"Shooting" the CAPM

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Abstract

We provide a disaster-based explanation for the failure of the CAPM in the post-Compustat sample as well as its success to explain the value premium in the long sample that includes the Great Depression. In an investment-based asset pricing model embedded with rare disasters, value stocks are more sensitive to disaster shocks than growth stocks. More important, disasters introduce strong nonlinearities in the relation between the pricing kernel and the return on wealth. The nonlinearities allow the model to explain the failure of the CAPM in samples in which disasters are not materialized. However, the CAPM explains the value premium in samples with disasters in the model, consistent with the data.

1 Introduction

The value premium puzzle says that on average, firms with high book-to-market ratios (value firms) earn higher returns than firms with low book-to-market ratios (growth firms), despite similar market betas across the two types of firms. In particular, Fama and French (1992) find that the Capital Asset Pricing Model (CAPM) fails to explain the value premium for the sample after 1965. However, recent work shows that the CAPM can explain the value premium for the 1926–1963 period as well as the 1926–2011 period (e.g., Campbell and Vuolteenaho (2004), Fama and French (2006), Ang and Chen (2007), and Lin and Zhang (2012)).

Motivated by the fact that the 1926–1963 period features the Great Depression, which is the most severe economic downturn in the twentieth Century, we study whether accounting for rare economic disasters can help explain the value premium puzzle. To this end, we embed rare disasters into a standard investment-based asset pricing model. The model features three key ingredients: (i) severe, but rare, declines in aggregate consumption and productivity growth; (ii) asymmetric adjustment costs; and (iii) recursive preferences. Critically, the three key ingredients allow the model to reproduce a sizeable value premium and the empirical fact that the CAPM holds in samples with disasters but fails in samples without disasters.

Consistent with Zhang (2005), we show that with asymmetric adjustment costs, when a disaster shock hits the economy, value firms are burdened with more unproductive capital, and find it more difficult to reduce their capital stock than growth firms. As such, value firms are more exposed to disaster risks than growth firms, giving rise to the value premium.

Going beyond Zhang (2005), we show that when a disaster state is realized, consumption growth and productivity growth drop precipitously. Because of the consumption smoothing of the representative agent, a large drop in consumption growth is reflected in a very sharp rise in marginal utility. In addition, with recursive preferences, the representative agent also cares about the intertemporal distribution of consumption risk. With preferences for an early resolution of uncertainty, the agent dislikes persistence in shocks to consumption growth. Given that the consumption disaster is somewhat persistent, the agent is even more sensitive to the disaster shock (than an agent with power utility). This effect induces an even sharper rise in marginal utility and in the curvature of the pricing kernel. Because value firms do poorly precisely during these very high marginal utility states, the model quantitatively replicates the sizeable average value premium in the data.

More important, the high sensitivity of the agent toward disasters induces a highly nonlinear relation between the pricing kernel and the return on wealth. This nonlinear relation allows the model to explain the failure of the CAPM in short samples without disaster realizations. When disasters are not materialized, the (estimated) CAPM betas only measure the covariance of stock returns with aggregate shocks during normal times. However, the value premium is mainly driven by the covariance of value stocks and the pricing kernel in the disaster states. As a result, the CAPM betas estimated from normal times fail to explain the value premium. On the other hand, when disasters do materialize in the sample, the CAPM betas do account for the large comovements between the returns of the value stocks and pricing kernel. Consequently, the CAPM explains the value premium in the sample with disasters. In all, we provide a peso-based explanation for the value premium puzzle.

Our work adds to a growing literature that tries to explain the failure of the CAPM in investment-based asset pricing models (e.g., Ai and Kiku (2012), Belo, Lin and Bazdresch (2012), Belo and Lin (2012), and Kogan and Papanikolaou (2012)). These models all use multiple sources of aggregate shocks to break the otherwise perfect correlation between the stochastic discount factor and the market return. Although successful in explaining the failure of the CAPM in the post-1965 sample, these models fail to explain the success of the CAPM in the long sample starting from 1926. In contrast, with only one aggregate shock, our model fails the CAPM with disaster-induced nonlinearities. More important, our model is consistent with both the failure of the CAPM in the short sample and the success of the CAPM in the long sample. Our work also contributes to the rare disasters literature. Rare disasters have been used to explain a growing list of asset pricing puzzles, mostly at the aggregate level, (e.g., Barro (2006, 2009), Martin (2012), Gabaix

(2012), and Gourio(2012)). We add to this literature by examining the impact of disaster risks on cross-sectional asset prices.

The rest of the paper is organized as follows. Section 2 constructs the model. Section 3 presents the calibration and the main quantitative implications of the model. Section 4 concludes.

2 The Model

The model consists of a representative agent with Epstein-Zin (1989) preferences and heterogenous firms. We obtain the pricing kernel from the representative agent. Firms take the pricing kernel as given when determining their optimal investment policy. The modeling of the pricing kernel follows Bhamra, Kuehn, and Strebulaev (2010), and the problem of the firms is similar to Zhang (2005). The production technology has decreasing returns to scale, and is subject to aggregate and firm-specific shocks. The aggregate productivity growth contains a disaster state, which is also shared by the consumption growth process. This model of disasters is from Danthine and Donaldson (1999).

2.1 The Pricing Kernel

The representative agent has recursive preferences defined over aggregate consumption C_t:

$$U_t = \left[(1-\beta)C_t^{1-\frac{1}{\psi}} + \beta\left(E_t\left[U_{t+1}^{1-\gamma}\right]\right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}}\right]^{\frac{1}{1-\frac{1}{\psi}}}, \tag{1}$$

in which β is the subjective discount factor, ψ is the intertemporal elasticity of substitution, and γ is the relative risk aversion. The pricing kernel is:

$$M_{t+1} = \beta\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\psi}}\left(\frac{U_{t+1}^{1-\gamma}}{E_t[U_{t+1}^{1-\gamma}]}\right)^{\frac{\frac{1}{\psi}-\gamma}{1-\gamma}}. \tag{2}$$

2.2 Disasters

The log consumption growth, denoted $\triangle c_t \equiv \ln(C_t/C_{t-1})$ is specified as:

$$\triangle c_t = \overline{g} + g_t, \tag{3}$$

in which g_t follows a first-order autoregressive process as in Mehra and Prescott (1985). Specifically,

$$g_{t+1} = \rho_g g_t + \sigma_g \epsilon_{t+1}, \tag{4}$$

in which ϵ_{t+1} is a standard normal shock. The unconditional mean of g_t is zero.

In practice, we assume that g_t can take only a discrete number (five) of values, $\{g_1, g_2, g_3, g_4, g_5\}$. The Rouwenhorst (1995) procedure uses the parameter values of ρ_g and σ_g to pin down the five values on the g_t grid. This procedure also produces a transition matrix, P, as follows:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{15} \\ p_{21} & p_{22} & \cdots & p_{25} \\ \vdots & \vdots & \ddots & \vdots \\ p_{51} & p_{52} & \cdots & p_{55} \end{bmatrix}. \tag{5}$$

In particular, p_{ij}, for $i, j = 1, \ldots, 5$, is the probability of $g_{t+1} = g_j$ conditional on $g_t = g_i$.

