoming* .

Ferguson, M. F., and R. L. Shockley. 2003. Equilibrium "Anomalies". *Journal of Finance* 58:2549–2580.

Garlappi, L., and H. Yan. 2011. Financial Distress and the Cross Section of Equity Returns. *Journal of Finance* 66:789 – 822.

Glover, B. 2011. The Expected Cost of Default. *Working Paper, Carnegie Mellon University* .

Goldstein, R., N. Ju, and H. Leland. 2001. An EBIT-Based Model of Dynamic Capital Structure. *Journal of Business* 74:483–512.

Gomes, J. F., L. Kogan, and L. Zhang. 2003. Equilibrium Cross Section of Returns. *Journal of Political Economy* 111:693–732.

Gomes, J. F., and L. Schmid. 2010. Levered Returns. *Journal of Finance* 65:467–494.

Griffin, J. M., and M. L. Lemmon. 2002. Book-to-Market Equity, Distress Risk, and Stock Returns. *Journal of Finance* 57:2317–2336.

Hahn, J., and H. Lee. 2008. Financial Constraints, Debt Capacity, and the Cross Section of Stock Returns. *Journal of Finance, forthcoming* .

Hansen, L. P., J. C. Heaton, and N. Li. 2008. Consumption Strikes Back? Measuring LongRun Risk. *Journal of Political Economy* 116:260–302.

Harrison, J. M. 1985. *Brownian motion and stochastic flow systems*. Wiley New York.

Hennessy, C. A., and T. M. Whited. 2005. Debt Dynamics. *Journal of Finance* 60:1129–1165.

Hennessy, C. A., and T. M. Whited. 2007. How Costly Is External Financing? Evidence from a Structural Estimation. *Journal of Finance* 62:1705–1745.

Kogan, L., and D. Papanikolaou. 2010. Growth Opportunities, Technology Shocks, and Asset Prices. *Journal of Finance, forthcoming* .

Korteweg, A. 2010. The Net Benefits to Leverage. *Journal of Finance* 65:2137–2170.

Leland, H. E. 1994. Corporate Debt Value, Bond Covenants, and Optimal Capital Structure. *Journal of Finance* 49:1213–1252.

Liu, L. X., T. M. Whited, and L. Zhang. 2009. Investment Based Expected Stock Returns. *Journal of Political Economy* 117:1105–1139.

Lo, A. W. 1986. Statistical tests of contingent-claims asset-pricing models: A new methodology. *Journal of Financial Economics* 17:143–173.

Morellec, E., B. Nikolov, and N. Schurhoff. 2008. Corporate governance and capital structure dynamics: Evidence from a structural estimation. *Journal of Finance, forthcoming* .

Pan, J. 2002. The jump-risk premia implicit in options: Evidence from an integrated time-series study. *Journal of Financial Economics* 63:3–50.

Roll, R. 1977. A critique of the asset pricing theory's tests Part I: On past and potential testability of the theory. *Journal of Financial Economics* 4:129–176.

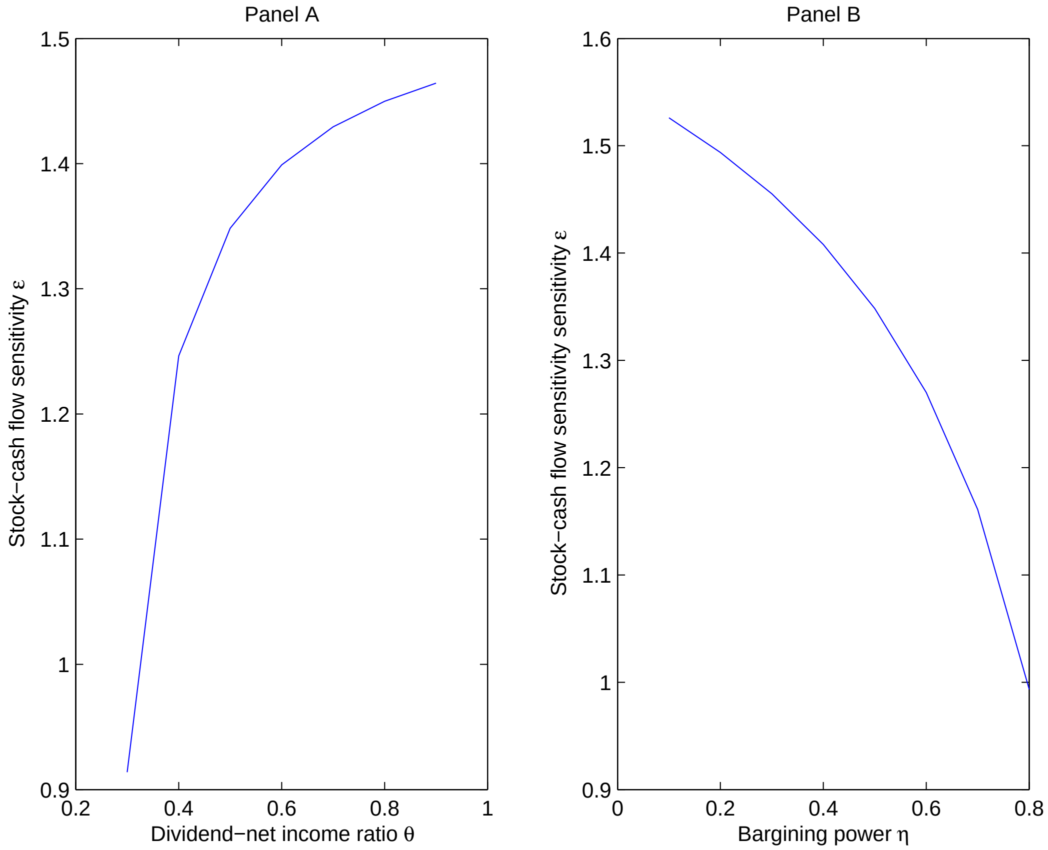
Santos, T., and P. Veronesi. 2010. Habit formation, the cross section of stock returns and the cash-flow risk puzzle. *Journal of Financial Economics* 98:385–413.

Schaefer, S. M., and I. A. Strebulaev. 2008. Structural Models of Credit Risk Are Useful: Evidence from Hedge Ratios on Corporate Bonds. *Journal of Financial Economics* 90:1–19.

Strebulaev, I. A. 2007. Do Tests of Capital Structure Theory Mean What They Say? *Journal of Finance* 62:1747–1787.

Vassalou, M., and Y. Xing. 2004. Default Risk in Equity Returns. *Journal of Finance* 59:831–868.

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 $r = 3.6\%$, $\tau_{eff} = 15\%$, $\mu_i = 0$, $\sigma_i = 0.25$, $\alpha = 0.30$, and $\kappa = 0$. X_i is normalized to one.



