Contingent-Claim-Based Expected Stock Returns

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Abstract

I develop and test a parsimonious contingent claim model for cross-sectional stock returns. By incorporating the KMV method into generalized method of moments (GMM), I perform a structural estimation for stock portfolios sorted on market leverage, book-to-market ratio, asset growth rate and equity size. My model outperforms the CAPM and the Fama-French model across all the testing portfolios. In my model stock returns are cash flow rates scaled by the sensitivity of stocks to operating cash flows. Empirically, I demonstrate that stocks are more sensitive to the changing cash flows in bad times than in good times. While the large spread in the stock-cash flow sensitivities explains the value, leverage and asset growth premiums, the spread in the cash flow rates accounts for the size premium.

Keywords: asset pricing, contingent claim model, GMM, structural estimation, stock returns

JEL Classification: G12, G13

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1 Introduction

Equity is a residual claim contingent on a firm's assets (Merton, 1974). I build a parsimonious contingent claim model for cross-sectional stock returns. My 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 market capitalization. I contribute the better performance of my model to its ability to capture the sensitivity of stocks to the underlying operating cash flows.

Following Cochrane (1996) and Liu, Whited, and Zhang (2009), I test my model via the Generalized Method of Moments (GMM). In my structural estimation I match average predicted returns with realized returns for four sets of equal-weighted quintile portfolios.[1] The first set included in this study is market leverage portfolios. They are natural choices for testing portfolios because equity is a contingent claim of operating cash flows after contractual debt payments. Consistent with my expectation, my model performs well in explaining the cross-sectional returns of the market leverage portfolios. The pricing error of the high-minus-low (H-L) portfolio is 1.94% per year, lower than 11.7% from the CAPM and 3.09% from the Fama-French model. The mean absolute error (m.a.e.) is 1.02% per year, compared with 6.84% from the CAPM and 3.67% from the Fama-French Model.

I take book-to-market and size portfolios as my next two sets of testing portfolios for two reasons. First, both value and size premiums are related to a firm's debt financing policy. Gomes and Schmid (2010) demonstrate that firms with high book-to-market equity are mature firms that have accumulated their debt during their expansions and hence have high financial leverage. Second, both value and size premiums have been found being associated with default risk because Fama and French (1996). Griffin and Lemmon (2002) and Vassalou and Xing (2004) document that both value and size premiums are more significant in firms with high default risk. Garlappi and Yan (2011) and Avramov, Chordia, Jostova,

[1] Different from Liu, Whited, and Zhang (2009), Liu and Lu (2011) and Li and Liu (2011) in their investment models, I use five portfolios to ensure that my structural model is solvable for all portfolio-year observations. There is no solution for certain observations with extremely high market leverage if ten portfolios were considered.

and Philipov (2011) further associate the value premium with default risk. Because the contingent claim model is the standard valuation framework for default risk, it is interesting to examine its performance for these two sets of portfolios. My model successfully captures the value and size premiums. For the book-to-market portfolios, the pricing error of the H-L portfolio from my model is 1.07% per year, lower than 6.77% from the CAPM and 3.90% from the Fama-French model. For the size portfolios, the pricing error of the small-minus-big (S-B) portfolio from my model is 1.28% per year, which is much lower than 10.73% from the CAPM and 5.84% from the Fama-French model.

The last set of portfolios of interest is asset growth portfolios.[2] The reason for including the asset growth portfolios is because the low-asset-growth firms are more likely to be the mature firms with high book equity in place and default risk. Additionally, Avramov, Chordia, Jostova, and Philipov (2011) show that the asset growth premium is associated with financial distress risk. The pricing error of the H-L portfolio from my model is -5.04% per year. Although it is the greatest among the four sets of testing portfolios, this error is still considerably lower than -11.71% from the CAPM and -10.61% from the Fama-French model.

In the model stock returns are cash flow rates scaled by the stock-cash flow sensitivity. My model is parsimonious in the sense it has only one state variable and two unknown policy parameters that determine the stock-cash flow sensitivity. The only state variable with uncertainty is the operating cash flows. Instead of looking for an *unobservable* market return (Roll, 1977), I take the *observable* cash flows as my state variable. My specification simply assumes that the states of economy and market movements are efficiently reflected in the changing operating cash flows. My choice of the observable state variable is the same idea as in Liu, Whited, and Zhang (2009). They essentially use observable investment returns as their main state variable.

The two policy parameters are related to dividend payout and strategic default policies,

[2]Cooper, Gulen, and Schill (2008) show 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.

through which equity holders determine their own exposure (or sensitivity) to the changing cash flows. While the cash flow rates can be estimated from the data, the stock-cash flow sensitivity is difficult to measure. This sensitivity is also related to firm characteristics, such as financial leverage, book-to-market equity ratio, size and asset growth rate. Firms with different characteristics have different payout and strategic default policies. While the dividend payout policy determines how much stock holders can claim on cash flows when the firms are solvent, the strategic default policy affects how much they receive through debt renegotiation at bankruptcy. Therefore, both policies have an impact on the sensitivities of stock holders to the changing cash flows. Garlappi and Yan (2011) and Favara, Schroth, and Valta (2011) derive theoretical implications of the strategic default policy for stock returns and test their predictions in a reduced form. In contrast, I directly evaluate both policies in a structural estimation and then estimate their impacts on time-varying stock-cash flow sensitivities and cross-sectional stock returns.

My work contributes to an emerging literature on dynamic contingent claim models that investigate cross-sectional stock returns. The first theoretical paper that applies a contingent claim model to studying asset prices can be dated back to Galai and Masulis (1976). Ferguson and Shockley (2003) extend their work and augment the CAPM with financial leverage and distress factors. Since Berk, Green, and Naik (1999), recent research papers that take a dynamic model to study cross sectional returns either use the simulated method of moments to estimate the model or test their predications in a reduced form.[3] Different from them, I perform a structural estimation via the GMM. To the best of my knowledge, my work is the first study that performs a *direct* test of a contingent claim model for cross-sectional stock returns.

My main empirical contributions and results can be summarized as follows. First, I propose an empirical procedure that embeds the KMV method (Crosbie and Bohn, 2003)

[3] A nonexclusive list that relates equity risk to firm characteristics in a dynamic model includes Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004), Gomes and Schmid (2010), Bhamra, Lars-Alexander, and Strebulaev (2009), Eisfeldt and Papanikolaou (2010), and Ai and Kiku (2011). My paper is also related to the recent literature on dynamic models of capital structure in the contingent claim framework. A partial list of recent papers includes Goldstein, Ju, and Leland (2001), Strebulaev (2007), Chen (2009), Morellec, Nikolov, and Schurhoff (2008) and Glover (2011).

into the GMM framework in my structural estimation. I estimate the *latent* risk neutral rate and cash flow volatility, and then use them to estimate the time-varying stock-cash flow sensitivity. Second, I find that the spreads in the stock-cash flow sensitivities are able to explain a large portion of cross-sectional 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. Third, stocks are more sensitive to cash flows during bad times, when cash flows rates are low, than they are in good times, when cash flows rates are high. However, the covariance between the cash flow rates and the stock-cash flow sensitivity makes a negligible contribution to the average stock returns.

The remainder of this paper proceeds as follows. Section 2 presents the simple contingent claim model. Section 3 explains the empirical specifications and procedures. Section 4 describes the data and the empirical measures. Section 5 uses the GMM to estimate the model, analyzes the cross-section and the time series of stock-cash flow sensitivity and examines the impacts of the sensitivities on average stock returns. Section 6 concludes the paper.

2 A Parsimonious Contingent Claim Model

I consider an economy with a large number of firms, indexed by subscript i. Assets are traded continuously in arbitrage-free markets. Under a risk neutral probability measure, the operating cash flow X_{it} is governed by

$$\frac{dX_{it}}{X_{it}} = \mu_i dt + \sigma_i^X dW_{it}, \tag{1}$$

where μ_i is a *expected* growth rate, σ_i^X is a constant volatility, and W_{it} is a standard Brownian motion. The counterpart of μ_i under the physical probability measure is $\hat{\mu_i} = r + \lambda_i$, where r is a constant risk-free rate common to all firms and λ_i is an individual risk premium. It is worth noting I do not explicitly specify the risk premium throughout this study.[4] The cash flow is independent of capital structure choices and investment policies.

At the beginning of time t, the firm i finances its asset investments with equity and debt. It issues a consol bond of B_i with a *fixed* coupon payment of C_i. After the firm pays coupons and government taxes, it distributes a fraction θ of its net income back to its equity holders, where $\theta \leq 1$ is the dividend-net income ratio, and the remainder of the net income is used for capital investments, cash retention and etc. I assume that the payout policy θ and a simple tax structure for all firms. The cash flow is taxed at a rate of τ_c, dividend is taxed at τ_d and interest income is taxed at τ_i. Hence, the effective tax rate is $\tau_{eff} = 1-(1-\tau_c)(1-\tau_d)$ and the final payoff that accrues to equity holders is the dividend, $D_{it} = \theta(X_{it} - C_i)(1 - \tau_{eff})$.

When the firm's condition deteriorates, it has an option to go bankrupt, which leads to *immediate* liquidation or debt renegotiation. Upon liquidation debt holders take over the remaining assets and liquidate them at a fractional cost of α. Renegotiation costs a constant fraction $\kappa < \alpha$ of the assets. Because liquidation is more costly than renegotiation, debt holders are willing to renegotiate with equity holders. The renegotiation surplus $\alpha - \kappa > 0$ is shared between equity and debt holders.[5] Given their bargaining power $\eta \leq 1$, equity holders are able to extract a fraction η of the renegotiation surplus $(\alpha - \kappa)$.

Anticipating the outcome of renegotiation, equity holders determine an optimal bankruptcy threshold X_{iB} to maximize the equity value $E_{it}(X_{it})$ according to the following conditions:

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

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

Equation (2) is the value matching condition, which states that equity holders extract $\eta(\alpha-\kappa)X_{iB}$ from the renegotiation surplus at bankruptcy X_{iB}. Equation (3) is the smooth

[4]In a CAPM setup, a risk premium could be specified as $\lambda_i = \beta_i\lambda_M$, where β_i is the market beta for firm i and λ_M is the market premium. I do not measure the market premium in this study because it is empirically unobservable (Roll, 1977).

[5]Recent studies that make the same assumption include Fan and Sundaresan (2000), Garlappi and Yan (2011), Morellec, Nikolov, and Schurhoff (2008) and Favara, Schroth, and Valta (2011).

pasting condition that enables equity holders to choose the optimal X_{iB} to exercise their bankruptcy option. When the costs of paying interests to keep the firm alive exceed the benefits from debt renegotiation and the future tax benefits, equity holders decide to declare bankruptcy at X_{iB} (Leland, 1994).

Proposition 1 *For $X_{it} > X_{iB}$, at time t the contingent-claim (CC) stock return r_{it}^{cc} of a firm, i, is*

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

where $r_{it}^{X} = dX_{it}/X_{it}$ is the operating cash flow rate, ϵ_{it} is the sensitivity of stocks to cash flows

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

and $E_{it}(X_{it})$ is the equity value

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

The optimal bankruptcy threshold X_{iB} and ω_i are provided in Appendix A.

Proof: See Appendix A.

Equation (4) states that the *instantaneous* stock return r_{it}^{cc} in this contingent claim framework is the risk free rate rdt plus an excess cash flow rate scaled by the stock-cash flow sensitivity ϵ_{it}. The excess cash flow rate is the *physical* cash flow rate r_{it}^{X}, defined in equation (A1), in excess of the expected risk neutral rate $\mu_i dt$. Unlike Garlappi and Yan (2011) and Favara, Schroth, and Valta (2011), I do not call ϵ_{it} the market beta because the market return is unobservable (Roll, 1977) and I do not assume any market model in this study.

The stock-cash flow sensitivity ϵ_{it} plays an important role in characterizing the stock return in equation (5), it consists of three components: The first component is the cash flow sensitivity normalized to one. The second component is the well-known financial leverage effect because C_i/r is equivalent to the value of a risk-free perpetual bond. Intuitively, the greater coupon payments C_i equity holders distribute back to debt holders, the less residual claim D_{it} they can receive. Hence, the stock-cash flow sensitivity increases with the coupon payments. More importantly, the dividend-net income ratio, θ, amplifies this financial leverage effect. The more dividends equity holders claim on the residual income after their debt service, the more cautious they become about their contractual coupon payment and the more sensitive they are to the after-coupon cash flows. To illustrate the impact of the dividend-net income ratio on the stock-cash flow sensitivity, I calibrate this simple model with standard parameter values from the literature. Panel A of Figure 1 shows that the stock-cash flow sensitivity significantly increases with the dividend-net income ratio, thereby confirming our intuition.