Following Danthine and Donaldson (1999), we incorporate disaster risks by modifying the discretized g_t process as follows. We insert a new (disaster) state, $g_0 = \lambda + \overline{g}$, in which $\lambda \leq 0$ is the size of the disaster, i.e., the contraction proportion of consumption growth when a disaster hits. We also modify the transition matrix, P, as follows:

$$P = \begin{bmatrix} \theta & \frac{1}{5}(1-\theta) & \frac{1}{5}(1-\theta) & \ldots & \frac{1}{5}(1-\theta) \\ \eta & p_{11} - \eta & p_{12} & \cdots & p_{15} \\ \eta & p_{21} & p_{22} - \eta & \cdots & p_{25} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \eta & p_{51} & p_{52} & p_{53} & p_{55} - \eta \end{bmatrix}, \tag{6}$$

in which η is the probability of entering the disaster state from any of the other states. The parameter θ is the probability of the economy remaining in the disaster state the next period given that it is in the disaster state in the current period. As such, θ determines the persistence as well as the duration of the disaster state. Our modeling of disasters entails only one aggregate shock in the economy.

2.3 Firms

Firms produce output using capital, and are hit with both aggregate productivity and firm-specific productivity shocks. Operating profits for firm i are given by:

$$\Pi_{it} = (X_t Z_{it})^{1-\alpha} K_{it}^{\alpha} - f K_{it}, \tag{7}$$

in which X_t is the aggregate productivity, Z_{it} is the firm-specific productivity, K_{it} is capital, α is the curvature parameter, and fK_{it} is the fixed costs of production. The fixed costs are scaled by K_{it} to ensure that the costs do not become trivially small along the balanced growth path.

We assume that the aggregate productivity growth, $\triangle x_t \equiv \ln(X_t/X_{t-1})$, has an exposure to the consumption shocks:

$$\triangle x_t = \overline{g} + \phi g_t, \tag{8}$$

in which $\phi \geq 0$. The firm-specific productivity for firm i, Z_{it}, has a transition function given by:

$$z_{it+1} = \rho_z z_{it} + \sigma_z e_{it+1}, \tag{9}$$

in which $z_{it+1} \equiv \log Z_{it+1}$, and e_{it+1} is an i.i.d. standard normal shock. We assume that e_{it+1} and e_{jt+1} are uncorrelated for any $i \neq j$, and that ϵ_{t+1} and e_{it+1} are uncorrelated for any i.

Upon observing X_t and Z_{it}, firm i chooses optimal investment, I_{it}, to maximize its market value of equity. Capital accumulates as follows:

$$K_{it+1} = I_{it} + (1-\delta) K_{it}, \tag{10}$$

in which δ is the rate of depreciation. Capital investment entails asymmetric adjustment costs:

$$\Gamma(I_{it}, K_{it}) = \begin{cases} a^+ K_{it} + \frac{c^+}{2}\left(\frac{I_{it}}{K_{it}}\right)^2 K_{it} & \text{for} \quad I_{it} > 0 \\ 0 & \text{for} \quad I_{it} = 0 \\ a^- K_{it} + \frac{c^-}{2}\left(\frac{I_{it}}{K_{it}}\right)^2 K_{it} & \text{for} \quad I_{it} < 0 \end{cases} \tag{11}$$

in which $a^- > a^+ > 0$, and $c^- > c^+ > 0$ capture the nonconvexities of adjustment costs.

The cum-dividend market value of equity, $V_{it} \equiv V(K_{it}, X_t, Z_{it})$, is given by:

$$V(K_{it}, X_t, Z_{it}) = \max_{\{I_{it}\}} \; \Pi_{it} - I_{it} - \Gamma(I_{it}, K_{it}) + E_t\left[M_{t+1}V(K_{it+1}, X_{t+1}, Z_{it+1})\right], \tag{12}$$

subject to equation (10). Evaluating the value function at the optimum yields $V_{it} = D_{it} + E_t[M_{t+1}V_{it+1}]$, with $D_{it} \equiv \Pi_{it} - I_{it} - \Gamma(I_{it}, K_{it})$. Equivalently, $E_t[M_{t+1}r^S_{it+1}] = 1$, in which $r^S_{it+1} \equiv V_{it+1}/(V_{it} - D_{it})$ is the stock return. Rewriting in the beta-pricing form yields: $E_t[r^S_{it+1}] = r_{ft} + \beta^M_{it}\lambda_{Mt}$, in which $r_{ft} \equiv 1/E_t[M_{t+1}]$ is the real interest rate, $\beta^M_i \equiv -\mathrm{Cov}_t[r^S_{it+1}, M_{t+1}]/\mathrm{Var}_t[M_{t+1}]$ is the true conditional beta, and $\lambda_{Mt} \equiv \mathrm{Var}_t[M_{t+1}]/E_t[M_{t+1}]$ is the price of risk.

3 Calibration and Numerical Solution

3.1 Calibration

We calibrate the model in monthly frequency. Table 1 summarizes the parameter values for the benchmark calibration. The first set of parameters is for the preferences, and is calibrated to the standard values in the long-run risks literature (e.g., Bansal and Yaron (2004), Kaltenbrunner and Lochstoer (2010), and Bansal, Kiku, and Yaron (2012)). The intertemporal elasticity of substitution, ψ, is set to be two. As shown in Bansal and Yaron, a value of ψ larger than unity is essential for reconciling the empirical evidence that volatility and valuation ratios are negatively related and that expected growth and valuation ratios are positively related. The coefficient of relative risk aversion γ is set to be five to match the level of equity premium. In addition, the parameter restriction $\gamma > 1/\psi$, which implies the agent's preferences for an early resolution of uncertainty, is crucial for the expected consumption growth shocks to carry a positive price of risk. In our setting, this restriction is important to strengthen the sensitivity to the persistent disaster states. Finally, the subjective discount factor β is calibrated to match the level of the real risk free rate.

The second set of parameters is related to disasters, including the disaster persistence, θ, the disaster probability, η, and the disaster size, λ. We set the contraction proportion λ to be $-29\%/12$, which implies that the consumption growth drops, on average, by 29% per annum when the disaster

Table 1 : Parameter Values in the Benchmark Monthly Calibration

Parameters	Value	Description
Preference		
β	0.99	Subjective discount factor
γ	5	Relative risk aversion
ψ	2	Elasticity of intertemporal substitution
Disaster		
η	0.0014	Probability entering disaster state
λ	-0.024	Disaster size
θ	0.97	Disaster persistence
Technology		
ϕ	1	Levered exposure of TFP growth
ρ_z	0.98	Idiosyncratic productivity persistence
σ_z	0.5	Idiosyncratic productivity volatility
α	0.7	Curvature parameter
δ	0.01	Depreciation rate of capital stock
f	0.001	Fixed cost of production
a^+	0.01	Upward nonconvex adjustment costs
a^-	0.025	Downward nonconvex adjustment costs
c^+	20	Upward convex costs
c^-	100	Downward convex costs
Consumption		
$\bar{g}$	0.019/12	Average consumption growth rate
ρ_g	0.6	Persistence of consumption growth
σ_g	0.0025	Conditional volatility of consumption growth

hits the economy. This magnitude is consistent with Barro (2006, 2009), who document that the contraction proportions for the observed twentieth century disasters range from 15% to 64%, with a mean of 29%. The probability of entering the disaster state from any normal state, η, is calibrated to be 0.14%, which matches approximately the annual disaster probability of $0.14\% \times 12 \approx 1.7\%$ in Barro (2006, 2009). The disaster persistence, θ, which is the probability that the economy remains in the disaster state in the next period given that it is currently in the disaster state, is set at 0.97. This value accords with the quarterly persistence of $0.97^3 \approx 0.914$ in Gourio (2012). As such, the average length of disasters is $1/(1-0.97) \approx 33$ months or roughly three years. This duration is consistent with the notion that disasters unfold over several years in the disasters literature (e.g., Barro and Ursua (2008) and Nakamura, Steinsson, Barro and Ursua (2011)).