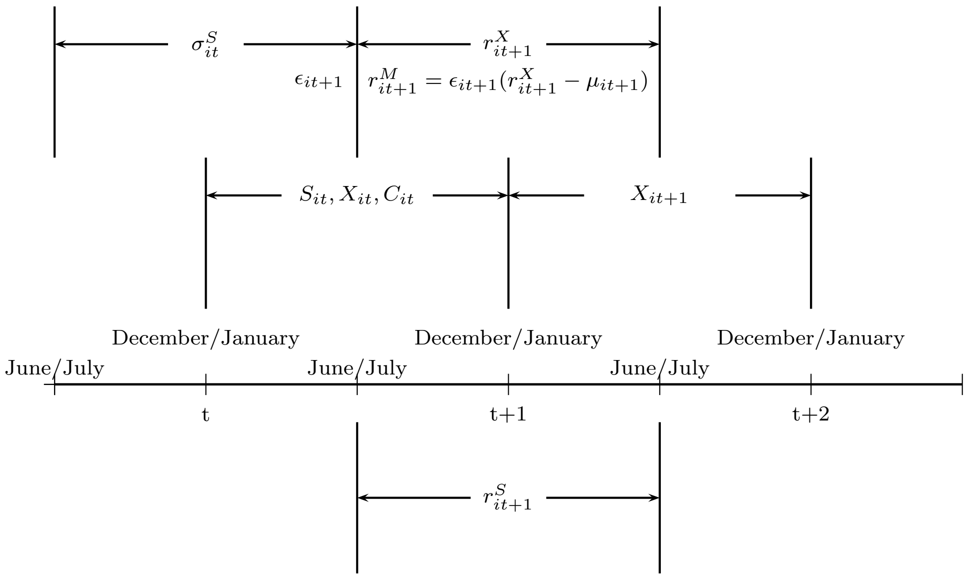


Figure 2: **Timing Alignment**

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 and the Fama–French model against the average realized returns. In the contingent claims model, the predicted returns are calculated based on equation (14) using the parameter estimates from Table 3 as well as the implied values of μ_{it+1} and σ_{it+1} from equations (10) and (11). High leverage denotes the high leverage quintile and low leverage denotes the low leverage quintile.

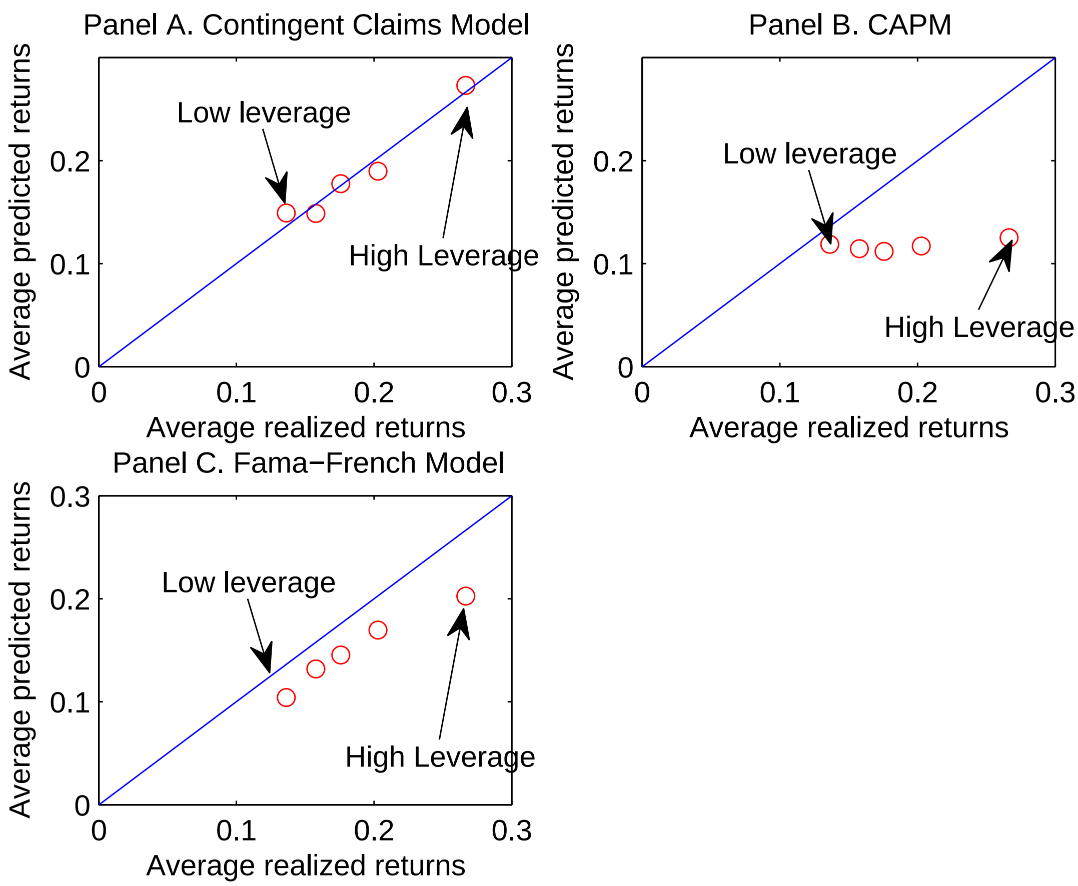


Figure 4: **Book-to-Market Portfolios: Average Predicted Stock Returns Versus Average Realized Returns**
This figure plots the time series averages of predicted returns from the contingent claims model, the CAPM and the Fama–French model against the average realized returns. In the contingent claims model, the predicted returns are calculated based on equation (14) using the parameter estimates from Table 3 as well as the implied values of μ_{it+1} and σ_{it+1} from equations (10) and (11). Value denotes the high BE/ME quintile and growth denotes the low BE/ME quintile.