The last component of equation (5) is the option to go bankrupt. The equity holders' strategic default policy, X_{iB}, is affected by their bargaining power at bankruptcy. Because of the costly liquidation following bankruptcy, debt holders are willing to share the renegotiation surplus with equity holders. The more bargaining power equity holders have, the more asset value they can extract through debt renegotiation at bankruptcy. Hence, equity holders with greater bargaining power are willing to file for bankruptcy earlier than others with lower power. Because such equity holders with greater power extract more rents from debt holders at bankruptcy, they have less exposure to downside risk and, consequently, become less sensitive to the changing cash flows. Garlappi and Yan (2011) show that the bargaining power help us understand the hump-shaped relationship between default probability and cross-sectional stock returns. Favara, Schroth, and Valta (2011) provide international evidence regarding the negative impact of bargaining power on equity risk. Consistent with the reasoning and the literature, the stock-cash flow sensitivity declines monotonically with the bargaining power as shown in Panel B of Figure 1.

3 Empirical Specification and Design

I test the equality between the observed stock returns, r^S_{it+1}, and the contingent-claim-based returns, r^{cc}_{it+1}, at time $t+1$ at the *portfolio* level as follows:

$$\mathbb{E}[r^S_{it+1} - r^{cc}_{it+1}] = 0, \tag{7}$$

where $\mathbb{E}[.]$ is the unconditional mean operator for a time series. I incorporate the KMV method (Crosbie and Bohn, 2003) into the GMM to test the model.

To calculate r^{cc}_{it+1} as in equation (4), X_{it}, E_{it} and C_i, are directly observed from the data and r, α, κ are drawn from the existing literature. The two important parameters, θ and α, are to be estimated because they are the determinants of the residual cash flows stock holders can receive when the firm is solvent and at bankruptcy, respectively. Given the estimated optimal θ and α, the risk-neutral rate μ_i and the cash flow volatility σ^X_i are calculated. Finally, ϵ_{it+1} and r^{cc}_{it+1} are obtained.

In empirical implementation, I assume that the firms restructure their debt at time t. Hence, the model prediction in equation (4) holds for each period t and for every state. Given the state variable X_{it} the observed coupon payment, C_{it}, is chosen optimally for each period t and I use the observed, time-varying C_{it} in my empirical design. It is worth noting that the time-varying E_{it} and C_{it} are not additional state variables because both are determined by X_{it}.[6] I provide robustness check in Internet Appendix when the optimal coupon is implied from the observed debt.

3.1 Latent Risk-Neutral Cash Flow Rate and Volatility

The latent parameters, *expected* risk neutral rate μ_i and volatility σ^X_i, are not observable. Following the literature (Vassalou and Xing (2004), Bharath and Shumway (2008) and Davydenko and Strebulaev (2007)), I take the widely accepted KMV method (Crosbie and Bohn, 2003) to calculate these two latent variables. Using the current accounting

[6] The derivation of the optimal coupon could be found in Goldstein, Ju, and Leland (2001).

information and the historical stock volatility, this procedure obtains estimates of $\mu_{it+1} \equiv \mathbb{E}_t[\mu_{it+1}]$ and $\sigma^X_{it+1} \equiv \mathbb{E}_t[\sigma^X_{it+1}]$ at time t.[7] The cash flow rate and the volatility parameter estimated from this procedure are *expected* values because the observed equity value is the present value of future cash flows discounted by the expected discount rate. I assume that their unconditional expectation converge to their true values, μ_i and σ^X_i, respectively. Although this procedure suffers from measurement errors, it is consistent with the standard portfolio formation in this study.

To estimate the expected cash flow volatility σ^X_{it+1}, I need the historical stock volatility σ^S_{it} as well. I use the past one-year daily stock returns to estimate σ^S_{it} as in the literature.[8] Conditional on the set of information $\Theta_t = (X_{it}, E_{it}, C_{it}, \sigma^S_{it}, r, \alpha, \kappa, \theta, \eta)$ up to time t, I solve the following system of equations to obtain μ_{it+1} and σ^X_{it+1}

$$\sigma^S_{it} = \mathbb{E}_t[\sigma^X_{it+1}\epsilon_{it+1}] \equiv \sigma^X_{it+1}\epsilon_{it+1} \tag{8}$$

$$E_{it} = \left[(\frac{X_{it}}{r-\mu_{it+1}} - \frac{C_{it}}{r})\theta + (\frac{C_{it}}{r}\theta + \frac{X_{iB}}{r-\mu_{it+1}}(\eta(\alpha-\kappa)-\theta))(\frac{X_{it}}{X_{iB}})^{\omega_{it+1}} \right](1-\tau_{eff}), \tag{9}$$

where the *expected* stock-cash flow sensitivity is

$$\epsilon_{it+1} = 1 + \frac{C_{it}/r}{E_{it}}\theta(1-\tau_{eff}) + \frac{(\omega_{it+1}-1)}{E_{it}}\left[\frac{C_{it}}{r}\theta + \frac{X_{iB}}{r-\mu_{it+1}}(\eta(\alpha-\kappa)-\theta)\right](1-\tau_{eff})(\frac{X_{it}}{X_{iB}})^{\omega_{it+1}}. \tag{10}$$

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

$$\frac{1}{2}(\sigma^X_{it+1})^2\omega_{it+1}(\omega_{it+1}-1) + \mu_{it+1}\omega_{it+1} - r = 0. \tag{11}$$

[7] An alternative choice is the maximum likelihood method proposed by Duan (1994). For each firm, the maximum likelihood method takes the *time series* of the equity and debt values to obtain two *point* estimates for μ_i, σ^X_i. However, I test the model at the portfolio level. The maximum likelihood procedure is not consistent with the standard portfolio formation procedure in Fama and French (1992). Because the maximum likelihood method uses the entire data sample to estimate these parameters, these two estimates contain information beyond time t when I form the portfolio and use them to calculate the predicted stock returns. Hence, although the maximum likelihood method involves less computation, it is *not* appropriate for this study when the portfolio formation is based on the observed accounting information. While Ericsson and Reneby (2005) demonstrate that the maximum likelihood method is more efficient, Duan, Gauthier, and Simonat (2004) show that the two methods are equivalent for the Merton's model.

[8] Strictly speaking, σ^X_{it+1} is not the expected cash flow volatility because we use the historical stock volatility in calculation.

Equation (8) is implied by Ito's lemma. Equation (9) is to calculate the equity value E_{it}, defined in equation (6), given the information set Θ_t. The time-varying sensitivity ϵ_{it+1} is a expected value as well because both μ_{it+1} and σ^X_{it+1} are estimated conditional on the set of information up to time t when the portfolios are formed.

3.2 GMM Testing Framework

Given the time-varying estimates of μ_{it+1} and σ^X_{it+1}, the discrete-time version of the contingent-claim-based return from equation (4) is

$$r^{cc}_{it+1} = r\Delta t + \epsilon_{it+1}(\frac{\Delta X_{it+1}}{X_{it}} - \mu_{it+1}\Delta t). \tag{12}$$

The model is tested at the annual frequency. Hence, $\Delta t = 1$. From equation (12), the conditional expectation of the instantaneous contingent-claim-based return is

$$\mathbb{E}_t[r^{cc}_{it+1}] = r + \mathbb{E}_t[\epsilon_{it+1}(\frac{\Delta X_{it+1}}{X_{it}} - \mu_{it+1})]. \tag{13}$$

This empirical version is close to the conditional version of the CAPM in Jagannathan and Wang (1996), although I do not take the market factor as the state variable in this study. In addition to potential specification errors, this discretization and the time-varying estimates of μ_i and σ^X_i might suffer from measurement errors (Lo, 1986). It is worth noting that because I assume that the firm lives infinitely when deriving the equity value (Leland, 1994), the nonlinear function of ϵ_{it+1} in equation (10) is independent of time and free of time discretization errors. However, I can still test the weaker condition of equations (7) as in Cochrane (1991) and Liu, Whited, and Zhang (2009). Therefore, the expected pricing error for each portfolio i is

$$\begin{aligned} e^{cc}_i &= \mathbb{E}[r^S_{it+1} - \mathbb{E}_t[r^{cc}_{it+1}]] \\ &= \mathbb{E}[r^S_{it+1} - (r + \epsilon_{it+1}(r^X_{it+1} - \mu_{it+1}))]. \end{aligned} \tag{14}$$

according to the law of iterated expectation.

The sample moments of pricing errors are $\mathbf{g}_T = [e_1^{cc}...e_n^{cc}]'$, where n is the number of testing portfolios. If the model is correctly specified and if empirical measures are accurate, $\mathbf{g}_T$ converges to zero, theoretically, given an infinite sample size. Both measurement and specification errors contribute to the expected pricing errors. Under the weak condition of equation (7), the objective of the GMM procedure is to choose a parameter vector, $\mathbf{b} \equiv [\theta, \eta]'$, to minimize a weighted sum of squared errors (Hansen, 1982)

$$
\begin{aligned}
&J_T = \mathbf{g}_T' \mathbf{W} \mathbf{g}_T, \\
\text{s.t. } &0 < \theta \leq 1, \\
&0 < \eta \leq 1.
\end{aligned}
$$

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}^X are recalculated for each trial set of $\mathbf{b}$ in the GMM optimization procedure. Following Cochrane (1991) and Liu, Whited, and Zhang (2009), I choose an identity matrix $\mathbf{W} = \mathbf{I}$ in one-stage GMM. By weighting the pricing errors from individual portfolios equally, the identity weighting matrix preserves the economic structure of the testing assets (Cochrane, 1996).

4 Data

The data universe for this study includes 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 2009. I 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, I restrict my sample of annual data to firm-year observations with non-missing values for operating income, debt and total assets and with positive total assets and debt.

4.1 Variable Measurement and Parameter Values

I follow Fama and French (1995) and Liu, Whited, and Zhang (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), I use operating income after depreciation (Compustat item OIADP) to proxy for the operating cash flows without considering capital depreciation.[9] Because of their importance, the operating income observations are trimmed at the upper and lower one-percentiles to eliminate the outliers and eradicate errors . E_{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}, E_{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 $t+1$.

The corporate tax rate is set to $\tau_c = 35\%$ and the tax rates on dividend and interest income are set to $\tau_d = 11.5\%$ and $\tau_i = 29.3\%$, respectively. The renegotiation cost is small and is set to $\kappa = 0$. The after-tax annual risk-free rate, r, is 3.65% and the Fama-French factors are obtained from Kenneth French's website. The expected default cost is set to $\alpha = 0.45$ according to the estimate by Glover (2011).[10]

4.2 Testing Portfolios

I employ four sets of testing portfolios: five market leverage portfolios, five book-to-market portfolios, five asset growth portfolios and five size portfolios. I choose five portfolios for each asset pricing anomaly to ensure that the simultaneous equations (8) and (9) are solvable

[9] Another work using earnings as a state variable is by Savor and Wilson (2011). They augment the CAPM with the firms' earning announcement factor. However, they execute their exercise in a reduced-form regression and for earning announcement only.

[10] Additionally, following Morellec, Nikolov, and Schurhoff (2008), I 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 my sample, close to their value of 0.51. Other studies that use the same formula to determine liquidation costs include Almeida and Campello (2007) and Hahn and Lee (2008).

for all portfolio-year observations. All the portfolios are equal-weighted as in Liu, Whited, and Zhang (2009).

I 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 stock. Depending on availability, I 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 asset growth rate for the asset growth portfolios. Following (Cooper, Gulen, and Schill, 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 $t-1$.

I 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, I first sort firms into quintiles to form equal-weighted portfolios at the end of each June of year t. Then, I rebalance them each June. Raw returns of equal-weighted portfolios are computed from July of year t to June of year $t + 1$.