The third set of parameters governs the technology processes in the economy. Following, Li, Livdan, and Zhang (2009), we set the curvature parameter $\alpha = 0.7$, the depreciation rate $\delta = 0.01$, and the adjustment cost parameters $a^+ = 0.01$, $a^- = 0.025$, $c^+ = 20$, and $c^- = 100$. The persistence ρ_z and conditional volatility σ_z of the firm-specific productivity are set to be 0.98 and 0.5, respectively, which are not far from the values in Zhang (2005) after adjusting for the curvature parameter α. Finally, we set the fixed costs parameter, $f = 0.001$, to match the average book-to-market equity in the economy.

We are left with the parameters in the consumption growth process and the aggregate productivity parameter, ϕ. As in the disasters literature (e.g., Barro (2006, 2009) and Gourio (2012)), these parameters determine the mean, standard deviation, and autocorrelations of consumption growth in normal periods. We set the average growth rate, $\bar{g} = 0.019/12$, the persistence $\rho_g = 0.6$, and the conditional volatility $\sigma_g = 0.0025$ to match the average growth rate, standard deviation, and autocorrelation of per-capita real consumption growth from 1947 to 2011 in the United States. Table 2 reports the results. Finally, we set the aggregate productivity parameter, $\phi = 1$, to match the ratio of output growth volatility relative to per capita real consumption growth volatility in the data.

3.2 Numerical Solution

Detrending

Because the model features a balanced growth path, we need to detrend the model before solving for its stationary equilibrium. Define the following stationary variables: $\tilde{U}_t \equiv U_t/C_t$, $\hat{\Pi}_{it} \equiv \Pi_{it}/X_{t-1}$, $\hat{V}_{it} \equiv V_{it}/X_{t-1}$, $\hat{K}_{it} \equiv K_{it}/X_{t-1}$, $\hat{I}_{it} \equiv I_{it}/X_{t-1}$, and $\hat{D}_{it} \equiv D_{it}/X_{t-1}$. We then rewrite key equations in terms of these stationary variables as follows:

- Utility-to-consumption ratio:

$$\tilde{U}_t = \left[(1-\beta) + \beta \left(E_t \left[\tilde{U}_{t+1}^{1-\gamma} (C_{t+1}/C_t)^{1-\gamma} \right] \right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right]^{\frac{1}{1-\frac{1}{\psi}}}. \tag{13}$$

Table 2 : Consumption Growth Dynamics

The data moments are based on annual per-capita real consumption (real nondurables and services deflated by CPI and population growth) and real gross domestic product observations from 1947 to 2011 from National Income and Product Accounts at Bureau of Economic Analysis. The model moments are averaged across 1,000 simulations based on the benchmark monthly calibration given in Table 1, each with 792 monthly observations, which are in turn time-aggregated to 65 annual observations of consumption growth rates. $\bar{C}$ is the mean of log consumption growth, σ^C is the volatility of log consumption growth, $\rho^C(1)$ is the first-order autocorrelation of log consumption growth, and σ^Y is the volatility of log output growth. The "Mean" column displays the mean across the simulations. The "5%" and "95%" columns display the estimated percentiles of the simulated distribution. The "p-value" column denotes the frequencies with which a given model moment is higher than its data counterpart.

	Data	Model			
		Mean	5%	95%	p-value
$\bar{C}$	1.93	1.90	1.46	2.34	0.46
σ^C	1.71	1.70	1.45	1.96	0.46
ρ^C	0.25	0.26	0.08	0.44	0.56
σ^Y	2.42	2.50	1.97	2.96	0.80

- Pricing kernel:

$$M_{t+1} = \beta(C_{t+1}/C_t)^{-\frac{1}{\psi}} \left[\frac{\tilde{U}_{t+1}^{1-\gamma}(C_{t+1}/C_t)^{1-\gamma}}{E_t\left[\tilde{U}_{t+1}^{1-\gamma}(C_{t+1}/C_t)^{1-\gamma}\right]} \right]^{\frac{\frac{1}{\psi}-\gamma}{1-\gamma}}. \tag{14}$$

- Profits:

$$\hat{\Pi}_{it} = (X_t/X_{t-1})^{1-\alpha} Z_{it}^{1-\alpha} \hat{K}_{it}^{\alpha} - f\hat{K}_{it}. \tag{15}$$

- Capital accumulation:

$$\hat{K}_{it+1}(X_t/X_{t-1}) = (1-\delta)\hat{K}_{it} + \hat{I}_{it}. \tag{16}$$

- The adjustment costs function: Define $\hat{\Gamma} \equiv \Gamma / X_{t-1}$

$$\hat{\Gamma}(\hat{I}_{it}, \hat{K}_{it}) = \begin{cases} a^{+}\hat{K}_{it} + \frac{c^{+}}{2}\left(\frac{\hat{I}_{it}}{\hat{K}_{it}}\right)^2 \hat{K}_{it} & \text{for} \quad \hat{I}_{it} > 0 \\ 0 & \text{for} \quad \hat{I}_{it} = 0 \\ a^{-}\hat{K}_{it} + \frac{c^{-}}{2}\left(\frac{\hat{I}_{it}}{\hat{K}_{it}}\right)^2 \hat{K}_{it} & \text{for} \quad \hat{I}_{it} < 0 \end{cases}. \tag{17}$$

- Cum-dividend firm value, $\hat{V}_{it} \equiv \hat{V}(\hat{K}_{it}, X_t/X_{t-1}, Z_{it})$:

$$\max_{\{\hat{I}_{it}\}} \hat{\Pi}_{it} - \hat{I}_{it} - \hat{\Gamma}(\hat{I}_{it}, \hat{K}_{it}) + E_t\left[M_{t+1}\hat{V}\left(\hat{K}_{it+1}, X_{t+1}/X_t, Z_{it+1}\right)\right] X_t/X_{t-1}. \tag{18}$$

- Dividends:

$$\hat{D}_{it} = \hat{\Pi}_{it} - \hat{I}_{it} - \hat{\Gamma}(\hat{I}_{it}, \hat{K}_{it}). \tag{19}$$

- Stock return:

$$r^S_{it+1} = \frac{\hat{V}_{it+1} X_t/X_{t-1}}{\hat{V}_{it} - \hat{D}_{it}}. \tag{20}$$

Solving for the Pricing Kernel

The log utility-to-consumption ratio is approximately log-linear in the exogenous state variable, g_t. As such, for computational efficiency, it is advantageous to iterate on the log utility-to-consumption ratio, $\tilde{u}_t \equiv \log(\tilde{U}_t)$, as a function of g_t:

$$\exp(\tilde{u}_t) = \left[(1-\beta) + \beta\left(E_t\left[\exp((1-\gamma)(\tilde{u}_{t+1} + \bar{g} + g_{t+1}))\right]\right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}}\right]^{\frac{1}{1-\frac{1}{\psi}}}, \tag{21}$$

in which $\tilde{u}_t \equiv \tilde{u}(g_t)$. In the special case in which $\psi = 1$,

$$\exp(\tilde{u}_t) = \left(E_t\left[\exp((1-\gamma)(\tilde{u}_{t+1} + \bar{g} + g_{t+1}))\right]\right)^{\frac{\beta}{1-\gamma}}. \tag{22}$$

The pricing kernel can be expressed in terms of the log utility-to-consumption ratio:

$$M_{t+1} \equiv M(g_t, g_{t+1}) = \beta \exp\left(-\frac{1}{\psi}(\bar{g} + g_{t+1})\right)\left(\frac{\exp((1-\gamma)(\tilde{u}_{t+1} + \bar{g} + g_{t+1}))}{E_t[\exp((1-\gamma)(\tilde{u}_{t+1} + \bar{g} + g_{t+1}))]}\right)^{\frac{\frac{1}{\psi}-\gamma}{1-\gamma}}. \tag{23}$$

For power utility, we can directly specify the pricing kernel as:

$$M_{t+1} = \beta \exp\left(-\frac{1}{\psi}(\bar{g} + g_{t+1})\right). \tag{24}$$

Solving for the Firm Value

We iterate on the following recursion to obtain the firm value and policy functions:

$$\hat{V}(\hat{K}_{it}, g_t, Z_{it}) = \max_{\{\hat{I}_{it}\}} \ \hat{\Pi}_{it} - \hat{I}_{it} - \hat{\Gamma}(\hat{I}_{it}, \hat{K}_{it}) + E_t\left[M_{t+1}\hat{V}(\hat{K}_{it+1}, g_{t+1}, Z_{it+1})\right]\exp(\overline{g} + \phi g_t). \tag{25}$$

We discretize the state space (K_t, g_t, z_{it}) using 81 grid points for K_t, six grid points for g_t (including the disaster state), and 15 points for z_{it}.