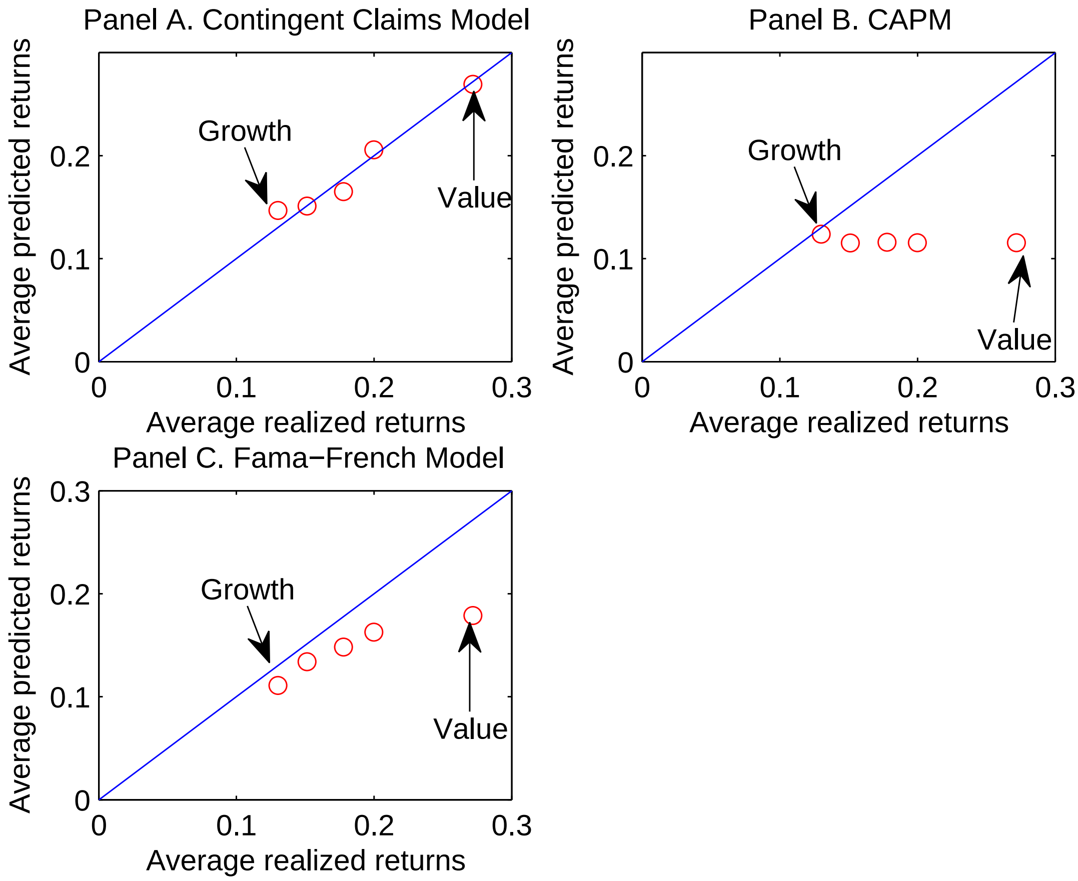


Figure 5: **Asset Growth Portfolios: Average Predicted Stock Returns Versus Average Realized Returns**
This figure plots the time series averages of predicted returns from the contingent claims model, the CAPM and the Fama–French model against the average realized returns. In the contingent claims model, the predicted returns are calculated based on equation (14) using the parameter estimates from Table 3 as well as the implied values of μ_{it+1} and σ_{it+1} from equations (10) and (11). High growth denotes the high asset-growth quintile and low growth denotes the low asset-growth quintile.

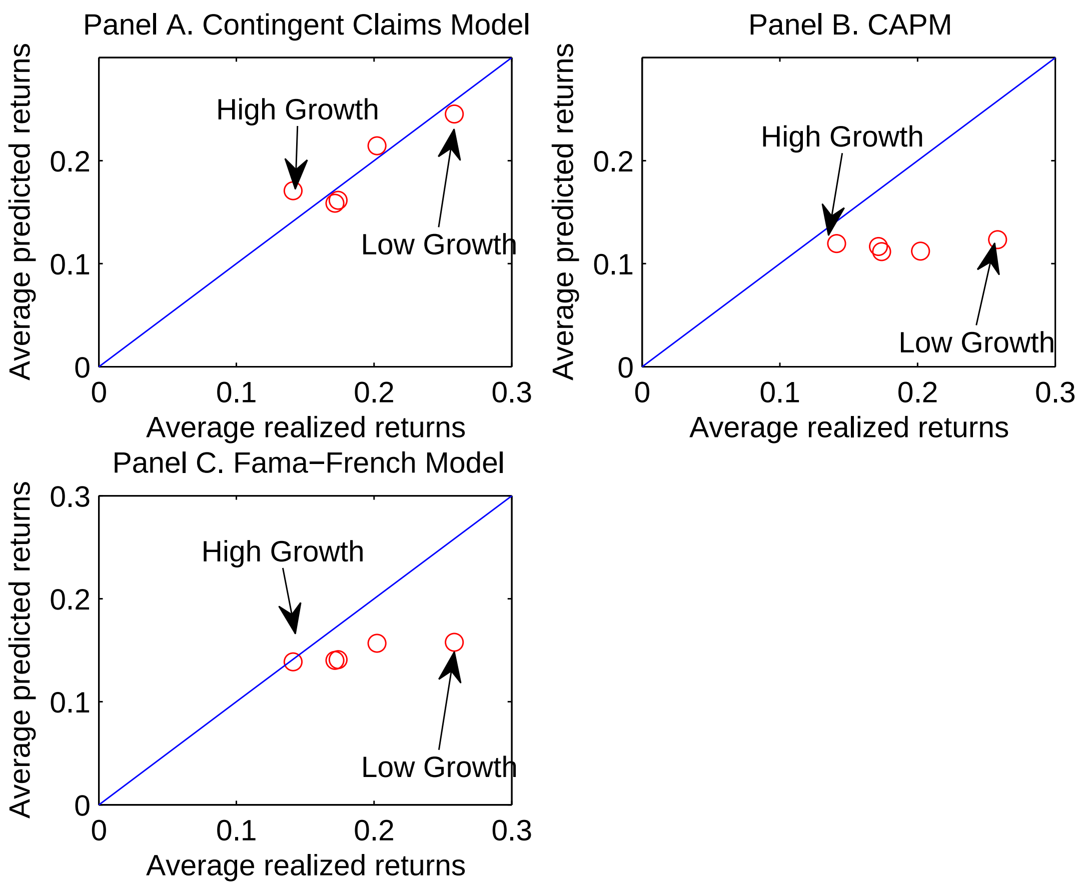


Figure 6: **Size Portfolios: Average Predicted Stock Returns Versus Average Realized Returns**
Each panel of this figure plots the time series averages of predicted returns from the contingent claims model, the CAPM and the Fama–French model against the average realized returns. In the contingent claims model, the predicted returns are calculated based on equation (14) using the parameter estimates from Table 3 as well as the implied values of μ_{it+1} and σ_{it+1} from equations (10) and (11). Small denotes the low market capitalization quintile and big denotes the high market capitalization quintile.

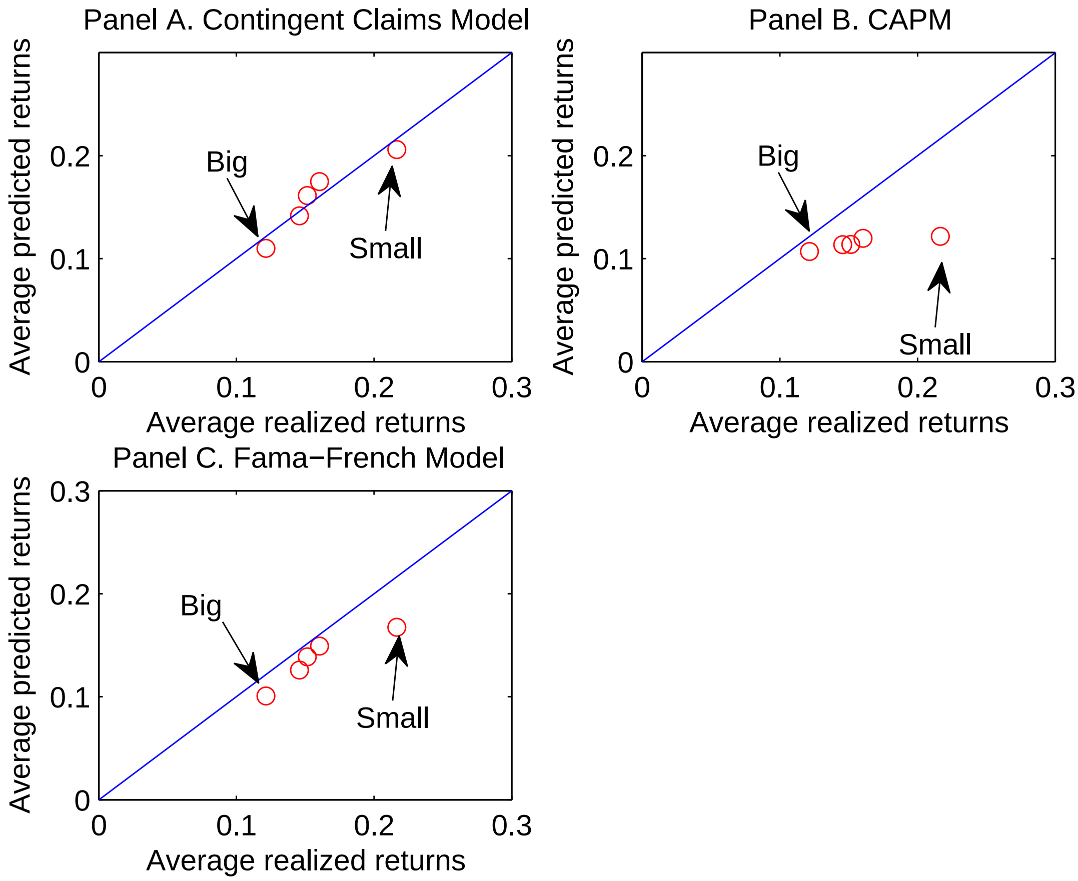


Figure 7: **Time Series of Risk-Neutral Default Probability**
Each panel of this figure plots time series of risk-neutral default probability, $\pi \equiv (X_{it}/X_{iB})^{\omega_i}$, against years. The shaded areas are for NBER recession years. The thick, solid lines are for the cross-sectional averages 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.