To match the observed stock returns r^S_{it+1} with the predicted returns r^{cc}_{it+1} from my model, I need to align the state variable and firm characteristics with the observed stock returns. The state variable X_{it} in the model is a flow variable. The operating cash flow rate r^X_{it+1} is calculated as the percentage change from the end of year t and t + 1. Hence, the cash flow rates largely matches with the stock returns. Appendix B contains further details for the timing alignment.

5 Empirical Results

In this section I take the model to the data. I perform the structural estimation by incorporating the KMV method into the GMM framework. After fitting the model into cross-sectional stock returns, I use the estimated policy parameters to calculate the expected risk neutral rate and cash flow volatility, and then analyze the cross sectional and time series properties of stock-cash flow sensitivity. Finally, in my decomposition of the expected stock returns and my comparative statics analysis, I demonstrate that the spread in stock-cash flow sensitivities is crucial for us to understanding the cross sectional stock returns.

5.1 Pricing Errors from Traditional Models

I first confirm the well-known pricing errors in my data sample. Table 1 reports the average returns in annual percent for equal-weighted quintile portfolios, sorted on the increasing rank of the anomaly variables, 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 12.21% per year more than do stocks with low leverage. The pricing error of the H-L portfolio from the CAPM is 11.75% (t = 4.03). This error decreases to 3.09% (t = 1.51) 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 6.84% per year for the CAPM and decreases to 3.67% for the Fama-French model.

BE/ME portfolios – The average returns in Panel B monotonically increase with the book-to-market ratio from 12.60% to 26.70% per year. After controlling for the market factor, the H-L portfolio earns 14.81% (t = 5.96) per year and the m.a.e. is 6.77%. The performance of the Fama-French model improves as its error of the H-L portfolio decreases to 7.53% (t = 4.14) and its m.a.e. declines to 3.90%.

Asset growth portfolios – As shown in Panel C, high-growth firms earn 12.10% lower stock returns per year than low-growth firms.[11] 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 -11.71% (t = -6.15) and -10.61% (t = -4.89), 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 7.09% from the CAPM and 4.22% from the Fama-French model.

Size portfolios – Panel D confirms the size effect. Small firms earn 12.58% greater returns per year than big firms. 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 10.73% (t = 3.00) and 5.84% (t = 3.13), respectively. The m.a.e. is 4.64% for the CAPM and is 2.53% for the Fama-French model.

Overall, I demonstrate that the well-documented pricing errors from the traditional models are largely the same in my data sample as in the literature. In the next two sections, I summarize the model inputs and compare the traditional models with my model.

[11]The difference is smaller than the difference of 20% per year documented by Cooper, Gulen, and Schill (2008) because my sample requires positive debt and has other restrictions.

5.2 Summary Statistics of Model Inputs and Portfolio Characteristics

Table 2 reports portfolio characteristics for the four sets of quintile portfolios. Instead of reporting the dollar amount for X_{it}, C_{it} and E_{it}, I report the earnings-price ratio X_{it}/E_{it} and the interest coverage ratio X_{it}/C_{it}. X_{it}/E_{it} is considered because the equity value E_{it} is contingent on the underlying earning X_{it} in the model. X_{it}/C_{it} measures the financial health of the firms and provides preliminary information about the financial leverage effect on stock-cash flow sensitivity, according to the second component of equation (5).

Market leverage portfolios – Unlike the monotonically increasing stock returns across the market leverage portfolios, the average cash flow rates r^X_{t+1} and their correlations with the stock returns r^S_{t+1} are slightly U-shaped. More interestingly, the correlations between them are relatively weak. While X_{it}/E_{it} increases from 0.09 to 0.23, X_{it}/C_{it} dramatically declines from 20.53 to 2.13 with market leverage. It is interesting to note that the stock volatility σ^S_{it} of the low-leverage portfolio is 26.34% per year is almost identical to that of the high-leverage portfolio. This result suggests that debt financing behavior is more complicated than our conventional wisdom that stock volatility increases with financial leverage (Gomes and Schmid, 2010).

BE/ME portfolios – Similar to the market leverage portfolios, both r^X_{t+1} and σ^S_{it} are slightly U-shaped. The magnitude of the increase in the earnings-price ratio across the book-to-market portfolios is comparable to that across the market leverage portfolios as well. The interest coverage ratio declines from 9.70 to 3.18. Hence, the decrease in X_{it}/C_{it} in the BE/ME portfolios is considerably smaller than the decline in the market leverage portfolios.

Asset growth portfolios – The patterns of portfolio characteristics in the asset growth portfolios are generally contrary to those observed in the book-to-market portfolios. The difference occurs because the firms with a low asset growth rate are more likely to be the firms with more book equity-in-place. The increment in the interest coverage ratio from the low-growth firms to the high-growth firms is only 1.58, the smallest change among the four sets of portfolios.

Size portfolios – Different from all other three sets of portfolios, r^X_{it+1} declines significantly from 21% to 7.57% per year across the size portfolios. The magnitude of the decrease in cash flow rates is comparable that in stock returns. Its correlation with the stock returns decrease as well. The monotonic decline in σ^S_{it} is the most evident among the four sets of portfolios. While the earnings-price ratio slightly decreases, the interest coverage increases significantly with the market capitalization. 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).

In short, the average cash flow rates increase or decrease in the same direction as the average stock returns do with the ranking variables for all the four sets of portfolios. Except for the size portfolios, the magnitude of the changes in the average cash flow rates are considerably smaller than that in the average stock returns, and the stock volatilities are all slightly U-shaped for the other three sets of portfolios. Moreover, the decline in the interest coverage ratio is the most evident for the market leverage portfolios.

5.3 Model Estimation and Pricing Errors from Structural Model

I estimate two parameters, dividend-net income ratio θ and shareholder bargaining power η, for this parsimonious contingent claim model within the 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 (7). The estimates of θ for the market leverage, BE/ME and asset growth portfolios suggest that 88–100% of the net incomes are distributed back to equity holders. The associated t-statistics indicate that these point estimates are statistically significant at a 95% confidence level. In contrast, the estimate of θ for the size portfolios is only 0.24 and is statistically insignificant.

The estimates of η are 0.58 for all the market leverage, BE/ME and asset growth portfolios. This value is slightly above the Nash equilibrium value of 0.5 chosen by Morellec, Nikolov, and Schurhoff (2008) and close to the value of 0.6 assumed in Favara, Schroth, and Valta (2011). For the size portfolio, the estimate is only 0.25 and is not statistically significant.

The χ^2 statistic, which tests whether all 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, with the asset growth portfolios having the lowest p-value. Compared to those in Liu, Whited, and Zhang (2009), the p-values are relatively low in my setting. This difference could result from my smaller data sample as each set in my estimation has only five portfolios .

Overall, the model performs well for all the sets of testing portfolios with a modest performance for the asset growth portfolios. Given the optimal estimates of θ and η, I construct the contingent-claim-based returns r_{it+1}^{cc} as in equation (12) and calculate the expected pricing error e_i^{cc} as in equation (14) for each individual portfolio.

Market leverage portfolios – The first row of Table 4 shows that the pricing errors vary from -1.76% to -0.57% per year. Additionally, the pricing error of the H-L portfolios is 1.19% (t = -1.02) and is not statistically significant. This error is smaller than 11.75% from the CAPM and 3.09% from the Fama-French model in Table 1. Figure 3 visually illustrates the model fitness and pricing errors. I 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, the H-L portfolio has a pricing error of 3.12% per year, which is smaller than 14.81% in the CAPM and 7.53% per year in the Fama-French model. This error is mostly due to the large deviation of 2.40% from the growth portfolio. The mean absolute error (m.a.e) is 1.16% per year, much lower than 6.77% from the CAPM and 3.90% 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 from 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 -5.48% per year, which however is much less than -11.71% from the CAPM and -10.61% 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 a sharp contrast, the predicted returns from the CAPM and the Fama-French model are almost flat.

Size portfolios – The pricing errors range from -0.80% to 2.67%. The greatest error of 2.67% is from the big portfolios with a t-statistic of 1.80. The error of the S-B portfolio is -3.46% per year. It is evident that, in Panel A of Figure 6, the predicted returns are aligned very well with the realized stock returns, particulary for the portfolio of small stocks. The performance of the CAPM remains poor, as shown by the horizonital line of its predicted returns. Although the Fama-French model performs much better than the CAPM, it still fails to capture a big outlier from the small portfolio.

In summary, my model does a good job for all the sets of portfolios and outperforms the CAPM and the Fama-French model. The model performs the best for the market leverage portfolios. Although the model does not fit the asset growth portfolios very well, it gives a much better fit than the CAPM and the Fama-French model.

5.4 Cross-Section of Risk Neutral Rates, Volatility and Stock-Cash Flow Sensitivities

Given the *optimal* estimates of θ and η, I calculate the implied risk neutral rate μ_{it+1} and cash flow volatility σ^X_{it+1} according to equations (8) and (9) for each portfolio-year observation. Then, I calculate the stock-cash flow sensitivity ϵ_{it+1} as in equation (10).

It is worth noting that 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 5 reports the distribution of the estimates of three parameters.

Market leverage portfolios – Three observations are from Panel A. First, the means and medians of μ_{it+1}'s are all small and negative. Their median decreases from -0.33% to -0.93% 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^X_{it+1} 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, the median of ϵ_{it+1}'s dramatically increases from 1.04 to 1.71 with market leverage due to the financial leverage effect in equation (5).

BE/ME portfolios – Both the estimated mean and median of μ_{it+1}'s decrease with the book-to-market ratio. The means are lower than the medians. The patterns and magnitudes of σ^X_{it+1} and ϵ_{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 (safe) book assets and fewer (risky) growth opportunities have higher financial leverage (Gomes and Schmid, 2010).

Asset growth portfolios – The differences in μ_{it+1}, σ^X_{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 in low growth firms is higher than that in high-growth firms. This decrease in the average sensitivities is the same as that in average stock returns.

Size portfolios – Unlike the negative rates in the other three sets of portfolios, the average μ_{it+1}'s in Panel D are about 2.26% per year. Small firms have more volatile cash flows than big firms. However, the median of σ^X_{it+1}'s decreases from 21.90% to 18.77% per year, sharing the same decreasing pattern with that of σ^S_{it} but with a much smaller magnitude. Consequently, due to the small differences in μ_{it+1} and σ^X_{it+1}, the spread in ϵ_{it+1} between the small and big portfolios is only 0.7, the smallest difference among all the sets of testing portfolios.

The main results from the 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 risk neutral rates are negative in the other three sets of portfolios. Second, the implied cash flow volatility, σ^X_{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 sensitivity values are all greater than one. Last, and most important, the spread in ϵ_{it+1} between the high and low quintile portfolios 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 5.7, I further show that the spread in the sensitivities is the key to understanding the value, size, leverage and asset growth premiums.

5.5 Time Series of Stock-Cash Flow Sensitivities

After investigating the cross sectional properties of the stock-cash flow sensitivity, I turn to its time series properties over business cycles. I use NBER recession years to classify the cycles.

Figure 7 plots the times series of the stock-cash flow sensitivity. It is evident that, in Panel A, high-leverage firms are considerably more sensitive to cash flows than low-leverage firms, particularly in NBER recession years. Panel B shows that the stock-cash flow sensitivity of book-to-market portfolios shares the same pattern with market portfolios but with a slightly smaller magnitude. The highest sensitivity of value stocks is about 2.4 in the early 1980's. Intuitively, both value firms and high-leverage firms have more debt and coupon payments so that they have substantially greater sensitivity to the changing cash flow in recessions than growth firms and low-leverage firms as suggested by equation (5).

As shown in Panel C, low-growth firms are more sensitive to the business cycles because they are more likely to the matures firms that have accumulated high debt during their expansions. However, the difference in stock sensitivity between the high- and low-growth firms is not as significant as that in the market leverage and book-to-market portfolios.

Panel D confirms that the spread in stock-cash flow sensitivity between the small and big portfolios is the smallest, compared with the other three sets of portfolios. The maximum spread is only about 0.2 in the 1980's.

Overall, the results from the time series of stock-cash flow sensitivities are consistent with their cross-sectional properties in Table 5. The difference in the sensitivities between the small and big portfolios is the smallest among all the testing sets of portfolios. Additionally, stocks are more sensitive to the underlying operating cash flows during business recessions when cash flow rates are low than during expansions when cash flow rates are high.