4 Quantitative Results

We first present evidence on the performance of the CAPM in explaining the value premium in the data. We then provide quantitative results from our model.

4.1 Does the CAPM Explain the Value Premium?

Table 3 reports the monthly CAPM regressions for the value-minus-growth decile in the data. The monthly returns data for the book-to-market deciles are from Kenneth French's Web site. Consistent with Ang and Chen (2007), we observe that the CAPM can explain the value premium over the long sample from 1926 to 2011. The average return of the value-minus-growth decile over this period is 0.49% per month, which is more than 2.3 standard errors from zero. The CAPM beta is 0.45, which is more than 3.5 standard errors from zero. As a result, the CAPM alpha for the zero-investment portfolio is only 0.21%, which is slightly more than one standard error from zero.

Excluding the observations that lead up to and reside in the Great Depression does not change the basic result. In the post-Depression sample from 1936 to 2011, the CAPM alpha of the value-minus-growth decile remains insignificant, 0.31% per month ($t = 1.5$). The CAPM beta remains (relatively) high, 0.29, which is about 2.5 standard errors from zero. The CAPM beta becomes close

Table 3 : CAPM Regressions for the Value-minus-growth Decile in the Data

The monthly returns data for the ten book-to-market deciles are from Kenneth French's Web site. For each sample period, we report the average return, the standard deviation, and the CAPM regressions including α, β, their t-statistics adjusted for heteroscedasticity and autocorrelations, and adjusted R^2 for the value-minus-growth decile. The value decile is the tenth book-to-market decile, and the growth decile is the first book-to-market decile. The average returns, standard deviations, and alphas are in monthly percent.

	1926–2011	1936–2011	1947–2011	1963–2011	1926–1963	1926–1947
Mean	0.49	0.48	0.40	0.50	0.47	0.76
Std	6.65	5.55	4.47	4.69	8.61	11.02
α	0.21	0.31	0.38	0.50	−0.16	0.15
t_α	1.03	1.50	1.94	2.11	−0.47	0.27
β	0.45	0.29	0.03	0.01	0.74	0.84
t_β	3.53	2.47	0.40	0.11	5.41	5.92
Adjusted R^2	0.14	0.06	0.00	0.00	0.31	0.37

to zero, 0.03, in the post-war sample from 1947 to 2011, and the CAPM alpha becomes (marginally) significant, 0.38% ($t = 1.94$). The post-Compustat sample, from 1963 to 2011, has received much attention in the empirical literature. Consistent with numerous prior studies, we see that the CAPM fails to explain the value premium in this sample. The CAPM beta is 0.01, giving rise to a significant CAPM alpha of 0.50% ($t = 2.11$), which is identical to the magnitude of the average return.

The remaining two columns of Table 3 show that the CAPM does a very good job in explaining the value premium in the pre-Compustat sample (1926–1963) and in the pre-war sample (1926–1947). The value premiums are 0.47% and 0.76% per month in the two samples, respectively, both of which are more than 8.5 standard errors from zero. The CAPM betas are large and significant, 0.74 and 0.84, respectively, both of which are more than five standard errors from zero. Accordingly, the CAPM alphas are economically small and statistically insignificant, −0.16% and 0.15%, which are both within 0.5 standard errors of zero. To summarize, the evidence suggests that the CAPM does a good job in explaining the value premium in the long sample that includes the Great Depression, but that the CAPM fails to explain the value premium in the short post-Compustat sample.

4.2 Explaining the Performance of the CAPM

We use the model's solution to simulate 1,000 artificial samples, each with 5,000 firms and $984 + 400 = 1,384$ months. We start the simulations by setting the initial capital stocks of all firms at their long-run average level and by drawing their firm-specific productivity levels from the unconditional distribution of Z_{it}. We drop the first 400 months to neutralize the impact of the initial condition. The remaining 984 months of simulated data are treated as those from the economy's stationary distribution. The sample size is comparable to the 1926–2011 period, from which we have the data for the value premium. We calculate model moments on each artificial sample and report cross-simulation averaged results.

Table 4 shows the key quantitative results of the model under the benchmark calibration. Panel A reports the CAPM regressions for ten book-to-market deciles in the samples with disaster realizations (719 out of 1,000 artificial samples). The average returns of the deciles increase monotonically with book-to-market. The average return of the value-minus-growth decile is 0.55% per month, close to 0.49% in the data (full sample). However, the standard deviation of the value-minus-growth decile is 2.03%, which is substantially lower than 6.65% in the data. More important, the unconditional CAPM holds in the samples with disasters. The CAPM α for the value-minus-growth decile is -0.24% ($t = -1.71$). In addition, the 95% confidence interval for the CAPM alpha spans $[-0.59\%, 0.06\%]$. The CAPM β is estimated to be 0.88, which is more than 6.5 standard errors from zero. The market β also aligns monotonically with book-to-market, ranging from 0.80 for the growth decile to 1.67 for the value decile.

Panel B reports the CAPM regressions for the book-to-market deciles in the samples without disasters (281 out of 1,000 artificial samples). The average returns of the deciles continue to align monotonically with book-to-market. The average return of the value-minus-growth decile, 0.48% per month, is not far from that from the disaster samples, 0.55%. However, we observe that the CAPM fails badly in the no-disaster samples. The CAPM α for the value-minus-growth decile is

Table 4 : CAPM Regressions for the Book-to-market Deciles in the Model

Results are based on 1,000 simulations. Panel A reports the CAPM regressions for the ten book-to-market deciles for the samples with disasters materialized. Panel B reports the CAPM regressions for the samples in which no disasters are materialized. Panel C reports the summary statistics averaged across the disaster samples, the no-disaster samples, and all samples. The mean returns and the CAPM alphas in Panel A and B are in monthly percent.