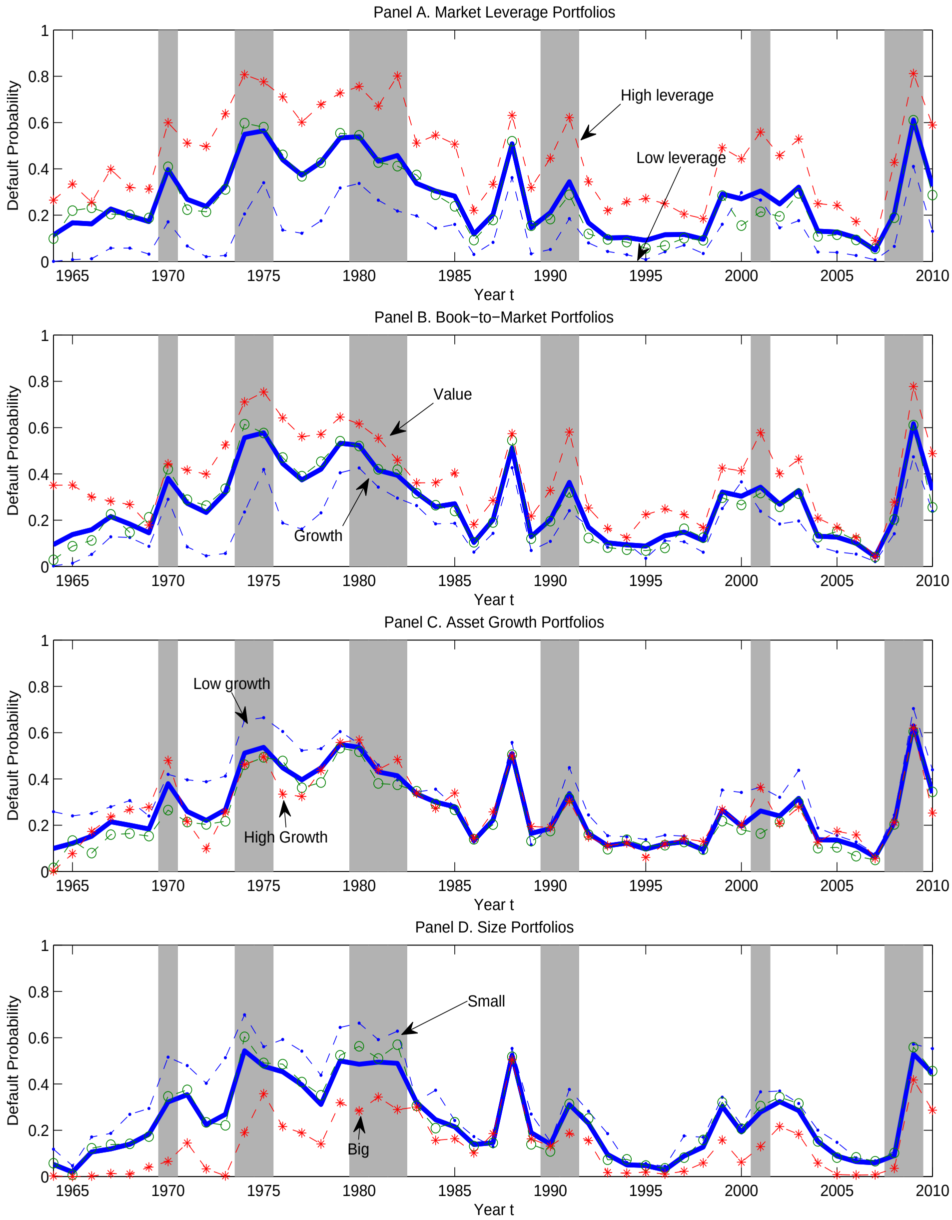


Figure 8: **Time series of Stock-Cash Flow Sensitivity**
Each panel of this figure plots time series of stock-cash flow sensitivity, ϵ_{it}, against years. The shaded areas are for NBER recession years. The stock-cash flow sensitivity is calculated based on equation (12) using the parameter estimates from Table 3 as well as the implied values of μ_{it+1} and σ_{t+1} from Table A1. 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.