5.6 Decomposition of Expected Claim-Claim-Based-Returns

Jagannathan and Wang (1996) show that a conditional version of the CAPM can help explain cross sectional stock returns when the market beta is time varying. However, Lewellen and Nagel (2006) present evidence that the covariance between the time-varying beta and the market risk premium is too small to explain the cross-sectional variation of stock returns. The empirical implementation of my contingent claim model in equation (13) has a similar form to the conditional CAPM of Jagannathan and Wang (1996). Hence, given the counter-cyclical stock-cash flow sensitivity shown in the previous section, it is worthwhile to investigate whether the covariance between cash flow rates and stock sensitivities contributes to the expected stock returns.

I decompose the contingent claim based return r^{cc}_{it+1} in excess of the risk free rate r into four components and examine their individual contributions. From equation (13), the unconditional excess stock returns predicted from the contingent claim model can be decomposed into four components:

$$\begin{aligned}\mathbb{E}[r^{cc}_{it+1} - r] &= \mathbb{E}[\epsilon_{it+1}(r^X_{it+1} - \mu_{it+1})] \\ &= \mathbb{E}(r^X_{it+1})\mathbb{E}(\epsilon_{it+1}) - \mathbb{E}(\mu_{it+1})\mathbb{E}(\epsilon_{it+1}) + cov(r^X_{it+1}, \epsilon_{it+1}) - cov(\mu_{it+1}, \epsilon_{it+1})\end{aligned} \tag{15}$$

The contributions of each of the four components to the expected r^{cc}_{it+1} are defined as follows:

$$\begin{aligned}\rho_1 &= \frac{\mathbb{E}(r^X_{it+1})\mathbb{E}(\epsilon_{it+1})}{\mathbb{E}(r^{cc}_{it+1}) - r}, \\ \rho_2 &= \frac{\mathbb{E}(\mu_{it+1})\mathbb{E}(\epsilon_{it+1})}{\mathbb{E}(r^{cc}_{it+1}) - r}, \\ \rho_3 &= \frac{cov(r^X_{it+1}, \epsilon_{it+1})}{\mathbb{E}(r^{cc}_{it+1}) - r}, \\ \rho_4 &= \frac{cov(\mu_{it+1}, \epsilon_{it+1})}{\mathbb{E}(r^{cc}_{it+1}) - r},\end{aligned}$$

and $\rho_1 - \rho_2 + \rho_3 - \rho_4 = 1$.

Table 6 presents the decomposition of the expected contingent claim return. The contribution from the product of the expected cash flow rates and the expected stock sensitivities, ρ_1, is the greatest among the four components for all four sets of portfolios. It accounts for at least 82% of the average predicted returns. Interestingly, in Panel D, ρ_1's in the size portfolios increases from 114.2% to 152.5.1%. However, the *excess* contribution from ρ_1's in the size portfolios are almost completely canceled out by the second componet, ρ_2, the product of the expected risk-neutral rates and the expected stock-cash flow sensitivities.

The pervasive negative ρ_3's in 19 out of the 20 testing portfolios imply that the cash flow rates r^X_{it+1} are negatively correlated with the sensitivity ϵ_{it+1}, confirming the visual illustration in Figure 7 that stocks are more sensitive to the changes in the underlying cash flows when the firms experience negative cash flows. Similarly, the negative ρ_4's suggest that stocks are more sensitive to the expected risk-neutral rates in bad times as well. However, both the values of ρ_3 and ρ_4 are less than 1% among all the 20 testing portfolios. This result is similar to the conclusion by Lewellen and Nagel (2006) that the covariance of the CAPM β and the market risk premium are not large enough to explain asset pricing anomalies.

In short, my results suggest that the product of the average cash flow rates and the average stock-cash flows accounts for at least 82% of the average predicted stock returns. The covariance between the cash flow rates and the stock-cash flow sensitivities has at most 1.3% contribution to the average predicted stock returns.

5.7 Pricing Errors from Comparative Statics Analysis

After examining the cross-sectional and time series properties of stock-cash flow sensitivity, I follow Liu, Whited, and Zhang (2009) and perform a comparative statics analysis to further examine impacts of the sensitivity on the pricing errors relative to the other portfolio characteristics. A large increase in the expected pricing errors implies that this certain input (or portfolio characteristic) is important for predicting stock returns.

Aside from the state variable X_{it}, the main inputs of my model are r^X_{it+1},σ^S_{it}, C_{it} and E_{it}. For r^X_{it+1}, I set it to its cross sectional average $\widetilde{r^X_{it+1}}$ each year. Then, I use its average and the parameter estimates from Table 3 to recalculate r^{cc}_{it+1} , while keeping all the other model inputs unchanged.

I repeat the same procedure for σ^S_{it}, C_{it} and E_{it}. However, after changing their values to their cross-sectional averages, I need to use the new inputs and the parameter estimates to recalculate μ_{it+1} and σ^X_{it+1} before I construct ϵ_{it+1} and r^{cc}_{it+1}. For C_{it} and E_{it}, rather than fixing them to their cross sectional averages, I set $E_{it} = X_{it}/\widetilde{X_{it}/E_{it}}$ and $C_{it} = X_{it}/\widetilde{X_{it}/C_{it}}$, where $\widetilde{X_{it}/E_{it}}$ and $\widetilde{X_{it}/C_{it}}$ are the cross-sectional earnings-price ratio and interest coverage ratio, respectively.[12]

[12] I use the ratios instead of the amount because I need to recalculate μ_{it+1} and σ^X_{it+1} after fixing the

Lastly, to evaluate the importance of ϵ_{it+1}, I use its cross-sectional average directly from the benchmark estimation without recalculating μ_{it+1} and σ^X_{it+1}. Because both of them do not need to invoke the recalculations of μ_{it+1} and σ^X_{it+1}, this exercise provides a direct comparison between ϵ_{it+1} and r^X_{it+1}.

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 increases to 10.46% per year from 1.194% per year in the benchmark model. The m.a.e. increases from 1.09% to 3.55%. The effects from the cash flow rates, interest coverage ratios, and stock volatilities 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} increases the m.a.e. from 1.16 to 3.32. 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 my model for the asset growth portfolios shown in Table 3, the effects of eliminating the cross-sectional variations of model inputs or portfolio characteristics are relatively small. The most important effect is still from the stock-cash flow sensitivity. After fixing ϵ_{it+1} to its cross sectional average, the m.a.e. increases to 3.25 from 1.74 in the benchmark model.

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 11.49% per year from -3.46% in the benchmark estimation and the m.a.e. increases from 1.28 to 2.95. Compared with its role in 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 m.a.e. increases slightly from 1.28 to 1.78. Hence, the increased pricing error caused by the stock-cash flow

variables to its cross-sectional average. For instance, if I fix the amount of interest expense C_{it} to its cross-sectional average instead of its average interest coverage ratio, its average amount could exceed X_it for a given portfolio-year observation, which cause the system of equations (8) and (9) to become unsolvable. However, the equations are solvable for observations with an average interest coverage ratio.

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 is very close to that in the stock returns across the size portfolios. Therefore, the stock-cash flow sensitivity becomes critical in matching the observed stock returns with the predicted returns.

In summary, while the cross sectional variation in the stock-cash flow sensitivity is the most important determinant for alleviating the pricing error 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 I consider.

6 Conclusion

I develop a parsimonious contingent claim model for cross-sectional stock returns with only one state variable and two policy parameters. The state variable is the operating cash flow and the two policy parameters are related to the dividend payout and strategic default policies. I estimate these two parameters and fit the model into stock returns of equal-weighted portfolios formed on firm characteristics, such as market leverage, book-to-market equity ratio, asset growth rate and market capitalization. My model outperforms the CAPM and the Fama-French three-factor model.

I contribute the success of my model to the right choice of the state variable and the correct measurement of the stock-cash flow sensitivity. Through my examination on the cross section and time series of stock-cash flow sensitivity, I find that the sensitivities of value stocks, high-leverage stocks and low-asset-growth stocks are substantially higher than those of growth stocks, low-leverage stocks and high-asset-growth stocks, particularly in recessions. It is the large spreads in the stock-cash flow sensitivity help 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 spreads in the cash flow rates. However, in my decomposition of the expected stock returns predicted from the model, the covariance between cash flow rates and stock-cash flow sensitivities has a very trivial contribution to the expected stock returns, while the product of their expected values explains a large portion of the cross-sectional variations for the four sets of portfolios.

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Appendix

A Proof for Proposition 1

Under a physical probability measure the operating incomes X_{it} is governed by

$$\frac{dX_{it}}{X_{it}} = \hat{\mu}_i dt + \sigma_i^X dW_t, \tag{A1}$$

where $\hat{\mu}_i$ is the physical growth rate of cash flows for firm i. I drop the subscripts i and t for ease of notation in this appendix.

Ito's lemma implies that the equity value E satisfies

$$\frac{dE}{E} = \frac{1}{E}(\frac{\partial E}{\partial t} + \hat{\mu} x \frac{\partial E}{\partial X} + \frac{\sigma}{2} X^2 \frac{\partial^2 E}{\partial X^2})dt + \frac{1}{E} X \sigma \frac{\partial E}{\partial X}. \tag{A2}$$

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

$$\frac{\partial E}{\partial t} + \mu X \frac{\partial E}{\partial X} + \frac{\sigma^2}{2} X^2 \frac{\partial^2 E}{\partial X^2} - rE + D = 0. \tag{A3}$$

Plugging the above equation back to equation (A2), we obtain the following

$$\frac{dE}{E} = \frac{1}{E}[(\hat{\mu} - \mu) X \frac{\partial E}{\partial X} + rE - D]dt + \frac{1}{E} X \sigma \frac{\partial E}{\partial X} dW. \tag{A4}$$

Simple algebraic manipulation yields

$$\frac{dE + Ddt}{E} - rdt = \frac{1}{E}[(\hat{\mu} - \mu) X \frac{\partial E}{\partial X}]dt + \frac{1}{E} X \sigma \frac{\partial E}{\partial X} dW, \tag{A5}$$

and

$$\frac{dE + Ddt}{E} - rdt = \frac{X}{E} \frac{\partial E}{\partial X} (\hat{\mu} dt + \sigma dW - \mu dt). \tag{A6}$$

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

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

Adding back the subscripts of i and t, we have our equation (4) proofed. Next, I provide the derivation of equity value $E(X)$ and its sensitivity to cash flows X. The general solution for equity value $E(X)$ to equation (A3) is

$$E(X) = (\frac{X}{r-\mu} - \frac{c}{r})\theta(1 - \tau_{eff}) + g_1 X^{\omega} + g_2 X^{\omega'} \tag{A8}$$

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

$$\frac{1}{2}(\sigma^X)^2\omega(\omega - 1) + \mu\omega - r = 0. \tag{A9}$$

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

$$g_1 = [(\frac{1}{X_B})^{\omega}(\frac{c}{r}\theta + \frac{X_B}{r-\mu}(\eta(\alpha-\kappa) - \theta)](1 - \tau_{eff}). \tag{A10}$$

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

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

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

$$X_B = \frac{\theta\omega C}{r(\omega - 1)}\frac{r-\mu}{\theta - \eta(\alpha-\kappa)}. \tag{A12}$$

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

Using the same approach for deriving the equity value, I obtain the market value of debt

$$B(X) = (1-\tau_i)\frac{C}{r} + \left[-(1-\tau_i)\frac{C}{r} + (1-\kappa-\eta(\alpha-\kappa))(1-\tau_{eff})\frac{X_B}{r-\mu}\right](\frac{X}{X_B})^{\omega}. \quad \text{(A13)}$$

The sensitivity of stocks to operating cash flows X is

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

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 Timing Alignment

As shown in Figure 2, the timing alignment in my study is largely consistent with Liu, Whited, and Zhang (2009) except that I need to incorporate the KMV procedure. The portfolio formation follows the standard Fama-French portfolio approach. I sort firms into quintiles at the end of June of each year t based on the ranking variables for the fiscal year ending in calendar year t - 1. Stock portfolio returns, r^S_{it+1}, are calculated from July of year t to June of year t+1.