	Growth	2	3	4	5	6	7	8	9	Value	V−G
	Panel A: Samples with disasters										
Mean	0.79	0.82	0.83	0.84	0.86	0.88	0.92	0.96	1.07	1.34	0.55
Std	1.59	1.68	1.73	1.80	1.86	1.93	2.05	2.19	2.46	3.22	2.03
α	0.06	0.05	0.03	0.01	−0.01	−0.03	−0.04	−0.07	−0.10	−0.18	−0.24
t_α	1.39	1.29	1.14	0.45	−0.36	−0.94	−1.24	−1.48	−1.64	−1.74	−1.71
$\alpha, 2.5\%$	−0.03	−0.03	−0.03	−0.04	−0.07	−0.10	−0.13	−0.18	−0.24	−0.46	−0.59
$\alpha, 97.5\%$	0.14	0.11	0.09	0.07	0.05	0.04	0.03	0.02	0.02	0.05	0.06
β	0.80	0.85	0.88	0.91	0.95	0.99	1.05	1.13	1.27	1.67	0.88
t_β	29.09	40.55	57.02	93.87	108.12	80.06	62.66	47.16	32.40	18.93	6.91
$\beta, 2.5\%$	0.69	0.78	0.83	0.87	0.91	0.93	0.96	1.02	1.11	1.36	0.47
$\beta, 97.5\%$	0.91	0.93	0.93	0.95	0.99	1.07	1.15	1.28	1.50	2.04	1.35
Adj-R^2	0.82	0.84	0.86	0.87	0.87	0.89	0.89	0.90	0.92	0.93	0.64
	Panel B: Samples without disasters										
Mean	0.85	0.87	0.88	0.89	0.89	0.90	0.94	0.97	1.07	1.32	0.48
Std	0.68	0.69	0.67	0.67	0.67	0.65	0.65	0.65	0.63	0.64	0.88
α	−0.17	−0.12	−0.06	−0.06	−0.08	−0.04	−0.00	0.04	0.17	0.43	0.61
t_α	−2.50	−1.66	−0.83	−0.85	−1.12	−0.64	−0.04	0.54	2.66	6.70	6.10
$\alpha, 2.5\%$	−0.32	−0.25	−0.16	−0.20	−0.21	−0.18	−0.13	−0.11	0.04	0.32	0.44
$\alpha, 97.5\%$	−0.03	0.03	0.07	0.08	0.07	0.10	0.13	0.15	0.29	0.55	0.79
β	1.07	1.04	0.99	1.00	1.02	1.00	0.99	0.99	0.95	0.93	−0.14
t_β	15.28	14.67	14.22	14.58	14.71	14.83	14.75	14.78	14.45	14.16	−1.39
$\beta, 2.5\%$	0.93	0.91	0.86	0.86	0.88	0.86	0.86	0.86	0.83	0.80	−0.32
$\beta, 97.5\%$	1.22	1.17	1.11	1.12	1.15	1.13	1.13	1.12	1.08	1.05	0.04
Adj-R^2	0.20	0.19	0.18	0.19	0.19	0.19	0.19	0.19	0.19	0.18	0.00

0.61%, which is more than six standard errors from zero. The 95% confidence interval for the CAPM alpha is $[0.44, 0.79]$. The α also increases monotonically with book-to-market, from -0.17 for the growth decile to 0.43 for the value decile. Moreover, the CAPM β for the value-minus-growth decile is insignificantly negative, -0.14 ($t = -1.39$). And its 95% confidence interval spans $[-0.32, 0.04]$. The market beta decreases weakly with book-to-market. The result shows that during normal times, growth stocks can be riskier than value stocks, consistent with the evidence in Petkova and Zhang (2005). We have also examined the CAPM regressions for the samples with disasters but with the disaster observations removed. The CAPM regression results are quantitatively similar with those from the samples without disasters (not reported). To summarize, the quantitative results in Table 4 on the performance of the CAPM accords well with the evidence in Table 3, suggesting that disasters seem important for explaining the cross-section of expected returns.

Fama and French (2006) refute the evidence that the CAPM explains the value premium in the long sample. They argue that value stocks have higher expected returns regardless of their betas, and that betas seem to be rewarded with average returns only when positively correlated with book-to-market. In particular, Fama and French split each book-to-market portfolio with pre=ranking market betas to create variations in betas that are independent of the variations in book-to-market. We implement the same procedure on simulated data.

Table 5 show the average returns, alphas, and betas for the 25 portfolios for the samples with and without disasters. The results are consistent with those from the one-way sorted book-to-market deciles. In particular, the CAPM betas for the high-minus-low book-to-market portfolios are on average large and positive, 0.51, with disasters, but are small and negative, -0.11, without disasters. Accordingly, the CAPM alphas for the high-minus-low book-to-market portfolios are on average large and positive, 0.38% per month, without disasters, but are small and negative, -0.13%, with disasters. In addition, sorting on estimated pre-ranking CAPM betas does not yield large average return spreads, probably due to measurement errors in betas (e.g., Lin and Zhang (2012)).

Table 5 : Two-way Sorted Portfolios on Book-to-market and Market Beta

Results are based on 1,000 simulations. Market betas are estimated from the CAPM regressions performed on 36 months window (month −42 to −6) prior to portfolio formation. H−L is the simple average of the returns on the five high-minus-low book-to-market portfolios, and H−L-β is the simple average of the returns on the five high-minus-low beta portfolios. The average returns and the CAPM alphas are in monthly percent.

	Mean					α					β				
	L-β	2	3	4	H-β	L-β	2	3	4	H-β	L-β	2	3	4	H-β
Panel A: Disaster sample															
Low	0.80	0.82	0.83	0.83	0.80	0.03	0.05	0.05	0.04	0.02	0.84	0.84	0.86	0.86	0.85
2	0.84	0.86	0.86	0.86	0.84	0.01	0.03	0.02	0.01	0.00	0.90	0.91	0.92	0.93	0.92
3	0.87	0.88	0.88	0.89	0.87	−0.01	−0.01	−0.01	−0.01	−0.02	0.96	0.97	0.98	0.99	0.98
4	0.93	0.94	0.94	0.94	0.93	−0.03	−0.03	−0.04	−0.04	−0.04	1.06	1.07	1.08	1.08	1.07
High	1.15	1.14	1.14	1.15	1.16	−0.08	−0.07	−0.09	−0.10	−0.12	1.34	1.33	1.35	1.37	1.41
H−L					0.33					−0.13					0.51
H−L-β					0.00					−0.02					0.03
Panel B: No-disaster Sample															
Low	0.85	0.88	0.89	0.88	0.85	−0.20	−0.05	−0.04	−0.06	−0.25	1.10	0.98	0.98	0.99	1.15
2	0.88	0.90	0.91	0.90	0.88	−0.09	−0.00	0.01	−0.00	−0.13	1.03	0.95	0.95	0.96	1.07
3	0.90	0.91	0.91	0.92	0.90	−0.07	−0.01	−0.02	−0.01	−0.11	1.03	0.97	0.98	0.98	1.07
4	0.96	0.96	0.96	0.96	0.95	0.01	0.05	0.03	0.03	−0.03	1.00	0.96	0.98	0.98	1.03
High	1.15	1.14	1.14	1.14	1.15	0.26	0.26	0.27	0.27	0.24	0.94	0.93	0.92	0.92	0.96
H−L					0.28					0.38					−0.11
H−L-β					0.00					−0.04					0.04

Instead of sorting on pre-ranking market betas calculated based on observations in the past 36 months, we repeat the tests using true betas that can be calculated within the model. The timing of the true betas is at the December of year $t-1$ for the portfolio formation year t. Table 6 show the average returns, alphas, and betas for the 25 book-to-market and true beta portfolios. The patterns of average returns, alphas, and betas along the book-to-market dimension are again consistent with the patterns for the one-way sorted deciles. In addition, along the true beta dimension, we observe a spread in the average return. The estimated CAPM betas and the true betas are positively correlated in the disaster samples. However, the estimated CAPM betas covary negatively with the true betas in the no-disaster samples, indicating severe measurement errors in the estimated betas.

Table 6 : Two-way Sorted Portfolios on Book-to-market and True Beta

Results are based on 1,000 simulations. H−L is the simple average of the returns on the five high-minus-low book-to-market portfolios, and H−L-β is the simple average of the returns on the five high-minus-low true beta portfolios. The average returns and alphas are in monthly percent.