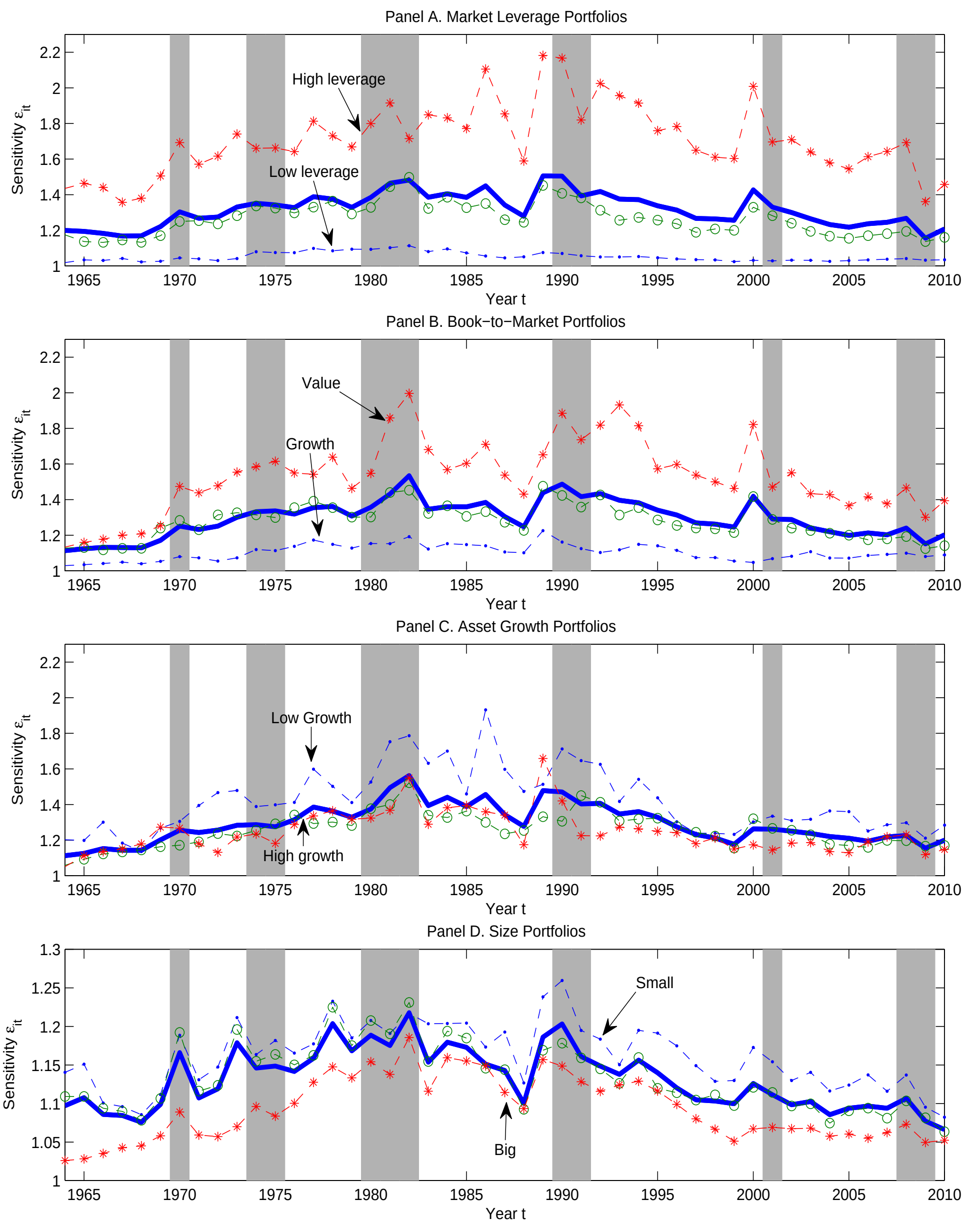


Table 1: **Pricing Errors of Testing Portfolio Returns from Traditional Models**

This table reports the annualized average stock return, $\overline{r^s_{it+1}}$, the pricing error from the CAPM regression, e_i^C, and the error from the Fama-French (FF) three-factor regression, e_i^{FF} for each quintile portfolio over the period of 1965 to 2010. $\overline{r^s_{it+1}}$, e_i^C, and e_i^{FF} 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 brackets. 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.
$\overline{r^S_{it+1}}$	13.63	15.78	17.58	20.28	26.66	13.03	
e_i^C	1.75	4.32	6.40	8.56	14.13	12.39	7.03
(t)	(0.79)	(2.34)	(3.22)	(3.65)	(4.40)	(4.22)	
e_i^{FF}	3.22	2.60	3.03	3.32	6.41	3.19	3.72
(t)	(2.03)	(1.95)	(2.50)	(2.22)	(3.49)	(1.53)	

Panel B. BE/ME Portfolios							
$\overline{r^S_{it+1}}$	13.02	15.13	17.78	19.99	27.18	14.16	
e_i^C	0.63	3.61	6.20	8.43	15.63	15.00	6.90
(t)	(0.28)	(1.96)	(2.95)	(3.69)	(5.41)	(5.91)	
e_i^{FF}	1.92	1.72	2.97	3.72	9.30	7.38	3.93
(t)	(1.30)	(1.39)	(2.21)	(2.65)	(5.06)	(3.79)	

Panel C. Asset Growth Portfolios							
$\overline{r^S_{it+1}}$	25.83	20.21	17.40	17.16	14.12	−11.70	
e_i^C	13.50	9.00	6.23	5.49	2.17	−11.33	7.28
(t)	(4.79)	(4.22)	(3.44)	(2.88)	(1.01)	(−5.83)	
e_i^{FF}	10.06	4.53	3.31	3.14	0.25	−9.81	4.26
(t)	(5.10)	(3.29)	(2.43)	(2.39)	(0.18)	(−4.42)	

Panel D . Size Portfolios							
	Small	2	3	4	Big	S–B	m.a.e.
$\overline{r^S_{it+1}}$	21.65	16.05	15.16	14.58	12.15	9.50	
e_i^C	9.50	4.07	3.77	3.22	1.47	8.03	4.41
(t)	(3.17)	(1.86)	(2.02)	(2.02)	(1.56)	(2.70)	
e_i^{FF}	4.90	1.14	1.28	2.00	2.09	2.81	2.28
(t)	(3.10)	(0.78)	(0.95)	(1.33)	(1.90)	(2.01)	

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, asset growth rate and market capitalization. $\overline{r_{it+1}^X}$ 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, $corr(r_{it+1}^X, r_{it+1}^S)$ is the time series correlation coefficient between r_{it+1}^X and r_{it+1}^S, and $\overline{\sigma_{it}^S}$ 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
$\overline{r_{it+1}^X}$	10.51	8.63	9.68	9.49	12.55	2.05
corr(r_{it+1}^X,r_{it+1}^S)	0.21	0.10	0.08	0.10	0.21	0.00
$\overline{X_{it}/S_{it}}$	0.09	0.12	0.15	0.17	0.23	0.14
$\overline{X_{it}/C_{it}}$	21.50	9.10	5.70	3.76	2.16	−19.34
$\overline{\sigma_{it}^S}$	26.67	24.53	24.55	25.15	27.97	1.30

Panel B. BE/ME Portfolios						
$\overline{r_{it+1}^X}$	10.06	8.60	8.99	11.31	13.71	3.64
corr(r_{it+1}^X,r_{it+1}^S)	0.15	−0.02	0.03	0.19	0.20	0.04
$\overline{X_{it}/S_{it}}$	0.09	0.13	0.15	0.17	0.20	0.11
$\overline{X_{it}/C_{it}}$	10.20	6.49	5.18	4.29	3.46	−6.74
$\overline{\sigma_{it}^S}$	28.53	25.67	25.00	24.97	26.65	−1.89

Panel C. Asset Growth Portfolios						
$\overline{r_{it+1}^X}$	12.94	11.56	8.15	8.58	9.85	−3.10
corr(r_{it+1}^X,r_{it+1}^S)	0.20	0.14	0.01	0.11	0.03	−0.16
$\overline{X_{it}/S_{it}}$	0.14	0.14	0.13	0.12	0.11	−0.03
$\overline{X_{it}/C_{it}}$	3.99	5.36	6.73	7.40	5.86	1.87
$\overline{\sigma_{it}^S}$	27.73	23.55	22.96	24.10	27.93	0.20

Panel D . Size Portfolios						
	Small	2	3	4	Big	S–B
$\overline{r_{it+1}^X}$	15.65	13.25	12.17	10.60	8.31	7.34
corr(r_{it+1}^X,r_{it+1}^S)	0.07	0.21	0.19	0.12	0.06	0.01
$\overline{X_{it}/S_{it}}$	0.16	0.16	0.15	0.14	0.12	0.04
$\overline{X_{it}/C_{it}}$	3.52	3.97	4.62	5.14	6.98	−3.46
$\overline{\sigma_{it}^S}$	26.93	27.22	25.56	24.19	22.08	4.85

Table 3: **Parameter Estimates and Model Fitness**
This table reports the parameter estimates from one-stage IS-GMM with an identity weighting matrix. The first moment conditions $\mathbb{E}[r^s_{it+1} - r^M_{it+1}] = 0$ is tested for all the quintile portfolios, in which $\mathbb{E}[.]$ is the sample mean of the series in 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.