To construct the annual contingent claim returns, r^{cc}_{it+1}, I need to obtain the operating cash flow rate r^X_{it+1} and estimate the expected stock-cash flow sensitivity ϵ_{it+1} . To calculate r^X_{it+1}, I use the operating income 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}. To estimate ϵ_{it+1}, I use the KMV procedure to obtain μ_{it+1} and σ^X_{it+1} . The stock price for calculating the equity value is at the end of June of year t and the stock volatility σ^S_{it+1} is the annualized standard deviation of the daily stock returns 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.

The changes in stock composition due to portfolio rebalancing in a given portfolio need more attention. 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, I keep the same set of firms in the portfolio in the formation year t until the rebalancing year $t + 1$.

C 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 $\mathbf{g}_T$. I 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, I construct the variance-covariance matrix for the pricing errors $\mathbf{g}_T$

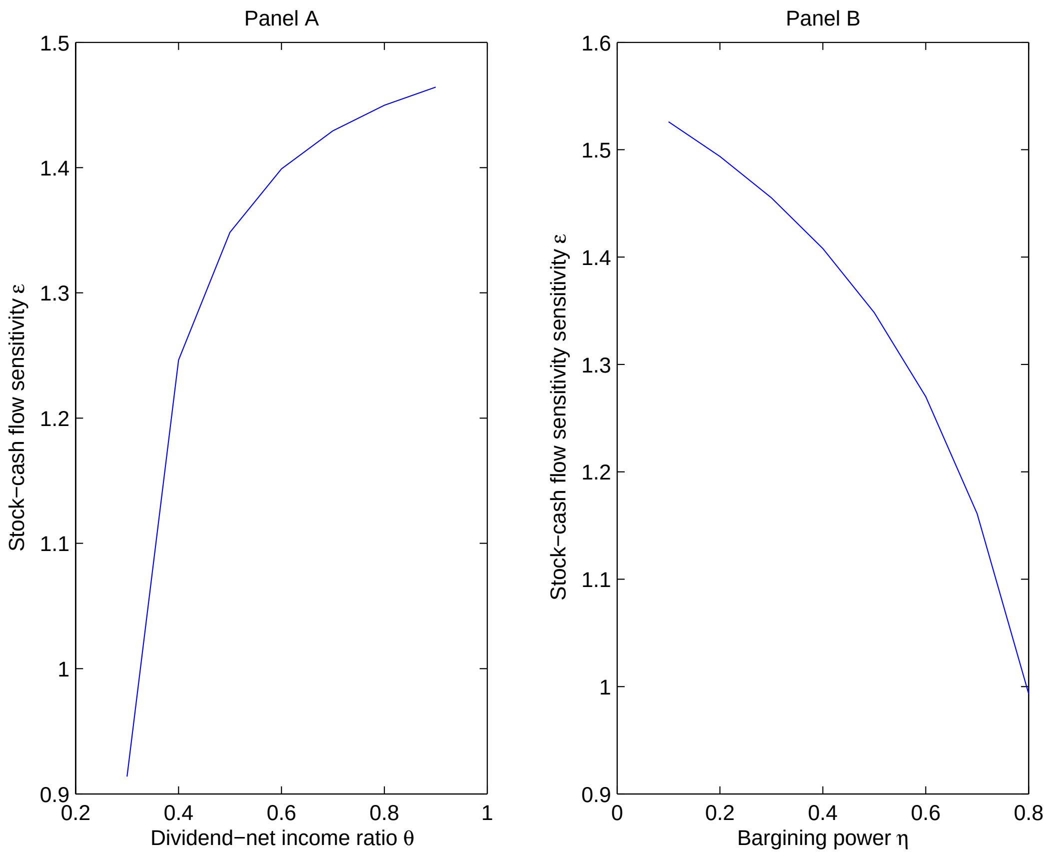
$$var(\mathbf{g}_T) = \frac{1}{T}[\mathbf{I} - \mathbf{D}(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}\mathbf{D}'\mathbf{W}]\mathbf{S}[\mathbf{I} - \mathbf{D}(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}\mathbf{D}'\mathbf{W}]'. \tag{A2}$$

To test whether all the pricing errors are jointly zero, I 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.

Figure 1: **Sensitivity of Stocks to Operating Cash Flows**
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 $r = 3.6\%$, $\tau_c = 35\%$, $\tau_d = 11.5\%$, $\tau_i = 29.3\%$, $\mu_i = 0$, $\sigma_i^X = 0.25$, $\alpha = 0.45$, and $\kappa = 0$. X_i is normalized to one.



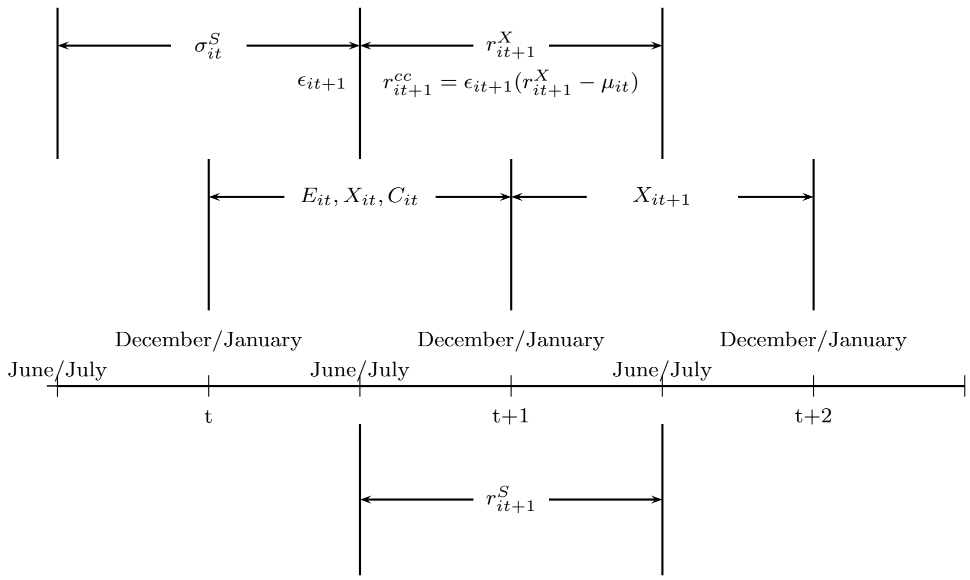


Figure 2: **Timing Alignment**
r_{it+1}^X is the rate of operating cash flows and r_{it+1}^S is the return of a stock portfolio from July of year t to June of year t+1. E_{it} is the equity value at the end of June of year t, X_{it} is the operating cash flows and C_{it} is the interest expenses at the end of year t. Stock volatility σ_{it}^S is the annualized standard deviation of the daily stock returns 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 claim model, the CAPM and the Fama-French model against the average realized returns. In the contingent claim model, the predicted returns are calculated based on equation (12) using the parameter estimates from Table 3 as well as the implied values of μ_{it+1} and σ^X_{t+1} from Table 5. High denotes the high leverage quintile and low denotes the low leverage quintile.

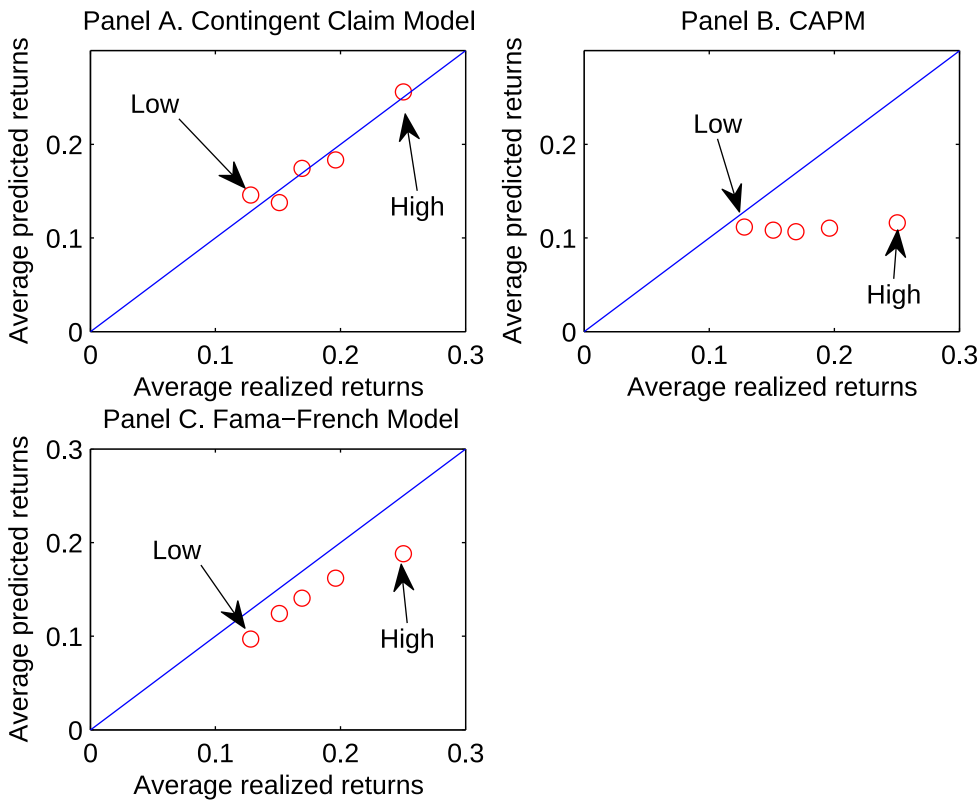


Figure 4: **Book-to-Market Portfolios: Average Predicted Stock returns versus Average Realized Returns**
This figure plots the time series averages of predicted returns from the contingent claim model, the CAPM and the Fama-French model against the average realized returns. In the contingent claim model, the predicted returns are 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}^X from Table 5. High denotes the high BE/ME quintile and low denotes the low BE/ME quintile.

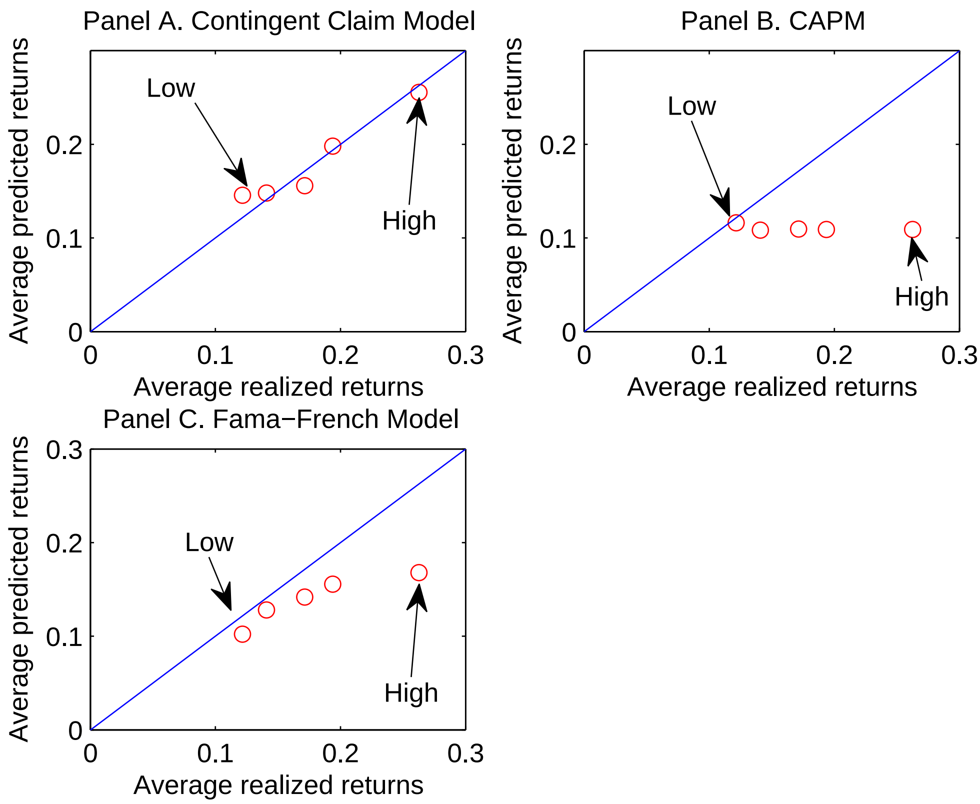


Figure 5: **Asset Growth Portfolios: Average Predicted Stock returns versus Average Realized Returns**
This figure plots the time series averages of predicted returns from the contingent claim model, the CAPM and the Fama-French model against the average realized returns. In the contingent claim model, the predicted returns are calculated based on equation (12) using the parameter estimates from Table 3 as well as the implied values of μ_{it+1} and σ^X_{t+1} from Table 5. High denotes the high asset-growth quintile and low denotes the low asset-growth quintile.