	Mean					α					β				
	L-β	2	3	4	H-β	L-β	2	3	4	H-β	L-β	2	3	4	H-β
Panel A: Disaster sample															
Low	0.73	0.81	0.87	0.93	1.01	0.02	0.05	0.06	0.06	0.04	0.77	0.83	0.89	0.95	1.06
2	0.76	0.85	0.90	0.96	1.04	0.01	0.03	0.03	0.02	−0.01	0.82	0.89	0.95	1.02	1.14
3	0.78	0.87	0.93	0.98	1.08	−0.00	−0.00	0.00	−0.01	−0.05	0.85	0.95	1.01	1.09	1.23
4	0.82	0.92	0.98	1.05	1.17	−0.02	−0.02	−0.03	−0.05	−0.11	0.92	1.02	1.11	1.20	1.40
High	0.91	1.07	1.18	1.31	1.62	−0.04	−0.06	−0.10	−0.14	−0.27	1.04	1.24	1.40	1.59	2.07
H−L					0.35					−0.17					0.57
H−L-β					0.38					−0.07					0.50
Panel B: No-disaster Sample															
Low	0.78	0.86	0.93	0.98	1.06	−0.50	−0.02	0.19	0.28	0.38	1.34	0.93	0.77	0.73	0.72
2	0.81	0.89	0.95	1.00	1.07	−0.43	0.08	0.23	0.29	0.38	1.30	0.86	0.76	0.75	0.72
3	0.82	0.90	0.96	1.01	1.09	−0.41	0.02	0.21	0.30	0.36	1.30	0.93	0.79	0.75	0.77
4	0.85	0.93	1.00	1.06	1.17	−0.32	0.11	0.19	0.31	0.41	1.23	0.86	0.86	0.79	0.81
High	0.93	1.08	1.18	1.29	1.57	−0.08	0.22	0.36	0.49	0.71	1.07	0.90	0.86	0.85	0.90
H−L					0.29					0.27					0.02
H−L-β					0.36					0.80					−0.47

4.3 Economic Mechanism

What is the key economic mechanism underlying the quantitative results of our model? We start from the pricing kernel M_{t+1}. Given the one shock structure of our model and the parsimonious six grid points $g_0, g_1, \ldots, g_5$ indicating aggregate states, the pricing kernel is fully characterized by $M_{ij}, i, j = 1, \ldots, 6$ which is the realized value of the stochastic discount factor when the current state is g_i and the next period's state is g_j. The matrix M_{ij} can be calculated directly from equation (2) with inputs from the benchmark calibration.

If the CAPM holds, the stochastic discount factor can be expressed as a linear function of the market return. Specifically, there exist constants, a and b, such that:

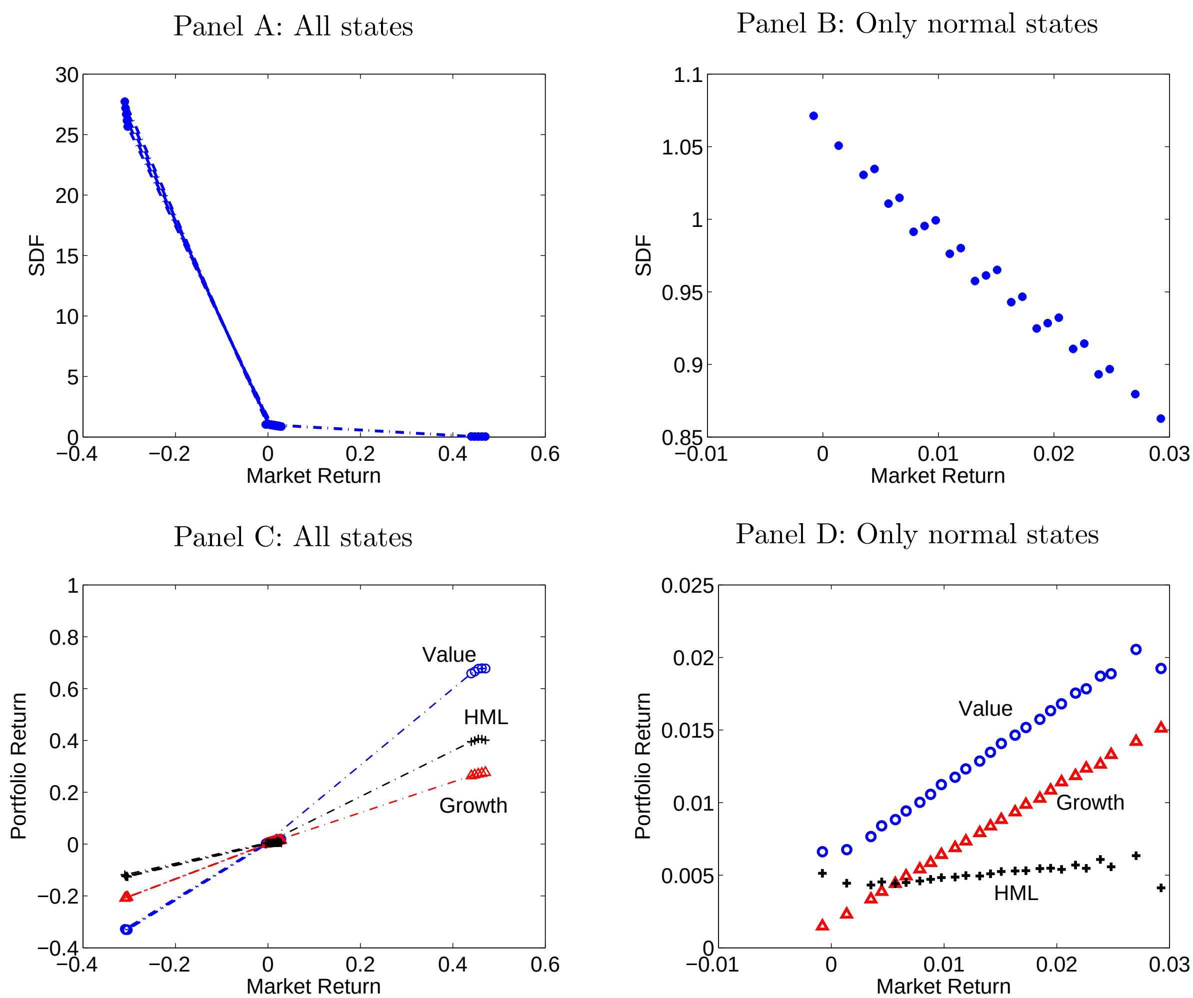
$$M_{t+1} = a + bR_{t+1}^{M}. \tag{26}$$

Figure 1 reports the scatterplots of M_{t+1} versus R_{t+1}^{M} as well as value, growth, and the value-minus-growth decile returns versus R_{t+1}^{M}. Panel A plots M_{t+1} versus R_{t+1}^{M} for all states, disasters and no-disasters, while Panel B only plots the relation in normal states with no disasters. We observe that the slope b that an econometrician could estimate using only the data from samples without disasters is the slope in Panel B, and is dramatically different from the slope from the samples with disasters. As such, when an econometrician only observes data for normal times, he might conclude that the CAPM does not work. When the data sample is long enough to include disasters, he can more accurately estimate the model and conclude that the CAPM does work. This line of reasoning exactly explains why in our model the CAPM works in the samples with disasters and does not work in the samples without disasters. This nonlinear relation between the pricing kernel and the market return is the key to our results. Without nonlinearity, when all the points align linearly as in Panel A, the partial sample in Panel B would allow the econometrician to accurately estimate the slope b. As a result, the CAPM holds regardless of samples.

Panel C shows the scatterplots of the portfolio returns of value, growth, and value-minus-growth versus the market returns. Panel D shows a partial picture for only the normal times. We observe that in normal times value is only weakly riskier than growth. As such, the value-minus-growth decile returns do not closely follow the market return, implying that the CAPM fails to explain the value premium in normal times. However, once the econometrician gets to see a full picture as in Panel C, the CAPM turns out to be more "correct." The reason is that value is significantly riskier than growth when the economy enters the disaster state. After observing these returns, the econometrician make correct inferences about the relative risks of value and growth firms. Consequently, the CAPM is able to explain the value premiums.