	Leverage	BE/ME	Asset Growth	Size
θ	0.56	0.52	0.67	0.24
	(2.11)	(2.03)	(2.44)	(1.12)
η	0.51	0.51	0.49	0.53
	(1.34)	(0.61)	(0.20)	(0.50)
χ^2	2.20	2.83	5.87	4.35
d.f.	3.00	3.00	3.00	3.00
p-value	0.53	0.42	0.12	0.23

Table 4: **Expected Pricing Errors from Fitted Models**
This table presents the pricing errors in percent for each quintile portfolio from one-stage IS-GMM with an identity weighting matrix. The expected return errors are defined as $e_i^M = \mathbb{E}[r^s_{it+1} - r^M_{it+1}]$, in which $\mathbb{E}[.]$ is the sample mean of the series in brackets. The H (B) denotes the highest (biggest) quintile portfolio and the L (S) denotes the lowest (smallest) quintile portfolio. The H–L (S–B) portfolio is long in the high (small) portfolio and short in the low (big) portfolio. The heteroscedasticity-and-autocorrelation-consistent t-statistics for the model errors are reported in brackets. 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	−1.29	0.92	−0.18	1.31	−0.64	0.65	0.87
	(−1.08)	(1.08)	(−0.19)	(1.06)	(−4.49)	(0.59)	
BE/ME	−1.67	0.02	1.29	−0.58	0.25	1.92	0.76
	(−1.39)	(0.03)	(1.14)	(−0.56)	(1.14)	(1.76)	
Asset Growth	1.30	−1.22	1.25	1.30	−2.95	−4.25	1.60
	(3.94)	(−1.22)	(1.22)	(1.41)	(−1.80)	(−2.71)	

	Small	2	3	4	Big	S–B	m.a.e.
Size	1.06	−1.44	−0.97	0.43	1.14	−0.08	1.01
	(1.79)	(−1.40)	(−1.29)	(0.84)	(1.35)	(−0.19)	

Table 5: **Expected Pricing Errors from Comparative Statics Analysis**
This table reports the pricing errors from a comparative statics analysis. For r^X_{it+1}, σ^S_{it} and ϵ_{it+1} 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 use the parameters reported in Table 3 to recalculate μ_{it+1} and σ_{it+1}, 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^M_{it}, while keeping all the other parameters unchanged. We report the expected return errors, defined as $e^r_i = \mathbb{E}[r^s_{it+1} - r^M_{it+1}]$, and the mean absolute errors (m.a.e.) for each quintile portfolio and for the high-minus-low (H–L) and small-minus-big (S–B) hedging portfolios. The H–L (S–B) portfolio is long in the high (small) portfolio and short in the low (big) portfolio.

Panel A. Market Leverage Portfolios							
	Low	2	3	4	High	H–L	m.a.e.
$\widetilde{r^X_{it+1}}$	−0.94	−0.87	−0.75	0.21	3.52	4.46	1.26
$X_{it}/\widetilde{X_{it}/S_{it}}$	−4.42	−0.54	−0.45	2.28	2.72	7.15	2.08
$X_{it}/\widetilde{X_{it}/C_{it}}$	−1.70	0.90	0.23	2.01	2.10	3.80	1.39
$\widetilde{\sigma^S_{it}}$	−1.29	0.94	−0.14	1.26	−0.95	0.33	0.92
$\widetilde{\epsilon_{it+1}}$	−3.49	1.07	1.41	4.49	6.64	10.13	3.42

Panel B. BE/ME Portfolios							
$\widetilde{r^X_{it+1}}$	−2.16	−2.24	−0.86	0.53	5.49	7.65	2.25
$X_{it}/\widetilde{X_{it}/S_{it}}$	−4.30	−0.72	1.38	0.18	2.75	7.05	1.87
$X_{it}/\widetilde{X_{it}/C_{it}}$	−2.03	−0.08	1.45	0.00	2.80	4.83	1.27
$\widetilde{\sigma^S_{it}}$	−1.67	0.04	1.30	−0.55	−0.00	1.67	0.71
$\widetilde{\epsilon_{it+1}}$	−3.30	0.63	2.99	1.93	6.01	9.31	2.97

Panel C. Asset Growth Portfolios							
$\widetilde{r^X_{it+1}}$	5.27	0.59	−1.35	−0.66	−3.53	−8.80	2.28
$X_{it}/\widetilde{X_{it}/S_{it}}$	2.26	−0.59	1.26	0.64	−3.96	−6.23	1.74
$X_{it}/\widetilde{X_{it}/C_{it}}$	2.80	−0.96	1.14	1.11	−3.07	−5.87	1.82
$\widetilde{\sigma^S_{it}}$	1.04	−1.18	1.29	1.33	−2.94	−3.98	1.56
$\widetilde{\epsilon_{it+1}}$	5.61	1.69	3.37	2.69	−1.87	−7.49	3.05

Panel D. Size Portfolios							
	Small	2	3	4	Big	S–B	m.a.e.
$\widetilde{r^X_{it+1}}$	5.33	−0.09	−0.75	−1.11	−2.84	8.17	2.02
$X_{it}/\widetilde{X_{it}/S_{it}}$	1.39	−1.21	−0.89	0.36	0.55	0.84	0.88
$X_{it}/\widetilde{X_{it}/C_{it}}$	1.45	−1.28	−0.95	0.38	1.04	0.40	1.02
$\widetilde{\sigma^S_{it}}$	1.04	−1.49	−0.98	0.45	1.16	−0.12	1.02
$\widetilde{\epsilon_{it+1}}$	0.72	−2.13	−1.91	−0.72	−0.57	1.29	1.21

Appendix

A Proof of Proposition 1

Define a new Brownian motion

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

where $\theta_i = \lambda_i/\sigma_i$ 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 in the appendix.

Ito's lemma implies that the equity value S satisfies

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

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

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

Plugging the above equation back to equation (A3), we obtain

$$\frac{dS}{S} = \frac{1}{S}\left[(\hat{\mu} - \mu)X\frac{\partial S}{\partial X} + rS - D\right]dt + \frac{1}{S}X\sigma\frac{\partial S}{\partial X}dW. \tag{A5}$$

Simple algebraic manipulation yields

$$\frac{dS + Ddt}{S} - rdt = \frac{1}{S}\left[(\hat{\mu} - \mu)X\frac{\partial S}{\partial X}\right]dt + \frac{1}{S}X\sigma\frac{\partial S}{\partial X}dW, \tag{A6}$$

and

$$\frac{dS + Ddt}{S} - rdt = \frac{X}{S}\frac{\partial S}{\partial X}(\hat{\mu}dt + \sigma dW - \mu dt). \tag{A7}$$

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

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

Adding back the subscripts of i and t, we have our equation (4) proofed.

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

$$S(X) = \left(\frac{X}{r - \mu} - \frac{c}{r}\right)\theta(1 - \tau_{eff}) + g_1 X^{\omega} + g_2 X^{\omega'} \tag{A9}$$

where $\omega < 0$ and $\omega' > 1$ are the roots of the following quadratic equation:

$$\frac{1}{2}\sigma^2\omega(\omega - 1) + \mu\omega - r = 0. \tag{A10}$$

The standard no-bubble condition, $\lim_{X\to\infty} S(X)/X < \infty$, implies $g_2 = 0$. The value matching condition in equation (2) gives

$$g_1 = \left[\left(\frac{1}{X_B}\right)^{\omega}\left(\frac{c}{r}\theta + \frac{X_B}{r - \mu}(\eta(\alpha - \kappa) - \theta)\right)\right](1 - \tau_{eff}). \tag{A11}$$

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

$$S = \left[\left(\frac{X}{r-\mu} - \frac{c}{r}\right)\theta + \left(\frac{c}{r}\theta + \frac{X_B}{r-\mu}(\eta(\alpha-\kappa)-\theta)\right)\left(\frac{X}{X_B}\right)^{\omega}\right](1-\tau_{eff}). \quad \text{(A12)}$$

The smooth pasting condition in equation (3) gives the optimal bankruptcy threshold

$$X_B = \frac{\theta\omega(C/r)}{(\omega-1)}\frac{r-\mu}{\theta-\eta(\alpha-\kappa)}. \quad \text{(A13)}$$

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 rents from debt holders through debt renegotiation.