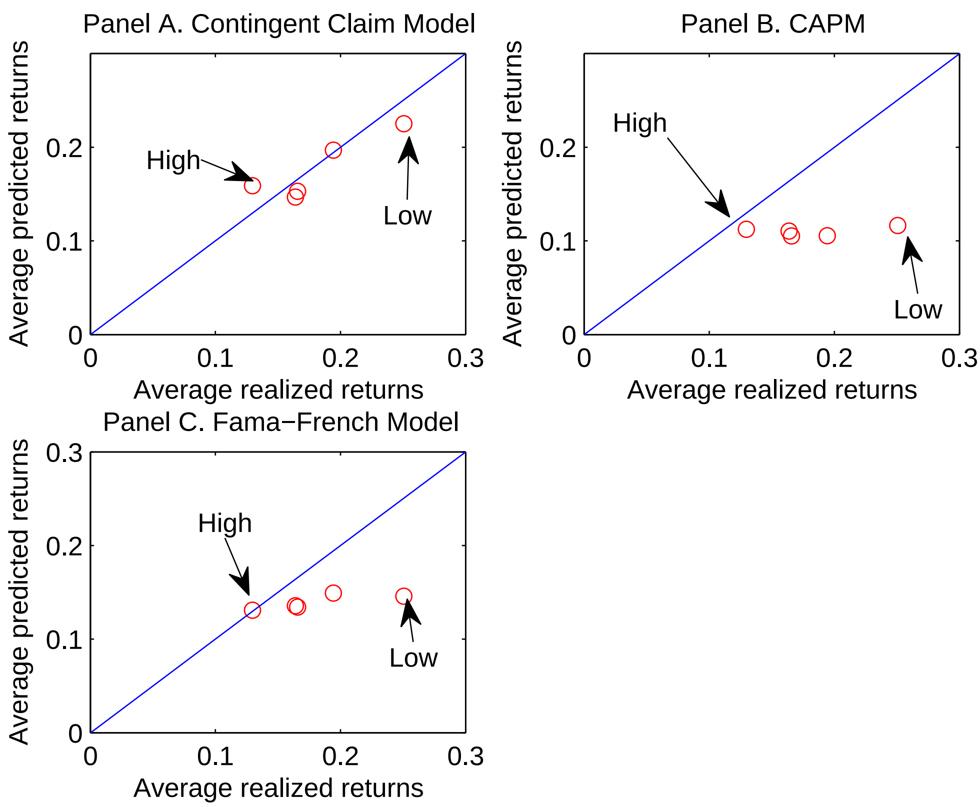


Figure 6: **Size Portfolios: Average Predicted Stock returns versus Average Realized Returns**
Each panel of this figure plots the time series averages of predicted returns from the contingent claim model, the CAPM and the Fama-French model against the average realized returns. In the contingent claim model, the predicted returns are calculated based on equation (12) using the parameter estimates from Table 3 as well as the implied values of μ_{it+1} and σ^X_{t+1} from Table 5. Small denotes the low market capitalization quintile and big denotes the high market capitalization quintile.

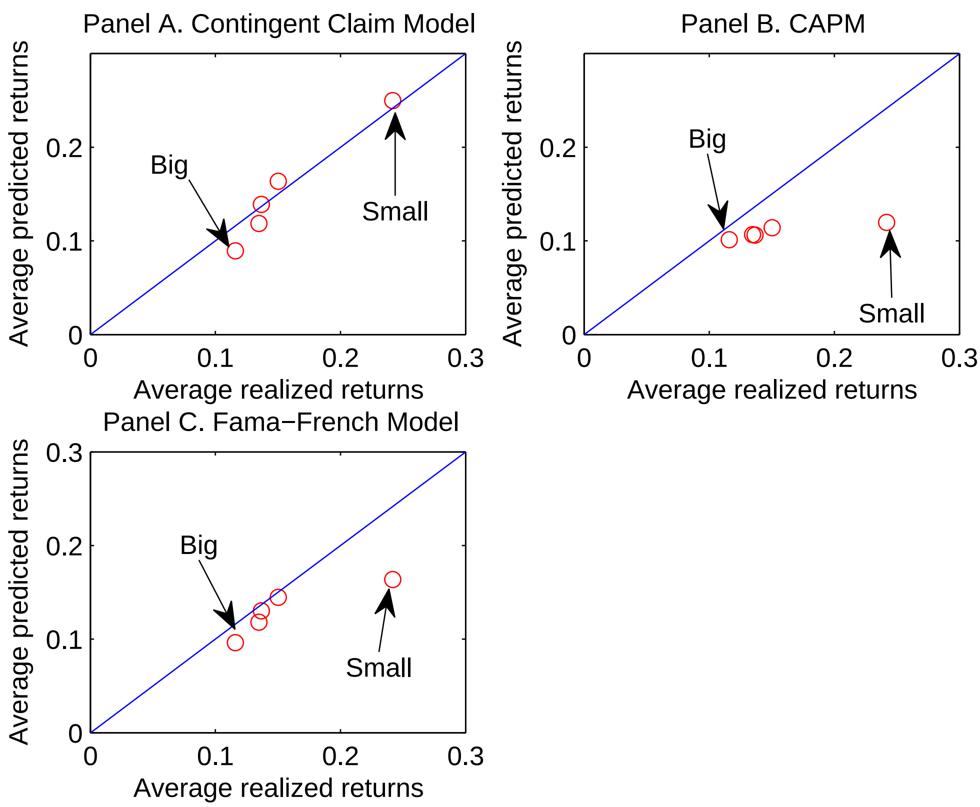


Figure 7: **Time series of Stock-Cash Flow Sensitivity**

Each panel of this figure plots a 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 (10) using the parameter estimates from Table 3 as well as the implied values of μ_{it+1} and σ^X_{t+1} from Table 5. The thick, solid lines are for the cross-sectional averages of the stock-cash flow sensitivity across all the quintile portfolios. The lines with dots (–.) are for the first quintile portfolio, the lines with circles (-o) for the third quintile portfolio and the lines with stars (-*) for the fifth quintile portfolio.

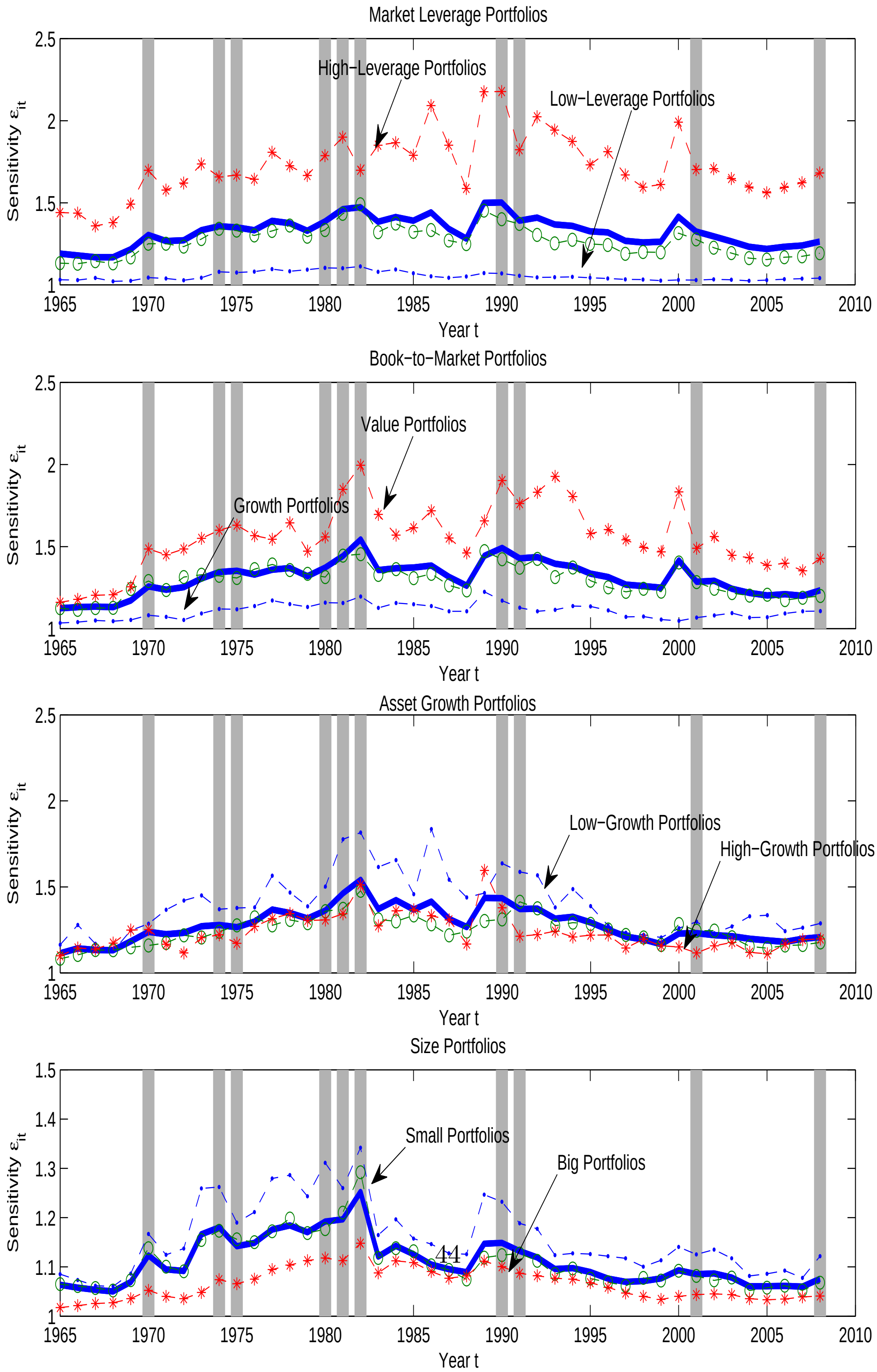


Table 1: **Pricing Errors of Testing Portfolio Returns from Traditional Models**
This table reports in annual percent the annualized average stock return ,$\overline{r^s_{it}}$, the pricing error from the CAPM regression, e^C_i, and the error from the Fama-French (FF) three-factor regression, e^{FF}_i for each quintile portfolio over the period of 1965 to 2009. 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.
$\overline{r^S_i}$	13.25	15.55	17.37	20.05	25.46	12.21	
e^C_i	1.66	4.29	6.26	8.58	13.41	11.75	6.84
(t)	(0.70)	(2.21)	(2.98)	(3.49)	(4.11)	(4.03)	
e^{FF}_i	3.12	2.70	2.88	3.43	6.21	3.09	3.67
(t)	(1.82)	(1.96)	(2.31)	(2.23)	(3.48)	(1.51)	

Panel B. BE/ME Portfolios							
$\overline{r^S_i}$	12.60	14.52	17.58	19.81	26.70	14.11	
e^C_i	0.55	3.26	6.20	8.46	15.36	14.81	6.77
(t)	(0.22)	(1.69)	(2.81)	(3.53)	(5.18)	(5.96)	
e^{FF}_i	1.95	1.29	2.97	3.83	9.48	7.53	3.90
(t)	(1.25)	(0.99)	(2.16)	(2.65)	(5.19)	(4.14)	

Panel C. Asset Growth Portfolios							
$\overline{r^S_i}$	25.51	19.87	17.01	16.83	13.40	-12.10	
e^C_i	13.43	8.89	6.05	5.35	1.72	-11.71	7.09
(t)	(4.57)	(3.96)	(3.15)	(2.68)	(0.77)	(-6.15)	
e^{FF}_i	10.49	4.52	3.14	2.84	-0.12	-10.61	4.22
(t)	(5.19)	(3.21)	(2.16)	(2.15)	(-0.09)	(-4.89)	