Figure 1 : Economic Mechanism

Panel A plots the state-by-state stochastic discount factor versus the market return (totally 36 points) for all the states. Panel B plots the state-by-state stochastic discount factor versus the market return (totally 25 points) for only the normal states. Panel C plots the state-by-state portfolio returns (value, growth, and the value-minus-growth decile) versus the market return (totally 36 points) for all the states. Panel D plots the state-by-state portfolio returns versus the market return (totally 25 points) for only the normal states.



4.4 Comparative Statics

Table 7 shows the CAPM regression results under alternative parameter values. We focus on the intertemporal elasticity of substitution, ψ, and the disaster persistence, θ. Panel A shows the results with respect to ψ. In particular, when we make ψ as the reciprocal of the relative risk aversion (i.e. $\psi < 1$), reducing the recursive preferences to power utility, we find that the equity premium is negative in the samples without disasters, and the value premium is negative in the samples with disasters. This result contradicts with the evidence that both the equity premium and the value premium remain largely similar magnitudes regardless of samples.

Panel B shows the results with respect to changes in the disaster persistence. When we reduce the disaster persistence to 0.9, which implies an average disaster duration of 10 months, we find both the value premium and the equity premium are much lower than the benchmark model. This result makes sense intuitively. When the agent knows that the economy will not stay in the disasters for long, he could only demand a lower risk premium for holding either the aggregate stock market or the value stocks. In the sample without disasters, we find that the CAPM alpha is significantly positive, implying that the CAPM fails to explain the value premium.

In the sample with disasters, both the CAPM alpha and the market beta are insignificant. The reason is that with an shorter duration of the disaster period, value stocks do not respond to disaster shocks as strongly as in the benchmark model, implying that both the drops and jumps in value stock returns at the beginning and end of the disaster period are not significantly different from those of growth stocks. As such, an econometrician could not observe the significant differences, and concludes that the CAPM does not capture the value premium. When we lower the disaster persistence to zero, disasters become i.i.d. shocks. Both the moments and the CAPM regression results are similar for both samples. The value premium and the equity premium are almost nonexist, and the CAPM alphas are insignificant, while the CAPM betas are significantly negative.

Figure 2 shows the impact of varying the disaster persistence, θ, on the nonlinear dynamics in

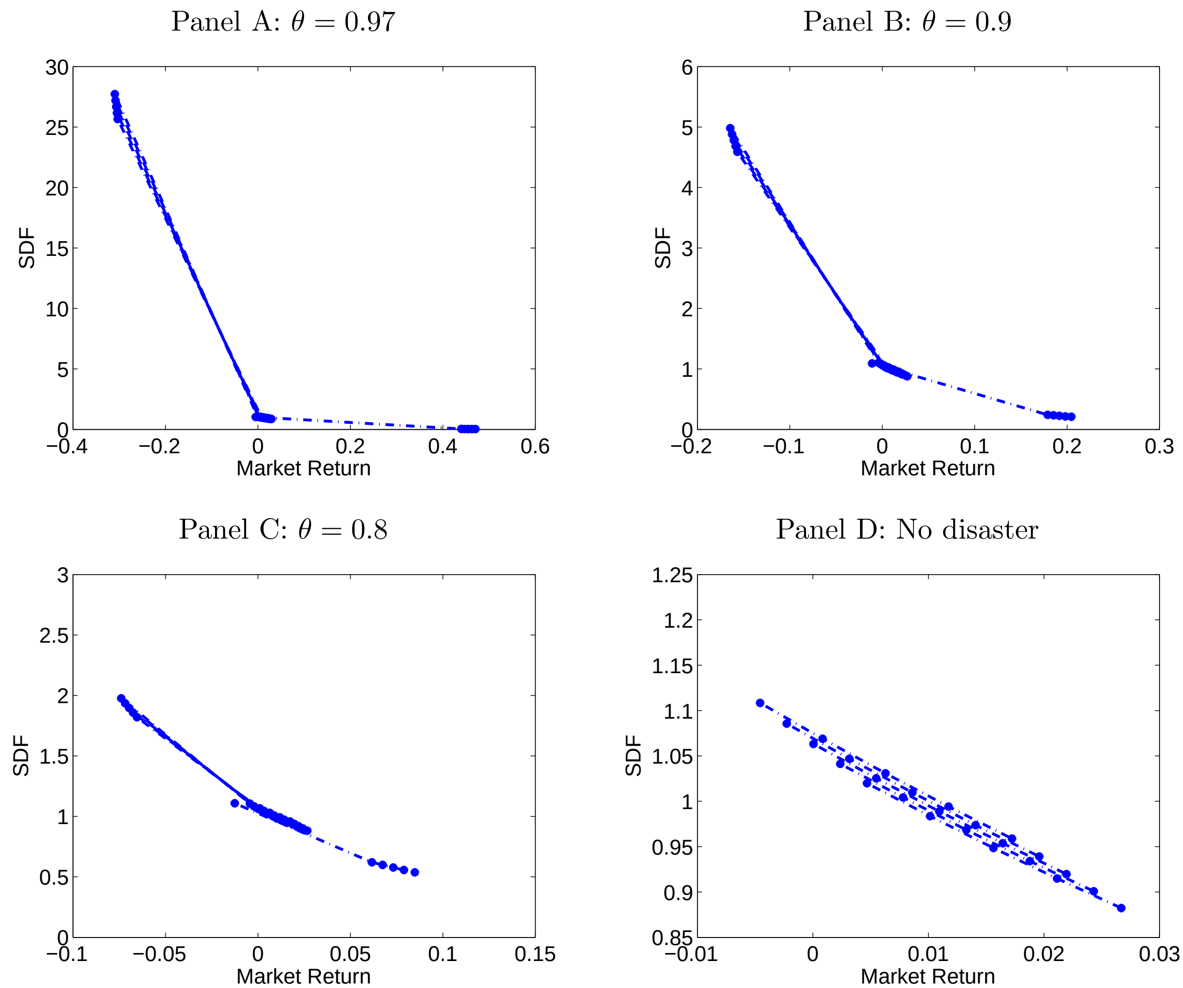
Table 7 : Comparative Static Experiments

All results are based on 1,000 simulations. Panel A shows the comparative statics results with respect to intertemporal elasticity of substitution. Panel B shows the comparative statics results with respect to disaster persistence. For all the experiments, only the parameter under study is changed with the subjective discount factor adjusted accordingly to make the risk-free rate in the ballpark (except for the power utility case we also lower relative risk aversion to two to make risk-free rate in the reasonable range). All other parameters remain in the benchmark calibration. As in Table 4, aggregate moments are annualized, while the CAPM alphas are in month percent.