The sensitivity of stocks to operating cash flows X is

$$\begin{aligned}
\epsilon =& \frac{X\partial S}{S\partial X} \\
=& \frac{1}{S}\left[\frac{\theta X}{\mu}(1-\tau_{eff}) + g_1\omega X^{\omega}\right] \\
=& \frac{1}{S}\left[S + \frac{c}{r}\theta(1-\tau_{eff}) - g_1X^{\omega} + g_1\omega X^{\omega}\right] \\
=& 1 + \frac{c/r}{S}\theta(1-\tau_{eff}) + \frac{(\omega-1)}{S}g_1X^{\omega} \\
=& 1 + \frac{c/r}{S}\theta(1-\tau_{eff}) - \frac{(1-\omega)}{S}\left[\frac{c}{r}\theta + \frac{X_B}{r-\mu}(\eta(\alpha-\kappa)-\theta)\right](1-\tau_{eff})\left(\frac{X}{X_B}\right)^{\omega}.
\end{aligned} \quad \text{(A14)}$$

Adding back the subscripts of i and t, we have have the time-varying stock-cash flow sensitivity ϵ_{it} as in equation (5) for each firm i.

B IS-GMM Procedure

Let $D = \partial \mathbf{g}_T / \partial \mathbf{b}$ and $\mathbf{S}$ 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.

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

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 $\mathbf{g}_T$

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

To test whether all the pricing errors are jointly zero, we perform the 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 to
Contingent-Claim-Based Expected Stock Returns

A Cross-Sectional Properties of Default Probabilities and Stock-Cash Flow Sensitivities

Given the *optimal* estimates of θ and η, we obtain the implied risk-neutral rate μ_{it+1} and cash flow volatility σ_{it+1} by solving equations (10) and (11) for each portfolio-year observation. Then, we calculate the risk-neutral default probability π_{it+1} and the stock-cash flow sensitivity ϵ_{it+1} according to equation (12).

It is worth noting again that ϵ_{it+1} from our method is a structural estimate instead of a reduced-form estimate from rolling regressions in other studies. Moreover, μ_{it+1} does not contain information on the riskiness of the underlying operating cash flows and that it is negatively correlated with the stocks returns according to equation (4). Table A1 reports the distribution of the estimates.

Market leverage portfolios: Three observations from Panel A are worth noting. First, the means and medians of μ_{it+1} are all small and negative. The median decreases from 0.10% to −1.02% per year along with the increasing rank of the debt ratios. The small and negative average risk-neutral rates are generally consistent with the results obtained by Glover (2011). Second, the fact that σ_{it+1} monotonically declines with leverage confirms our conventional wisdom that firms with low operating risk have better access to debt markets and therefore have greater financial leverage. However, the decreasing cash flow volatility differs from the U-shaped stock volatility in Table 1. This difference implies that the stock volatility is not necessarily a good proxy for the underlying cash flow volatility. Third, firms with more debt have higher default probability and stock-cash flow sensitivity, as shown in the increasing means and medians of π_{it+1} and ϵ_{it+1} along the financial leverage.

BE/ME portfolios: Both the estimated mean and median of μ_{it+1} decrease with the book-to-market ratio. The means are lower than the medians. The patterns and magnitudes of σ_{it+1}, ϵ_{it+1} and π_{it+1} for the BE/ME portfolios are very similar to those for the market 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 (Gomes and Schmid, 2010), which in turn result in high default probability and stock-cash flow sensitivity.

Asset growth portfolios: The differences in μ_{it+1}, σ_{it+1}, π_{it+1} and ϵ_{it+1} between the low- and high-asset-growth portfolios are relatively small. The implied cash flow volatility increases with the asset growth rate because high-asset-growth firms are more likely to engage in risky projects and have more volatile cash flows. The stock-cash flow sensitivity and default probability in low-growth firms are higher than that in high-growth firms.

Size portfolios: Unlike the negative rates in the other three sets of portfolios, the medians of μ_{it+1} in Panel D range from 1.43% to 1.62% per year. Small firms have more volatile cash flows than big firms. However, the median of σ_{it+1}'s decreases from 20.77% to 17.55% per year, sharing the same decreasing pattern with that of σ_{it}^{S}'s but with a much smaller magnitude. Consequently, due to the small differences in μ_{it+1} and σ_{it+1}, the spread in the median of ϵ_{it+1} between the small and big portfolios is only 0.07, the smallest difference among all the sets of testing portfolios. Moreover, smaller firms face much greater likelihood of default, consistent with our conventional wisdom.

The main results from this section can be summarized as follows. First, compared with the physical cash flow rate r^X_{it+1}, all the expected risk-neutral rates, μ_{it+1}, are fairly small, implying that the risk premiums are relatively large for all the 20 individual portfolios. Except for the size portfolios, the average risk-neutral rates are negative in the other three sets of portfolios. Second, the implied cash flow volatility, σ_{it+1}, declines sharply with the ranking variable across the market leverage and book-to-market portfolios, but the observed stock volatility σ^S_{it} is slightly U-shaped. Third, both the average stock-cash flow sensitivities and the average stock returns increase or decrease in the same direction with the ranking variables across all the four sets of portfolios. The average sensitivity values are all greater than one. Fourth, while the spread in π_{it+1} between the high (small) and low (big) quintile portfolios is the largest in leverage portfolios, it is the smallest in asset growth firms. Last, and most important, the spread in ϵ_{it+1} is sizable in the market leverage portfolios and BE/ME portfolios but is relatively small in the asset growth and size portfolios. Through a comparative statics analysis in Section 5.5, we further show that the cross-sectional spread in the sensitivities is the key to understanding the value, size, leverage and asset growth premiums.

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 A2 reports the parameter estimates from a two-stage IS-GMM estimation using an inverse variance-covariance weighting matrix. The estimates are very close to those from the one-stage IS-GMM estimation. The t-statistics become greater because two-stage IS-GMM is more efficient in terms of the smaller variance. Particularly, the t-statistic of η increases to 2.20 for the market leverage portfolios, which however, have the modest performance. Table A3 presents the pricing errors. The model performs well for all the four sets of testing portfolios. The results are very similar to those generated from the one-stage IS-GMM estimation.

C Different Liquidation Cost

The *expected* default cost is set to $\alpha = 0.45$ according to the estimate by Glover (2011). He argues that the previous estimates are underestimated due to a sample selection bias.[14]

Table A4 reports the parameter estimates. The estimates are very close to those from those from one-stage IS-GMM. Table A5 shows that the performance of the model is comparable to that of the benchmark model for all the four sets of testing portfolios.

[14]Additionally, following Morellec et al. (2008), we calculate the default costs for all the firms as follows:

$$\alpha = 1 - \text{Tangibility/Total Assets},$$

where Tangibility = cash (Compustat item CHE) + 0.715*Receivables (item RECT) + 0.547*Inventory (item INVT) + 0.535*Capital (item PPENT). The average value of α is 0.49 in our sample, close to their value of 0.51. Other studies that use the same formula to determine liquidation costs include Almeida and Philippon (2007) and Hahn and Lee (2008).