Panel D . Size Portfolios							
	Small	2	3	4	Big	S-B	m.a.e.
$\overline{r^S_i}$	24.61	15.47	14.10	13.91	12.04	12.58	
e^C_i	12.22	3.63	3.04	2.82	1.49	10.73	4.64
(t)	(3.44)	(1.50)	(1.59)	(1.72)	(1.50)	(3.00)	
e^{FF}_i	7.81	0.56	0.65	1.67	1.98	5.84	2.53
(t)	(4.42)	(0.36)	(0.51)	(1.10)	(1.70)	(3.13)	

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. $\overline{r^X_{it+1}}$ is the time series average of cash flow rates in annual percent from time t to time $t+1$ after portfolios are formed at time t, $corr(r^X_{it+1}, r^S_{it+1})$ is the time series correlation coefficient between r^X_{it+1} and r^S_{it+1}, and $\overline{\sigma^S_{it}}$ is the time series average of annualized daily stock volatility in percent calculated from one-year daily stock returns before the portfolio formation. $\overline{X_{it}/E_{it}}$ 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
$\overline{r^X_{it+1}}$	10.16	7.54	9.14	8.71	11.34
corr(r^X_{it+1},r^S_{it+1})	0.17	0.04	0.06	0.08	0.18
$\overline{X_{it}/E_{it}}$	0.09	0.12	0.15	0.18	0.23
$\overline{X_{it}/C_{it}}$	20.53	8.63	5.62	3.68	2.13
$\overline{\sigma^S_{it}}$	26.34	23.91	23.72	24.05	26.47

Panel B. BE/ME Portfolios					
$\overline{r^X_{it+1}}$	9.85	7.96	7.71	10.27	12.41
corr(r^X_{it+1},r^S_{it+1})	0.15	-0.08	0.00	0.15	0.18
$\overline{X_{it}/E_{it}}$	0.09	0.13	0.16	0.17	0.20
$\overline{X_{it}/C_{it}}$	9.70	6.29	5.09	4.18	3.18
$\overline{\sigma^S_{it}}$	28.20	25.09	24.20	23.98	25.42

Panel C. Asset Growth Portfolios					
$\overline{r^X_{it+1}}$	11.88	10.56	7.72	7.91	9.16
corr(r^X_{it+1},r^S_{it+1})	0.17	0.10	0.00	0.08	0.01
$\overline{X_{it}/E_{it}}$	0.15	0.14	0.13	0.12	0.11
$\overline{X_{it}/C_{it}}$	3.93	5.18	6.37	7.07	5.51
$\overline{\sigma^S_{it}}$	26.59	22.45	22.15	23.50	27.38

Panel D . Size Portfolios					
	Small	2	3	4	Big
$\overline{r^X_{it+1}}$	21.00	13.65	11.52	9.90	7.57
corr(r^X_{it+1},r^S_{it+1})	0.17	0.18	0.16	0.08	0.03
$\overline{X_{it}/E_{it}}$	0.15	0.16	0.15	0.14	0.12
$\overline{X_{it}/C_{it}}$	2.61	3.55	4.36	5.04	6.56
$\overline{\sigma^S_{it}}$	28.07	26.79	25.27	23.62	21.50

Table 3: **Parameter Estimates and Model Fitness**
This table reports the parameter estimates from one-stage GMM with an identity weighting matrix. The first moment conditions $\mathbb{E}[r^s_{it+1} - r^{cc}_{it+1}] = 0$ 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	0.92	0.88	1.00	0.24
	(2.15)	(2.16)	(2.37)	(0.83)
η	0.58	0.58	0.58	0.25
	(1.44)	(0.59)	(0.19)	(0.12)
χ^2	4.08	3.16	5.07	3.73
d.f.	3.00	3.00	3.00	3.00
p-value	0.25	0.37	0.17	0.29

Table 4: **Expected Pricing Errors from Fitted Models**
This table presents the pricing errors for each quintile portfolio from one-stage GMM with an identity weighting matrix. The expected return errors are defined as $e^{cc}_i = \mathbb{E}[r^s_{it+1} - r^{cc}_{it+1}]$, 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	-1.76	1.35	-0.49	1.29	-0.57	1.19	1.09
	(-1.38)	(1.48)	(-0.47)	(1.02)	(-3.44)	(1.03)	
BE/ME	-2.40	-0.70	1.57	-0.43	0.72	3.12	1.16
	(-1.83)	(-0.77)	(1.27)	(-0.37)	(2.76)	(2.63)	
Asset Growth	2.56	-0.25	1.29	1.71	-2.92	-5.48	1.74
	(8.23)	(-0.27)	(1.53)	(1.62)	(-1.77)	(-3.44)	

	Small	2	3	4	Big	S-B	m.a.e.
Size	-0.80	-1.34	-0.22	1.63	2.67	-3.46	1.33
	(-2.23)	(-1.32)	(-0.21)	(3.28)	(1.80)	(-2.95)	

Table 5: **Cross Section of Cash Flow Rate, Volatility, and Stock-Cash Flow Sensitivity**
This table reports the distribution of the *expected* cash flow rate μ_{it+1} and volatility σ^X_{it+1} in annual percent, given the estimates of θ and η from Table 3. 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^X_{it+1}			ϵ_{it+1}		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Low	-0.23	0.33	1.69	25.05	23.71	8.19	1.05	1.04	0.03
2	-1.25	-0.54	1.76	20.68	20.37	5.94	1.16	1.15	0.05
3	-1.77	-0.81	1.99	18.76	17.81	5.95	1.27	1.26	0.09
4	-1.87	-0.93	2.20	17.06	15.95	6.16	1.42	1.42	0.13
High	-1.59	-0.93	2.22	15.46	13.29	6.51	1.72	1.70	0.19

Panel B. BE/ME Portfolios									
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Low	-0.00	0.46	1.42	25.58	24.01	7.83	1.11	1.11	0.04
2	-1.26	-0.45	1.97	20.86	19.71	5.95	1.20	1.19	0.06
3	-1.67	-0.90	2.04	18.87	17.80	6.38	1.29	1.30	0.09
4	-1.63	-0.84	2.16	17.50	15.80	6.40	1.38	1.38	0.15
High	-1.64	-0.97	2.18	16.51	14.59	7.07	1.55	1.55	0.20

Panel C. Asset Growth Portfolios									
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Low	-1.49	-0.59	2.22	19.32	17.56	7.22	1.40	1.38	0.17
2	-1.74	-0.93	1.93	17.23	15.85	6.13	1.32	1.31	0.11
3	-1.66	-0.98	1.72	17.81	16.50	5.74	1.25	1.25	0.09
4	-1.33	-0.50	1.89	19.65	18.82	6.19	1.20	1.19	0.08
High	-0.96	-0.43	1.70	22.40	21.46	7.29	1.24	1.21	0.10

Panel D . Size Portfolios									
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Small	2.41	2.81	0.98	24.17	21.90	8.51	1.16	1.13	0.07
2	2.26	2.63	0.86	23.69	22.90	6.77	1.13	1.11	0.05
3	2.29	2.62	0.74	22.79	21.06	6.68	1.11	1.09	0.05
4	2.35	2.62	0.63	21.61	20.15	6.68	1.09	1.08	0.04
Big	2.58	2.78	0.57	20.16	18.77	6.36	1.07	1.06	0.03

Table 6: **Decomposition of Contingent-Claim-Based Returns**
This table reports individual contributions of cash flow rates r^X_{it+1}, risk-neutral rates μ_{it+1} and stock-cash flow sensitivities, ϵ_{it+1}, to the expected stock returns r^{cc}_{it+1} predicted from the contingent claim model. The four components are defined as follows: $\rho_1 = [\mathbb{E}(r^X_{it+1})\mathbb{E}(\epsilon_{it+1})]/[\mathbb{E}(r^{cc}_{it+1}) - r]$, $\rho_2 = [\mathbb{E}(\mu_{it+1})\mathbb{E}(\epsilon_{it+1})]/[\mathbb{E}(r^{cc}_{it+1}) - r]$, $\rho_3 = cov(r^X_{it+1}, \epsilon_{it+1})/[(\mathbb{E}(r^{cc}_{it+1}) - r]$, $\rho_4 = cov(\mu_{it+1}, \epsilon_{it+1})/[\mathbb{E}(r^{cc}_{it+1}) - r]$ and $\rho_1 - \rho_2 + \rho_3 - \rho_4 = 1$. The H (B) denotes the highest (biggest) quintile portfolio and the L (S) denotes the lowest (smallest) quintile portfolio.

Panel A. Market Leverage Portfolios					
	Low	2	3	4	High
ρ_1	0.978	0.861	0.841	0.843	0.891
ρ_2	-0.022	-0.142	-0.162	-0.181	-0.125
ρ_3	-0.004	-0.010	-0.008	-0.028	-0.013
ρ_4	-0.004	-0.006	-0.004	-0.004	0.004
$\rho_1 - \rho_2 + \rho_3 - \rho_4$	1.000	1.000	1.000	0.999	1.000

Panel B. BE/ME Portfolios					
ρ_1	0.999	0.861	0.834	0.881	0.880
ρ_2	-0.000	-0.136	-0.180	-0.140	-0.116
ρ_3	-0.003	-0.004	-0.020	-0.020	0.010
ρ_4	-0.004	-0.007	-0.005	0.001	0.006
$\rho_1 - \rho_2 + \rho_3 - \rho_4$	1.000	1.000	1.000	1.000	1.000

Panel C. Asset Growth Portfolios					
ρ_1	0.883	0.867	0.827	0.861	0.924
ρ_2	-0.110	-0.143	-0.178	-0.145	-0.097
ρ_3	0.007	-0.012	-0.010	-0.014	-0.028
ρ_4	-0.000	-0.002	-0.005	-0.008	-0.007
$\rho_1 - \rho_2 + \rho_3 - \rho_4$	1.000	1.000	1.000	1.000	1.000

Panel D. Size Portfolios					
	Small	2	3	4	Big
ρ_1	1.142	1.210	1.247	1.319	1.525
ρ_2	0.131	0.200	0.248	0.313	0.519
ρ_3	-0.013	-0.013	-0.002	-0.008	-0.009
ρ_4	-0.002	-0.003	-0.003	-0.002	-0.003
$\rho_1 - \rho_2 + \rho_3 - \rho_4$	1.000	1.000	1.000	1.000	1.000

Table 7: **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} I set them to their cross sectional averages each year for each quintile portfolio. For C_{it} and E_{it}, instead of fixing them to their cross sectional averages, I set $E_{it} = X_{it}/\widetilde{X_{it}/E_{it}}$ 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^X_{it+1}, where $\widetilde{X_{it}/E_{it}}$ and $\widetilde{X_{it}/C_{it}}$ are the cross-sectional earnings-price ratio and interest coverage ratio respectively. Then, I reconstruct the theoretical return r^{cc}_{it}, while keeping all the other parameters unchanged. I report the expected return errors, defined as $e^r_i = \mathbb{E}[r^s_{it+1} - r^{cc}_{it+1}]$, 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	-0.77	-0.72	0.23	2.86	3.80	1.11
$X_{it}/\widetilde{X_{it}/E_{it}}$	-5.23	-0.27	-0.73	2.41	2.89	8.12	2.31
$X_{it}/\widetilde{X_{it}/C_{it}}$	-2.12	1.34	-0.17	1.74	1.30	3.42	1.33
$\widetilde{\sigma^S_{it}}$	-1.76	1.36	-0.46	1.25	-0.79	0.97	1.12
$\widetilde{\epsilon_{it}}$	-4.09	1.55	1.17	4.56	6.37	10.46	3.55

Panel B. BE/ME Portfolios							
$\widetilde{r^X_{it+1}}$	-2.14	-2.69	-1.01	0.53	5.42	7.56	2.36
$X_{it}/\widetilde{X_{it}/E_{it}}$	-5.40	-1.47	1.86	0.44	3.21	8.61	2.48
$X_{it}/\widetilde{X_{it}/C_{it}}$	-2.73	-0.73	1.69	0.05	2.90	5.63	1.62
$\widetilde{\sigma^S_{it}}$	-2.40	-0.69	1.57	-0.40	0.50	2.90	1.11
$\widetilde{\epsilon_{it}}$	-4.19	0.11	3.59	2.28	6.41	10.60	3.32