Panel A: Intertemporal elasticity of substitution, ψ						
	Benchmark ($\psi = 2$)		$\psi = 1$		Power utility ($\psi = 1/5$)	
	Disaster	No Disaster	Disaster	No Disaster	Disaster	No Disaster
The value premium	6.65	5.70	0.03	0.02	−0.53	1.27
The equity premium	10.96	11.39	−0.34	−0.31	1.52	−3.75
The risk-free rate	1.76	2.25	1.95	2.43	5.94	9.76
α	−0.24	0.61	0.00	−0.00	−0.01	0.18
t_α	−1.71	6.10	0.04	−0.23	−0.23	14.33
α, 2.5%	−0.59	0.44	−0.00	−0.00	−0.05	0.15
α, 97.5%	0.06	0.79	0.00	0.00	0.05	0.21
β	0.88	−0.14	−0.09	−0.09	−0.30	0.23
t_β	6.91	−1.39	−6.96	−8.54	−17.98	12.01
β, 2.5%	0.47	−0.32	−0.12	−0.11	−0.34	0.19
β, 97.5%	1.35	0.04	−0.06	−0.06	−0.18	0.28
Panel B: Disaster Persistence θ						
	Benchmark ($\theta = 0.97$)		$\theta = 0.9$		$\theta = 0$	
The value premium	6.65	5.70	0.11	0.05	0.01	0.00
The equity premium	10.96	11.39	1.72	1.77	−0.03	0.03
The risk-free rate	1.76	2.25	1.72	2.07	2.03	2.03
α	−0.24	0.61	0.01	0.04	−0.00	0.00
t_α	−1.71	6.10	0.58	3.61	−0.02	0.18
α, 2.5%	−0.59	0.44	−0.01	0.01	−0.00	−0.00
α, 97.5%	0.06	0.79	0.02	0.06	0.00	0.00
β	0.88	−0.14	0.03	−0.22	−0.05	−0.05
t_β	6.91	−1.39	0.48	−7.12	−14.21	−15.96
β, 2.5%	0.47	−0.32	−0.06	−0.30	−0.06	−0.06
β, 97.5%	1.35	0.04	0.13	−0.16	−0.04	−0.05

Figure 2 : Market Return Versus SDF, Comparative Statics with the Disaster Persistence

We plot the market return versus the SDF on a state-by-state basis. All the plots are under the benchmark calibration, with only θ (the disaster persistence) varying, and Panel D shuts off the disaster state. Returns on wealth are calculated numerically.



the model. We observe that as θ decreases, the nonlinearity that is critical for the model's ability to fail the CAPM gradually disappears.

4.5 A Disaster Realization

We examine the responses of asset returns in the case of a disaster realization. Figure 3 shows the responses of market returns, value, and growth portfolio returns to a typical disaster realization starting at month zero, which lasts for approximately 40 months. At the onset of a disaster period, consumption growth drops by a considerable amount, and the agent would expect a drop in future expected dividends, which tends to depress stock prices. On the other hand, the agent has an increased desire to save to substitute consumption, which tends to raise stock prices. With $\psi = 2$, the former effect dominates the latter, and as a result, aggregate stock returns decline at the beginning of a disaster. Disaster shocks also affect the aggregate productivity of firms, and further their outputs. Relative to growth firms, value firms are more adversely affected, implying a significant reduction in their dividend payouts, which lowers the stock returns more than growth firms in the short run. When the economy exits the disaster state, the market return will spike up instantly since the agent expects a sharp rise in future expected returns. Both value and growth firms experience productivity booms. Value firms could easily take advantage of its unproductive capital and increase investment, therefore we see returns on value stocks spike up more than those on growth stocks. In all, when the economy experiences a disaster period, value firms will respond more than growth firms at both the beginning and end of the period.

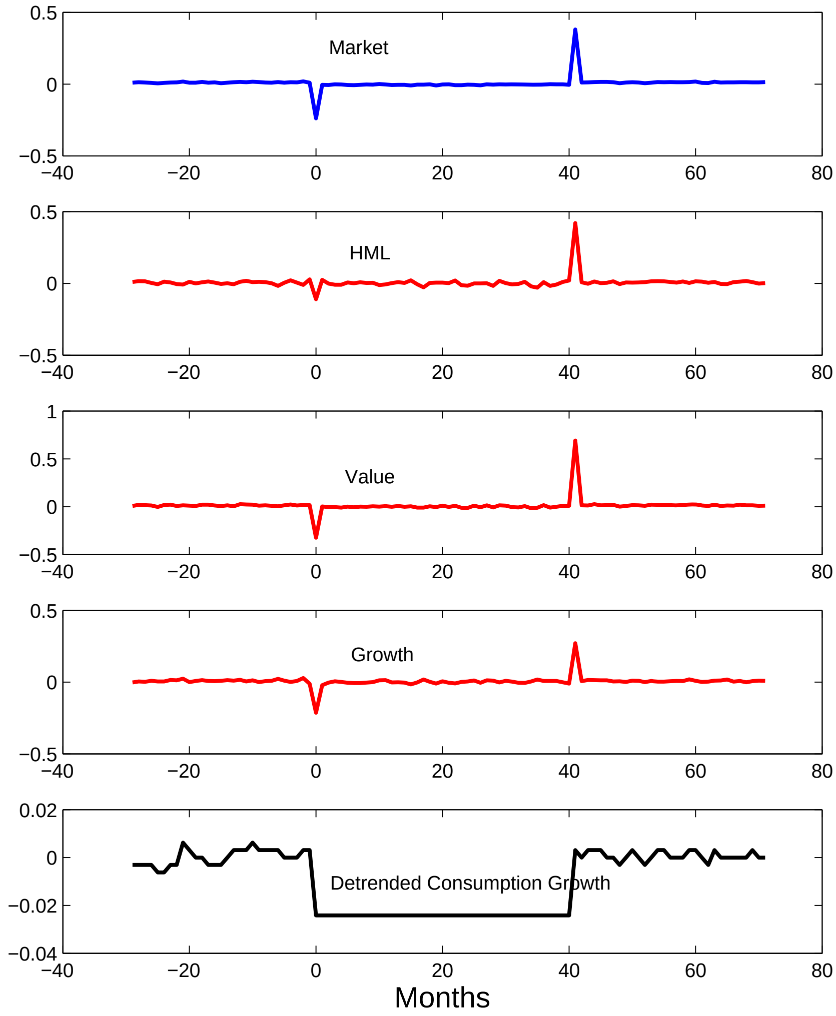
Koijen, Lustig and Nieuwerburgh (2012) provide relevant empirical evidence that lends support to our story. They showed that the fall in value stock dividends is much larger in really bad aggregate times than in shallower recessions. For example, they report that that the relative log change in value-minus-growth dividends during the Great Depression was -461%, while this number is only -37% during the Great Recession of 2007–2009. Based on those evidence, they argued that those "low-value events", i.e. periods during which value stocks and value-minus-growth experience exceptionally low returns, are important for a risk-based resolution of the value premium puzzle. Our paper echoes their evidence by proposing a peso-based explanation for the value premium puzzle.

5 Conclusion

Motivated by the seemingly contradictory empirical evidence on the CAPM's ability to explain the value premium, we investigate whether rare economic disasters could explain the average returns on book-to-market sorted portfolios. We embed rare disasters into an investment-based asset pricing model with recursive preferences. On simulated data out of our model, the CAPM fails to explain

Figure 3 : A Disaster Realization

This figure plots the responses of asset returns in the realization of a disaster for the benchmark calibration.



the value premium in the sample without disasters, and it could successfully capture the value premium when the disasters materialize in the sample. Our model provides a peso-based explanation of the cross-section of average returns.

The mechanism in our model highlights nonlinearity between the pricing kernel and the aggregate market returns. When the disasters are not materialized, an econometrician would misestimate the sensitivity of stock returns to aggregate shocks, based on only observations in normal times. However, value premium still arises in normal times because the representative agent fears the realization of a disaster and hence he demands a value premium to hold value stocks, which are more adversely affected during disasters. As a result, the CAPM fails to explain the value premium in normal times. While the disasters materialize in a sample, value stocks will be more adversely affected because of their unproductive capital and adjustment costs. These are manifested as larger drops (jumps) of value stock returns when the economy enters (exits) a disaster state, relative to growth stock returns. Observing those, the econometrician is able to more accurately estimate the risks embodies in value and growth stocks. Consequently, the CAPM could explain the value premium for a sample with disasters materialized.

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