Table A1: **Cross Section of Cash Flow Rate, Volatility, Default Probability and Stock-Cash Flow Sensitivity**

This table reports the mean, median (Med.) and standard deviation (SD) for the expected cash flow rate μ_{it+1} and volatility σ_{it+1} in annual percent, given the estimates of θ and η from Table 3. The expected risk-neutral default probability π_{it+1} is calculated as $(X_{it}/X_{iB})^{\omega_i}$ and the expected stock-cash flow sensitivity ϵ_{it+1} is calculated according to equation (5). The H (B) denotes the highest (biggest) quintile portfolio and the L (S) the lowest (smallest) quintile portfolio.

Panel A. Market Leverage Portfolios

	μ_{it+1}			σ_{it+1}			π_{it+1}			ϵ_{it+1}		
	Mean	Med.	SD	Mean	Med.	SD	Mean	Med.	SD	Mean	Med.	SD
L	−0.38	0.10	1.49	25.40	23.50	9.12	0.13	0.08	0.11	1.05	1.04	0.03
2	−1.32	−0.92	1.54	21.33	20.11	7.66	0.20	0.16	0.14	1.15	1.15	0.05
3	−1.73	−1.06	1.76	19.56	18.07	8.04	0.26	0.21	0.16	1.26	1.26	0.09
4	−1.84	−0.97	1.92	18.16	16.19	9.33	0.32	0.31	0.18	1.41	1.39	0.13
H	−1.68	−1.02	1.98	16.74	13.40	9.87	0.46	0.46	0.20	1.71	1.69	0.20

Panel B. BE/ME Portfolios

	Mean	Med.	SD	Mean	Med.	SD	Mean	Med.	SD	Mean	Med.	SD
L	−0.09	0.33	1.21	25.96	24.07	8.51	0.18	0.14	0.13	1.10	1.10	0.04
2	−1.16	−0.50	1.69	21.57	19.81	7.82	0.23	0.19	0.15	1.19	1.19	0.06
3	−1.46	−0.77	1.75	19.78	17.97	8.53	0.27	0.26	0.16	1.28	1.29	0.10
4	−1.52	−0.88	1.85	18.60	16.18	9.05	0.30	0.29	0.17	1.37	1.37	0.14
H	−1.70	−0.97	2.08	17.70	14.79	9.84	0.39	0.36	0.18	1.53	1.54	0.20

Panel C. Asset Growth Portfolios

	Mean	Med.	SD	Mean	Med.	SD	Mean	Med.	SD	Mean	Med.	SD
L	−1.89	−1.20	2.09	20.01	17.44	9.37	0.33	0.32	0.17	1.42	1.39	0.18
2	−2.13	−1.35	1.81	18.06	15.78	8.77	0.27	0.25	0.15	1.33	1.31	0.12
3	−2.06	−1.42	1.65	18.38	16.50	7.59	0.24	0.20	0.15	1.26	1.25	0.10
4	−1.76	−0.97	1.77	20.05	18.49	7.77	0.22	0.17	0.15	1.21	1.20	0.09
H	−1.34	−0.92	1.62	22.73	21.28	9.09	0.27	0.25	0.15	1.25	1.22	0.12

Panel D . Size Portfolios

	Mean	Med.	SD	Mean	Med.	SD	Mean	Med.	SD	Mean	Med.	SD
S	0.90	1.43	1.31	22.85	20.77	8.48	0.32	0.29	0.20	1.16	1.16	0.04
2	0.92	1.41	1.14	23.53	22.30	8.57	0.30	0.27	0.18	1.15	1.15	0.04
3	0.99	1.38	0.96	22.36	21.52	8.25	0.26	0.22	0.17	1.13	1.12	0.04
4	1.06	1.37	0.85	21.37	19.43	8.18	0.22	0.19	0.16	1.12	1.12	0.04
B	1.39	1.62	0.74	20.16	17.55	7.65	0.14	0.13	0.13	1.09	1.08	0.04

Table A2: **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.

	Leverage	BE/ME	Asset Growth	Size
θ	0.73	0.58	0.72	0.24
	(2.96)	(2.90)	(3.10)	(1.37)
η	0.68	0.59	0.82	0.50
	(2.20)	(0.87)	(0.74)	(0.73)
χ^2	2.22	2.83	5.86	4.35
d.f.	3.00	3.00	3.00	3.00
p-value	0.53	0.42	0.12	0.23

Table A3: **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 brackets. The H (B) denotes the highest (biggest) quintile portfolio and the L (S) denotes the lowest (smallest) quintile portfolio. The H–L (S–B) portfolio is long in the high (small) portfolio and short in the low (big) portfolio. The heteroscedasticity-and-autocorrelation-consistent t-statistics for the model errors are reported in brackets. 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	−2.62	−0.88	−2.35	−1.02	−3.04	−0.42	1.98
	(−1.49)	(−1.13)	(−0.97)	(−0.56)	(−1.01)	(−0.19)	
BE/ME	−2.22	−0.72	0.45	−1.52	−0.83	1.39	1.15
	(−1.00)	(−0.39)	(0.17)	(−0.77)	(−0.26)	(0.90)	
Asset Growth	1.12	−1.64	0.77	0.83	−3.39	−4.51	1.55
	(0.85)	(−1.55)	(0.57)	(0.73)	(−1.26)	(−1.46)	

	Small	2	3	4	Big	S–B	m.a.e.
Size	0.91	−1.54	−1.06	0.38	1.12	−0.21	1.00
	(0.77)	(−0.98)	(−2.06)	(0.71)	(0.62)	(−0.08)	

Table A4: **Parameter Estimates and Model Fitness Given a Different Liquidation Cost**

This table reports the parameter estimates from one-stage IS-GMM when liquidation cost is set to $\alpha = 0.45$. 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.

	Leverage	BE/ME	Asset Growth	Size
θ	0.61	0.50	0.68	0.23
	(2.25)	(1.97)	(2.49)	(1.11)
η	0.49	0.26	0.49	0.30
	(2.44)	(0.37)	(0.41)	(0.30)
χ^2	2.24	2.83	5.87	4.34
d.f.	3.00	3.00	3.00	3.00
p-value	0.53	0.42	0.12	0.23

Table A5: **Expected Pricing Errors from Fitted Models Given a Different Liquidation Cost**

The table presents the pricing errors for each quintile portfolio from one-stage IS-GMM when liquidation cost is set to $\alpha = 0.45$. The expected return errors are defined $e^M_i = \mathbb{E}[r^s_{it+1} - r^M_{it+1}]$, in which $\mathbb{E}[.]$ is the sample mean of the series in brackets. The H (B) denotes the highest (biggest) quintile portfolio and the L (S) denotes the lowest (smallest) quintile portfolio. The H–L (S–B) portfolio is long in the high (small) portfolio and short in the low (big) portfolio. The heteroscedasticity-and-autocorrelation-consistent t-statistics for the model errors are reported in brackets. 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	−1.68	0.42	−0.73	0.85	0.14	1.82	0.76
	(−1.42)	(0.49)	(−0.76)	(0.69)	(0.91)	(1.70)	
BE/ME	−1.56	0.16	1.43	−0.49	0.04	1.60	0.74
	(−1.30)	(0.19)	(1.27)	(−0.47)	(0.19)	(1.47)	
Asset Growth	1.46	−1.26	1.14	1.18	−3.06	−4.52	1.62
	(4.53)	(−1.26)	(1.12)	(1.28)	(−1.85)	(−2.85)	

	Small	2	3	4	Big	S–B	m.a.e.
Size	0.98	−1.43	−0.96	0.50	1.23	−0.25	1.02
	(1.66)	(−1.39)	(−1.25)	(0.95)	(1.40)	(−0.54)	