Panel C. Asset Growth Portfolios							
$\widetilde{r^X_{it+1}}$	6.16	1.17	-0.84	-0.11	-3.39	-9.55	2.34
$X_{it}/\widetilde{X_{it}/E_{it}}$	3.46	0.41	1.31	1.03	-3.89	-7.35	2.02
$X_{it}/\widetilde{X_{it}/C_{it}}$	3.77	-0.04	1.21	1.58	-3.02	-6.79	1.92
$\widetilde{\sigma^S_{it}}$	2.36	-0.22	1.32	1.72	-2.91	-5.27	1.70
$\widetilde{\epsilon_{it}}$	6.16	2.22	2.98	2.69	-2.21	-8.36	3.25

Panel D. Size Portfolios							
	Small	2	3	4	Big	S-B	m.a.e.
$\widetilde{r^X_{it+1}}$	8.67	-0.36	-1.49	-1.42	-2.81	11.49	2.95
$X_{it}/\widetilde{X_{it}/E_{it}}$	-0.85	-1.11	-0.11	1.60	2.30	-3.15	1.19
$X_{it}/\widetilde{X_{it}/C_{it}}$	0.17	-1.15	-0.19	1.55	2.60	-2.43	1.13
$\widetilde{\sigma^S_{it}}$	-0.94	-1.36	-0.22	1.64	2.67	-3.61	1.37
$\widetilde{\epsilon_{it}}$	-2.07	-3.30	-2.47	-0.87	-0.19	-1.87	1.78

Internet Appendix: Robustness Check

A Two-Stage GMM

Table B.1 reports the parameter estimates from a two-stage GMM estimation using an inverse variance-covariance weighting matrix. The estimates are very close to those from the one-stage GMM estimation, but with greater t-statistics. The difference arises because the two-stage GMM is more efficient in terms of the smaller variance. Table B.2 presents the pricing errors and Figure B.1 plots average predicted stock returns against observed returns. The model performs well for all the four sets of testing portfolios. The results are very similar to those generated from the one-stage GMM estimation.

B Implied Interest Expenses

My model assumes a perpetual bond, different from corporate bonds with finite maturities in the data. Equation (A13) gives a relation between the coupon payment and the market value of a *perpetual* bond. Assuming bonds are issued at par, I could infer interest expenses for a *perpetual* bond instead of using the observed coupons for short- and long-term bonds from the Compustat. Following Liu, Whited, and Zhang (2009), I use the book value of total debt to proxy for its market value and solve the following system of three equations for $\mu_{it+1}, \sigma^X_{it+1}$, and C_{it} simultaneously.

$$\sigma^S_{it} = \mathbb{E}_t[\sigma^X_{it+1}\epsilon_{it+1}] \equiv \sigma^X_{it+1}\epsilon_{it+1} \tag{B.1}$$

$$E_{it} = \left[(\frac{X_{it}}{r-\mu_{it+1}} - \frac{C_{it}}{r})\theta + (\frac{C_{it}}{r}\theta + \frac{X_{iB}}{r-\mu_{it+1}}(\eta(\alpha-\kappa)-\theta))(\frac{X_{it}}{X_{iB}})^{\omega_{it+1}} \right](1-\tau_{eff}), \tag{B.2}$$

$$B_{it} = (1-\tau_i)\frac{C_{it}}{r} + \left[-(1-\tau_i)\frac{C_{it}}{r} + (1-\kappa-\eta*(\alpha-\kappa))(1-\tau_{eff})\frac{X_{iB}}{r-\mu_{it+1}} \right](\frac{X_{it}}{X_{iB}})^{\omega} \tag{B.3}$$

where B_{it} is the observed book value of total debt at year t. The first two equations are the same as in the benchmark model and the third one is the valuation function for debt from equation (A13).

Table B.3 reports the parameter estimates when C_{it} are implied from the book value of B_{it}. The estimates are very close to those from one-stage GMM estimation except that the estimate of η for the BE/ME portfolios hits the low bound of zero. Table B.4 and Figure B.2 show that the performance of this modified model is comparable to that of the benchmark model for all the four sets of testing portfolios.

Table B.1: **Parameter Estimates and Model Fitness from Two-Stage GMM**
This table reports the parameter estimates from two-stage GMM with an inverse variance-covariance weighting matrix. The first moment conditions $\mathbb{E}[r^s_{it+1} - r^{cc}_{it+1}] = 0$ 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	1.00	0.92	1.00	0.37
	(2.53)	(2.71)	(2.62)	(1.58)
η	0.60	0.44	0.58	0.54
	(1.66)	(0.39)	(0.28)	(1.09)
χ^2	1.24	3.16	4.95	3.68
d.f.	3.00	3.00	3.00	3.00
p-value	0.74	0.37	0.18	0.30

Table B.2: **Expected Pricing Errors from Fitted Models from Two-Stage GMM**
The table presents the pricing errors for each quintile portfolio from two-stage GMM estimation with an inverse variance-covariance weighting matrix. The expected return errors are defined $e^{cc}_i = \mathbb{E}[r^s_{it+1} - r^{cc}_{it+1}]$, 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	-2.19	0.77	-1.21	0.49	-1.62	0.57	1.26
	(-1.18)	(0.76)	(-0.50)	(0.36)	(-0.58)	(0.27)	
BE/ME	-2.67	-1.09	1.11	-1.05	-0.47	2.21	1.28
	(-1.15)	(-0.60)	(0.45)	(-0.58)	(-0.13)	(1.01)	
Asset Growth	2.56	-0.25	1.29	1.71	-2.92	-5.48	1.74
	(3.29)	(-0.25)	(2.25)	(1.81)	(-1.16)	(-1.69)	

	Small	2	3	4	Big	S-B	m.a.e.
Size	-2.22	-2.74	-1.52	0.39	1.67	-3.89	1.71
	(-1.24)	(-1.14)	(-1.48)	(0.26)	(0.68)	(-1.18)	

Table B.3: **Parameter Estimates and Model Fitness When Coupon Payments are Implied from Debt Values**
This table reports the parameter estimates from one-stage GMM when the coupon payments are implied from the system of equations (B.1), (B.2) and (B.3). The first moment conditions $\mathbb{E}[r^s_{it+1} - r^{cc}_{it+1}] = 0$ 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	0.92	0.83	1.00	0.26
	(2.24)	(2.18)	(2.48)	(0.89)
η	0.57	0.00	0.59	0.23
	(2.23)	(0.00)	(0.14)	(0.06)
χ^2	4.04	3.05	5.22	3.79
d.f.	3.00	3.00	3.00	3.00
p-value	0.26	0.38	0.16	0.29

Table B.4: **Expected Pricing Errors from Fitted Models When Coupon Payments are Implied from Debt Values**
The table presents the pricing errors for each quintile portfolio from one-stage GMM when the coupon payments are implied from the system of equations (B.1), (B.2) and (B.3). The expected return errors are defined $e^{cc}_i = \mathbb{E}[r^s_{it+1} - r^{cc}_{it+1}]$, 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	-1.75	1.35	-0.47	1.09	-0.46	1.29	1.02
	(-1.34)	(1.45)	(-0.45)	(0.93)	(-3.87)	(1.06)	
BE/ME	-2.08	-0.42	1.72	-0.14	0.23	2.30	0.92
	(-1.58)	(-0.47)	(1.48)	(-0.13)	(1.00)	(2.00)	
Asset Growth	2.85	-0.14	1.28	1.70	-3.00	-5.85	1.79
	(10.29)	(-0.14)	(1.60)	(1.62)	(-1.72)	(-3.36)	

	Small	2	3	4	Big	S-B	m.a.e.
Size	-0.67	-1.50	-0.31	1.48	2.52	-3.19	1.30
	(-1.63)	(-1.53)	(-0.29)	(3.13)	(1.80)	(-2.91)	

Figure B.1: **Average Predicted Stock returns versus Average Realized Returns, Two-Stage GMM**
This figure plots the time series averages of predicted returns from the contingent claim model against the average realized returns for the market leverage, book-to-market equity (BE/ME), asset growth and size portfolios. When the two-stage GMM procedure is employed, the predicted returns are calculated based on equation (12) using the estimates from Table B.1.

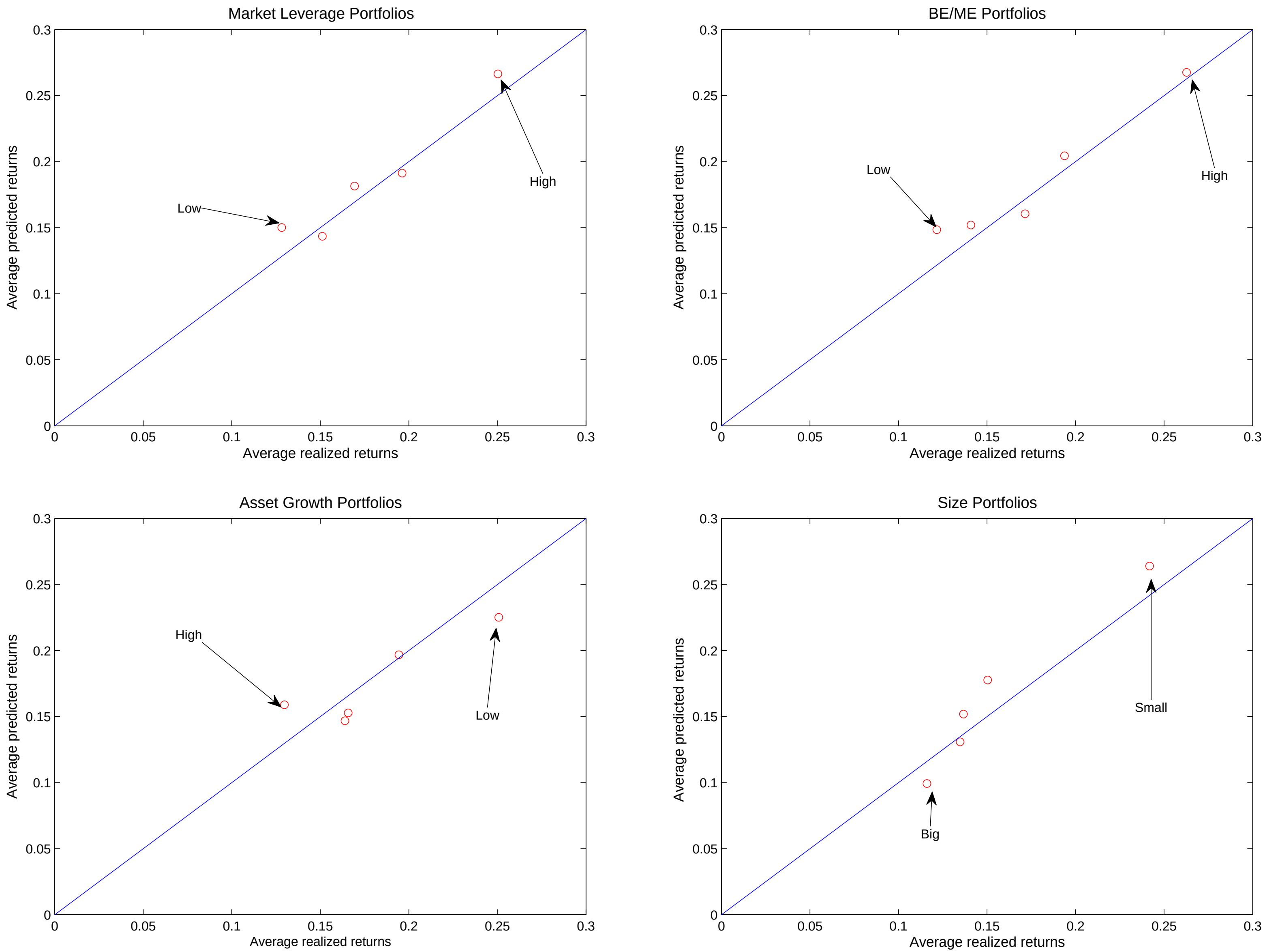


Figure B.2: **Average Predicted Stock returns versus Average Realized Returns when Coupons are Implied from Debt Values**
This figure plots the time series averages of predicted returns from the contingent claim model against the average realized returns for the market leverage, book-to-market equity (BE/ME), asset growth and size portfolios. The predicted returns are calculated based on equation (12) using the estimates from Table B.3 and the implied coupon from the system of equations (B.1), (B.2) and (B.3).